

Package ‘BayesianFROC’

July 2, 2020

Type Package

Title FROC Analysis by Bayesian Approaches

Version 0.3.0

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Description Execute `BayesianFROC::fit_GUI_Shiny()` (or `fit_GUI_Shiny_MRMC()`) for a graphical user interface via Shiny. Provides new methods for the so-called Free-response Receiver Operating Characteristic (FROC) analysis. The ultimate aim of FROC analysis is to compare observer performances, which means comparing characteristics, such as area under the curve (AUC) or figure of merit (FOM). In this package, we only use the notion of AUC for modality comparison, where by “modality”, we mean imaging methods such as Magnetic Resonance Imaging (MRI), Computed Tomography (CT), Positron Emission Tomography (PET), ..., etc. So there is a problem that which imaging method is better to detect lesions from shadows in radiographs. To solve modality comparison issues, this package provides new methods using hierarchical Bayesian models proposed by the author of this package. Using this package, one can obtain at least one conclusion that which imaging methods are better for finding lesions in radiographs with the case of your data. Fitting FROC statistical models is sometimes not so good, it can easily confirm by drawing FROC curves and comparing these curves and the points constructed by False Positive fractions (FPFs) and True Positive Fractions (TPFs), we can validate the goodness of fit intuitively. Such validation is also implemented by the Chi square goodness of fit statistics in the Bayesian context which means that the parameter is not deterministic, thus by integrating it with the posterior predictive measure, we get a desired value. To compare modalities (imaging methods: MRI, CT, PET, ... , etc), we evaluate AUCs for each modality. FROC is developed by Dev Chakraborty, his FROC model in his 1989 paper relies on the maximal likelihood methodology. The author modified and provided the alternative Bayesian FROC model. Strictly speaking, his model does not coincide with models in this package. In FROC context, we means by multiple reader and multiple case (MRMC) the case of the number of reader or modality is two or more. The MRMC data is available for functions of this package. I hope that medical researchers use not only the frequentist method but also alternative Bayesian methods. In medical research, many problems are considered under only frequentist methods, such as the notion of p-values. But p-value is sometimes misunderstood. Bayesian methods provide very simple, direct, intuitive answer for research questions. Combining frequentist methods with Bayesian methods, we can obtain more reliable answer for research questions. Please execute the following R scripts from the R (R studio) con-

sole, demo(demo_MRMC, package = ``BayesianFROC"); demo(demo_srsc, package = ``BayesianFROC"); demo(demo_stan, package = ``BayesianFROC"); demo(demo_drawcurves_srsc, package = ``BayesianFROC"); demo_Bayesian_FROC(); demo_Bayesian_FROC_without_pause(). References: Dev Chakraborty (1989) <doi:10.1118/1.596358> Maximum likelihood analysis of free - response receiver operating characteristic (FROC) data. Pre-print: Issei Tsunoda; Bayesian Models for free-response receiver operating characteristic analysis.

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Imports knitr, readxl, xlsx, stats, graphics, tcltk, grDevices, ggplot2, methods, car, crayon, DiagrammeR, bridgesampling, rhandsontable, shiny, pracma, shinydashboard, shinythemes

Suggests openxlsx, hexbin, MASS, ggmcmc, magrittr, markdown

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AFROC

*AFROC curve (alternative free-response ROC curve)***Description**

An AFROC curve is a plane curve whose area under the curve (AUC) indicates an observer performance ability. In the following, $\Phi()$ denotes the cumulative distribution function on the standard Gaussian distribution.

The so-called *AFROC* curve is defined by

$$(\xi(t), \eta(t)) = (1 - e^{-t}, \Phi(b\Phi^{-1}(\exp(-t)) - a))$$

for all $t > 0$ and some fixed real numbers a, b .

By specifying two real numbers a and b , we can plot an AFROC curve.

The area under the AFROC curve, or briefly AUC, is calculated as follows, which are used to evaluate how physicians detect lesions in radiographs.

$$AUC = \int \eta(t) d\xi(t) = \frac{a}{\sqrt{1+b^2}}.$$

Note that the so-called FROC curve can be interpreted as the curve of expectations of data points. On the other hand, AFROC curve cannot be interpreted as the fitted curve, but its AUC is finite. Because AFROC can be obtained by modifying FROC curve, it reflects observer performance.

Usage

AFROC(t, a = 0.14, b = 0.19, x.coordinate.also = FALSE)

Arguments

t A real number which moves in the domain of FROC curve
a, b One of the parameter of model which characterize AFROC curve
x.coordinate.also Logical, whether a vector of $1 - \exp(-t)$ is included in a return value.

Value

if x.coordinate.also = TRUE, then A list, contains two vectors as x,y coordinates of the AFROC curve for drawing curves. if x.coordinate.also = FALSE, then return is a vector as y coordinates of the AFROC curve excluded its x-coordinates. (x coordinates is omitted.)

Examples

```

#=====
#           Plot AFROC curve
#=====

tt <- seq(0, 1, length.out = 111)
ttt <- stats::runif(1000,0.001,100)
t <- c(tt,ttt)
a <- AFROC(t,x.coordinate.also=TRUE)

plot(a$x,a$y)

# We note that the x-coordinates of AFROC curve is not t but  $x = 1 - \exp(-t)$ .
# To emphasize that x-coordinates is not t, we prepare the another example

#=====
#           Plot AFROC curve
#=====

tt <- seq(0, 1, length.out = 111)
ttt <- stats::runif(1000,0.001,100)
t <- c(tt,ttt)
y <- AFROC(t,x.coordinate.also=FALSE)

plot(1-exp(-t),y)

```

AFROC_curve

FROC curve as an embedding map

Description

FROC curve as an embedding map

Usage

```
AFROC_curve(x, a = 0.13, b = 0.19)
```

Arguments

x	A real number which moves in the domain of FROC curve
a	a generated parameter of model which characterize AFROC curve
b	a generated parameter of model which characterize AFROC curve

Details

Technique of plotting AFROC is difficult because it has two points in which the gradients are infinity and it causes the following warnings. Revised 2019 Nov. 20

Warning messages: 1: In stats::qnorm(exp(1 - x)) : NaNs produced 2: In stats::qnorm(exp(1 - x)) : NaNs produced 3: Removed 50 rows containing missing values (geom_path).

Value

none

Examples

```
# This function is under construction.
x <- runif(1000,1,10)
y <- AFROC_curve(x)
plot(x,y)
```

array_easy_example *Example array*

Description

Make a three dim array whose component is its index. For example

$a[2, 3, 4] = 234$

Usage

```
array_easy_example(I = 2, J = 3, K = 4)
```

Arguments

I	natural number less than 10
J	natural number less than 10
K	natural number less than 10

Value

An array of three dimension.

Examples

```
a <-array_easy_example(2,3,4)
```

```
array_of_hit_and_false_alarms_from_vector
```

Array of hits and false alarms; 2019 Jun 18

Description

Return value is a three dimensional array of type $[C,M,Q]$ representing the number of confidence levels and modalities and readers, respectively. This array includes the number of hit and the number of false alarms.

Revised 2019 Nov. 20

Usage

```
array_of_hit_and_false_alarms_from_vector(dataList)
```

Arguments

`dataList` A list, consisting of the following R objects: `m`, `q`, `c`, `h`, `f`, `NL`, `C`, `M`, `Q` each of which means from the right

- `m` : A vector, indicating the modality ID = 1,2,... which does not include zero.
- `q` : A vector, indicating the reader ID = 1,2,... which does not include zero.
- `c` : A vector, indicating the confidence = 1,2,... which does not include zero.
- `h` : A vector, indicating the number of hits
- `f` : A vector, indicating the number of false alarm
- `NL` : An positive integer, indicating the number of lesions for all images
- `C` : An positive integer, indicating the highest number of confidence level
- `M` : An positive integer, indicating the number of modalities
- `Q` : An positive integer, indicating the number of readers.

The detail of these dataset, please see the example datasets, e.g. [dd](#).

Details

The author also implemented this in the [metadata_to_fit_MRMC](#) which is an old version. However, the old version uses "for" sentences, and it is not so better. On the other hand, this function use the function [aperm\(\)](#) and [array\(\)](#) and they are better than "for" sentence.

Revised 2019 Nov. 20 Revised 2019 Dec. 12

Value

A list, whose components are arrays of the number of hits h and the number of false alarms f of dimension $[c, M, Q]$. Do not confuse $[c, Q, M]$ or $[M, Q, C]$, etc. Revised 2019 Nov. 20

See Also

[Chi_square_goodness_of_fit_in_case_of_MRMC_Posterior_Mean](#)

Examples

```
#-----
#                               Validation of program
#-----

h1 <- array_of_hit_and_false_alarms_from_vector(dd)$harray
h2 <- metadata_to_fit_MRMC(dd)$harray

h1 == h2

f1 <- array_of_hit_and_false_alarms_from_vector(dd)$farray
f2 <- metadata_to_fit_MRMC(dd)$farray

f1 == f2

#-----
#                               subtraction for ( hit - hit.expected)
#-----
# In the chi square calculation,
# we need to subtract expected value of hit from hit rate,
# thus the author made this function.

## Not run:

# Prepare example data

dd <- BayesianFROC::dd

# Fit a model to data

fit <- fit_Bayesian_FROC( dataList = dd,
                        ite = 1111 )

# Extract a collection of expected hits as an array
```

```
harray.expected <- extract_EAP_by_array(fit,ppp)*dd$NL

# Prepare hit (TP) data as an array

harray <- array_of_hit_and_false_alarms_from_vector(dd)$harray

# Calculate the difference of hits and its expectation..

Difference <- harray - harray.expected

# The above calculation is required in the chi square goodness of fit

#=====
#                               array format hit and false
#=====

harray <- array_of_hit_and_false_alarms_from_vector(dataList = ddd)$harray
farray <- array_of_hit_and_false_alarms_from_vector(dataList = ddd)$farray

## End(Not run)
```

Description

This is for the author.

Usage

```
Author_vs_classic_for_AUC(StanS4class)
```

Arguments

StanS4class An S4 object of class `stanfitExtended` which is an inherited class from the S4 class `stanfit`. This R object is a fitted model object as a return value of the function `fit_Bayesian_FROC()`.
It can be passed to `DrawCurves()`, `ppp()` and ... etc

Value

AUCs

Author(s)

Issei Tsunoda

BayesianFROC

Theory of FROC Analysis via Bayesian Approaches

Description

The object of this note will be to show that the author's generative FROC model which is obtained by sharpening the classical FROC model so that new model can generate data of TPs.

The crucial difference of the author's model and the classical Chakraborty's model is that the former is a '*generative*' model but the later is "not." In the general theory of Statistic, the fake data synthesized from models are important. Thus, the author made such generative models and implements these models in the package.

The following two **Shiny** basfed GUIs are available.

`fit_GUI_Shiny()` GUI for a single reader and single modality

`fit_GUI_Shiny_MPMC()` GUI for multiple readers and multiple modalities

The aim of FROC analysis is to compare imaging *modalities*, which are imaging methods such as MRI, CT, PET, etc. We want to find an imaging method with which we can find more many lesions in radiographs.

To investigate modality comparison, we have to do a trial in order to obtain a dataset consisting of *TP* and *FP*.

Details

Here is what this package implements.

Overview of FROC analysis

In general data-analysis such as generalized linear models, the data can be plotted such as scatter plot, and we fit a model to the data such that the model can be visualized as an expected curve of data. And we can check how model fits to data intuitively. This procedure is available in the FROC paradigm. First, FROC data are plotted as scatter plot, each point is a pair of the so-called *false positive fraction (FPF)* and *true positive fraction (TPF)*. And the fitted curve to this scatter plot is called *FROC curve*. However, the FROC curve has an infinite area under the curve (AUC), thus we modify the curve so that the AUC of modified curve has finite AUC, more precisely between zero and one. The modified curve is called *AFROC curve*. Using the AUC of AFROC curve, we evaluate the observer performance. Namely, high AUC means physicians can find more lesions in x-ray films.

To compare imaging modalities such as MRI, CT, PET, etc, we do a **trial** from which **Data** arise and we fit a **model** to the data. Using the resulting model, we can compare modalities or evaluate the observer performance based on AUC.

In the sequel, we give a complete description about the following three terms.

Trial from which data arise.

Data consist of the number of TPs and FPs.

Modeling calculates the probability law in which data (TPs and FPs) arise

Trial .

To introduce FROC trial, let us consider the following terms.

A reader (in other words, player) who is a physician or radiologist challenges to find lesions (in other words, it is called signals, targets, nodules, ...) from radiographs.

images (in other words, radiographs, x-ray films such as CT, MRI, PET, etc.) containing shadows (not necessarily caused by lesions). We assume that N_L lesions make shadows as targets. (Note that each image can contain one more lesions and this multiple signals for a single image distinct FROC trial from the ordinal ROC trial). The number of images are denoted by N_I .

A researcher (in other words, data-analyst) knows true lesion locations (signal) and she can count reader's True Positives and False Positives after his lesion finding task.

For the sake of simplicity, we consider a single reader.

Throughout this explanation, we follow the convention that readers are male and the researcher is female. So, "he" means the reader, and "she" means a data-analyst.

FROC trial and data

The following table is a dataset to be fitted a model.

Let us see how it arises.

confidence level	No. of false alarms (FP:False Positive)	No. of hits (TP:True Positive)
------------------	--	-----------------------------------

<i>definitely</i> present	5	F_5	H_5
<i>probably</i> present	4	F_4	H_4
equivocal	3	F_3	H_3
subtle	2	F_2	H_2
<i>very</i> subtle	1	F_1	H_1

Suppose that **Bob** is a reader (physician) and **Alice** is a researcher (Data-analyst).

A "Hi, Bob."

B "Hi, Alice"

A "Now, there are radiographs."

B "What are you gonna do today?"

A "Ahem, now, I evaluate your observer performance ability, namely ability of finding lesions from radiographs."

B "Seriously? Duh..."

He was disappointed because he wanted to yada yada yada with her.

A "Find the tumors from these images and I check your answer, by assigning a true positive or a false positive to your answer."

Alice gave Bob the first image (radiograph).

B "OK! Let's start. Hmmm ... Hmmm... It seems to me that the first image contains two suspicious tumors."

A "Localize your two suspicious tumors locations in the first image."

She gave him a pen.

B "OK! ... Swish, Swish"

He marked two locations in the first image.

A "In addition, assign your *confidence levels* to your two suspicious tumors."

B "How?"

A "It is a number, 1,2,3,4,5. If you think a shadow is *definitely* tumor, then you choose 5. Similarly, 4 is *probably*, ..., 2 is *subtle*, 1 is *very subtle*."

	confidence level
<i>definitely</i> present	5
<i>probably</i> present	4
equivocal	3
subtle	2
<i>very</i> subtle	1

B "OK! Now, I doubt two shadows are tumors, thus I need two ratings. I think that one is *absolutely*

tumor, so I rate 5 for this shadow. On the other hand, for the another shadow, I think that it is *probably* a tumor, so I rate 3 for it."

Swish, Swish, He rated for his two suspicious locations. Namely, he associated his confidence levels for his localizing shadows.

A "Let's check your answer for the first image! Your first suspicious tumor with rating 5 is correctly localized."

B "I did it! Yay! Hooray!! Woohoo!!! Booyah!!!!!"

A " But your second suspicious shadow localized with rating 3 is not correct, so,..., it is not a tumor."

B "Oops, I did it."

A "Moreover, in the first image, there are several tumors being not detected and we ignore them in this FROC trial."

B "Oopsies. Gah!"

A "So, now, you have one hit with rating 5 and one false alarm with rating 3 as following table. Next, we will work for the second images."

FROC data of the first image

	confidence level	No. of false alarms (FP:False Positive)	No. of hits (TP:True Positive)
<i>definitely present</i>	5	$F_5=0$	$H_5 = 1$ <- attention please
<i>probably present</i>	4	$F_4=0$	$H_4=0$
<i>equivocal</i>	3	$F_3 = 1$ <- attention please	$H_3=0$
<i>subtle</i>	2	$F_2=0$	$H_2=0$
<i>very subtle</i>	1	$F_1=0$	$H_1=0$

Alice gave Bob the second image (radiograph).

B "In the second image, I think there are three suspicious shadows."

A "OK, localize your suspicious locations."

B "Swish Swish Swish"

Bob localized his three suspicious locations.

A "OK, rate your confidence level for each localized shadow."

B "The first shadows is 3, the second shadow is 5, the third shadows is 2."

A "OK, I check your answer. So, the answer is true, true, false."

B. " Uh-huh, mm hm"

A "So, in the second image you have one hits with confidence level 3 and one hits with rating 5 and one false alarms with rating 2. Combining the first image and the second image, now, you have two hits with rating 5, and one hit with rating 3, and one false alarm with rating 2 and one false alarm with rating 3. Next, we consider the third image."

FROC data of the 1st and 2nd images

	confidence level	No. of false alarms (FP:False Positive)	No. of hits (TP:True Positive)
<i>definitely</i> present	5	$F_5 = 0$	$H_5 = 1 + 1$
<i>probably</i> present	4	$F_4 = 0$	$H_4 = 0$
equivocal	3	$F_3 = 1$	$H_3 = 1$
subtle	2	$F_2 = 1$	$H_2 = 0$
<i>very</i> subtle	1	$F_1 = 0$	$H_1 = 0$

#'

Alice and Bob did this trial for all images, and they summarized the number of hits and false alarms in the following table.

FROC data over all images

NI=63, NL=124 In R console ->	confidence level c	No. of false alarms f	No. of hits h
<i>definitely</i> present	c[1] = 5	f[1] = $F_5 = 1$	h[1] = $H_5 = 41$
<i>probably</i> present	c[2] = 4	f[2] = $F_4 = 2$	h[2] = $H_4 = 22$
equivocal	c[3] = 3	f[3] = $F_3 = 5$	h[3] = $H_3 = 14$
subtle	c[4] = 2	f[4] = $F_2 = 11$	h[4] = $H_2 = 8$
<i>very</i> subtle	c[5] = 1	f[5] = $F_1 = 13$	h[5] = $H_1 = 1$

A "Phew, I summarized the evaluation in the following table"

B ."How kind of you!"

A "Phew, you are finished for the day. Sayonara, Bob!"

B "Boo!"

He was impatient because, today, he wanted to yada yada yada with her.

B "Hey, Alice"

A "!?"

B "Hey, I am done at work now, so I am free to yada yada yada with you today!!"

A "Eww, today, I cannot, cuz I have to fit a FROC model to the data and draw a fitted FROC curve and calculate AUC to evaluate your observer performance ability!"

B "Ugh,...., Duh"

Unfortunately, Bob's yada yada plan was a complete failure. Amen.

1. **First trial start** The researcher gives the reader the *first* image which contains suspicious shadows, each of which is noise or lesion.
2. **LESION FINDING TASK for the first image (trial)** The reader marks (localizes) his suspicious locations of shadow (multiple answer is allowed) each of which is also assigned a *integer* indicating his *confidence* levels (if he thinks some shadow is obviously a lesion, then he gives a higher integer with respect to the shadow). So, reader marks two things: location and confidence for each suspicious shadow.
3. **Second trial and LESION FINDING TASK for the second image (trial)** The researcher gives the reader the second image and reader does the above LESION FINDING TASK for the second image.
4. **repeat this trial for all images.** The reader do the *LESION FINDING TASK* for all images
5. **evaluation of TP and FP** The researcher count the number of their true marking positions (*hit*) and false making positions (*false alarm*).

Consequently, we obtain the following table.

Example data and its Format:

A single reader and a single modality case

NI=63, NL=124 In R console ->	confidence level c	No. of false alarms f	No. of hits h
<i>definitely</i> present	c[1] = 5	f[1] = $F_5 = 1$	h[1] = $H_5 = 41$
<i>probably</i> present	c[2] = 4	f[2] = $F_4 = 2$	h[2] = $H_4 = 22$
equivocal	c[3] = 3	f[3] = $F_3 = 5$	h[3] = $H_3 = 14$
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<i>very</i> subtle	c[5] = 1	f[5] = $F_1 = 13$	h[5] = $H_1 = 1$

We use two notations for the same number of FPs, e.g., one is f[1] and the other is F_5 . We use the former f[1] for programming and the later F_5 is used for descriptions of the theory.

This is the biggest failure of my programming. I regretted that I should be define so that f[c] is F_c for all c. Too late to fix. Ha,,, I regret...damn.

By the R code `BayesianFROC::viewdata(BayesianFROC::dataList.Chakra.1.with.explanation)`, we can see example data named "dataList.Chakra.1.with.explanation".

Modeling 1. Traditional way Let us denotes the model parameter to be estimated by θ_c, μ, σ .

Define

$$p_c(\theta) := \int_{\theta_c}^{\theta_{c+1}} \text{Gaussian}(z|\mu, \sigma) dz,$$

$$q_c(\theta) := \int_{\theta_c}^{\theta_{c+1}} \frac{d}{dz} \log \Phi(z) dz.$$

Note that $\theta_0 := -\infty$.

We extend the vector from $(H_c)_{c=1,2,\dots,C}$ to $(H_c)_{c=0,1,2,\dots,C}$, where $H_0 := N_L - (H_1 + H_2 + \dots + H_C)$.

Then, we assume

$$(H_c)_{c=0,1,2,\dots,C} \sim \text{Multinomial}((p_c)_{c=0,1,2,\dots,C})$$

and

$$F_c \sim \text{Poisson}(q_c(\theta)N_I).$$

Recall that N_I denotes the number of images (radiographs, such as X-ray films) and N_L the number of lesions (signals, nodules,).

Finish! Very simple! fuck! Gratias! We should credo in unum model. Here, we use the logic of latent variable, so I am tired you know what it is. Dona nobis pacem.

This is a very important and the author will copy and paste this in three times ha.

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Define

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$$q_c(\theta) := \int_{\theta_c}^{\theta_{c+1}} \frac{d}{dz} \log \Phi(z) dz.$$

Note that $\theta_0 := -\infty$.

We extend the vector from $(H_c)_{c=1,2,\dots,C}$ to $(H_c)_{c=0,1,2,\dots,C}$, where $H_0 := N_L - (H_1 + H_2 + \dots + H_C)$.

Then, we assume

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and

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Recall that N_I denotes the number of images (radiographs, such as X-ray films) and N_L the number of lesions (signals, nodules,).

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$$q_c(\theta) := \int_{\theta_c}^{\theta_{c+1}} \frac{d}{dz} \log \Phi(z) dz.$$

Note that $\theta_0 := -\infty$.

We extend the vector from $(H_c)_{c=1,2,\dots,C}$ to $(H_c)_{c=0,1,2,\dots,C}$, where $H_0 := N_L - (H_1 + H_2 + \dots + H_C)$.

Then, we assume

$$(H_c)_{c=0,1,2,\dots,C} \sim \text{Multinomial}((p_c)_{c=0,1,2,\dots,C})$$

and

$$F_c \sim \text{Poisson}(q_c(\theta)N_I).$$

Recall that N_I denotes the number of images (radiographs, such as X-ray films) and N_L the number of lesions (signals, nodules,).

Finish! Very simple! fuck! Gratias! We should credo in unum model. Here, we use the logic of latent variable, so I am tired you know what it is. Dona nobis pacem. #'

Modeling 2 the author'S redandunt way

Our goal now is to define a model of the random variables H_c, F_c , namely, to give a family of probability law of H_c, F_c .

Let

$$X(\omega) := (H_1(\omega), H_2(\omega), H_3(\omega), H_4(\omega), H_5(\omega), F_1(\omega), F_2(\omega), F_3(\omega), F_4(\omega), F_5(\omega))$$

be a random variable from a probability space $(\Omega, \sigma - \text{field}, P_{truth})$ to N^{10} which denotes the set of 10-dimensional non-negative integers, where ω denotes an element of Ω .

We have to find a family of probability spaces, consisting three tuples $(\Omega, \sigma - \text{field}, P_\theta)$. In other words, what we want is to define a family of likelihoods $(\pi(x|\theta))_{\theta \in \Theta}$ such that for any event E of a subset of N^{10} , such that the following equation holds

$$P_\theta(X^{-1}E) = \int_E \pi(x|\theta)dx.$$

where $X^{-1}E$ denotes the pre-image of E and x is an element of N^{10} as a realization of the random variable X . The quantity of the last equation is the so-called image measure (or push-forward measure) of the random variable X . The space Ω is abstract, on the otherhand the space of non-negative integers are very familiar, so we use the push-forward measure rather than the measure on Ω . More explicitly, if we write the realization of the random variable X by $x = (h, f) = (h_1, h_2, h_3, h_4, h_5, f_1, f_2, f_3, f_4, f_5)$, then the above equation is

$$P_\theta(X^{-1}E) = \int_E \pi(h_1, h_2, h_3, h_4, h_5, f_1, f_2, f_3, f_4, f_5|\theta)dh_1h_2h_3h_4h_5f_1f_2f_3f_4f_5.$$

or briefly

$$P_\theta(X^{-1}E) = \int_E \pi(h, f|\theta)dhd f.$$

This is an elementary formula of push-forward measure. In this package, using Stan, we estimates the parameter θ^* so that the two probability measures P_{θ^*} and P_{truth} is close in some sense. Many statistical methods use the Kullback-Leibler divergence to evaluate the distance of the probability measures. Of course, we can never know the probability measure P_{truth} belongs to the family of models P_θ or not.

Ha, multiple chemical sensitivity is very very very veryvery.

Modeling by reducing to easy case as a first step

First, we shall discuss our model **rigorously** (ignore the confidence). First, to simplify our argument, first we reduce the FP and TP dataset from H_c, F_c to H, F by ignoring the confidence level. Suppose that there are N_L targets (signal), and radiological context, target is lesion. Suppose that a radiologist try to find these lesions from radiographs. Suppose that now, **the reader find H lesions** from radiographs which contains N_L lesions, then it is natural to assume that

$$H \sim \text{Binomial}(\theta_H, N_L)$$

where, θ_H denotes the Bernoulli success rate is one of parameter for our model, which should be estimated. Of course $0 < \theta_H < 1$.

In addition, suppose that **the reader fails F times**, namely, the reader marked F locations in radiographs each of which is not a true lesion location. In other words, the reader marked F false positives. Then it is natural to assume that

$$F \sim \text{Poisson}(\theta_F)$$

where, θ_F is also an another parameter of model, which should be estimated from given data. So, our model has a vector θ_H, θ_F as a model parameter.

The above two is very simple, since data is only H, F , indicating the number of TP and the number of FP.

Unfortunately, the FROC data is more complex than above, namely, we have to take account the confidence levels, and so we have to make a model for data $F_c, H_c, c = 1, \dots, 5$ instead of the above simplified data H, F . That is, reader answers with his confidence level for each suspicious location, which is usually an integer such as 1, 2, 3, 4, 5.

We give a probability law for the random variables F_c and H_c for $c = 1, \dots, 5$.

Suppose that there are N_L targets, and radiological context, each target is a lesion contained in N_I Radiographs. Suppose that a radiologist try to find lesions. Suppose that now, he found H_c lesions with his c -th confidence, then we assume that each random variable H_c is distributed by the following law.

$$H_5 \sim \text{Binomial}(p_5(\theta), N_L)$$

$$H_4 \sim \text{Binomial}\left(\frac{p_4(\theta)}{1 - p_5(\theta)}, N_L - H_5\right)$$

$$H_3 \sim \text{Binomial}\left(\frac{p_3(\theta)}{1 - p_5(\theta) - p_4(\theta)}, N_L - H_5 - H_4\right)$$

$$H_2 \sim \text{Binomial}\left(\frac{p_2(\theta)}{1 - p_5(\theta) - p_4(\theta) - p_3(\theta)}, N_L - H_5 - H_4 - H_3\right)$$

$$H_1 \sim \text{Binomial}\left(\frac{p_1(\theta)}{1 - p_5(\theta) - p_4(\theta) - p_3(\theta) - p_2(\theta)}, N_L - H_5 - H_4 - H_3 - H_2\right)$$

where, hit rates $p_1(\theta), p_2(\theta), p_3(\theta), p_4(\theta)$ and $p_5(\theta)$ are some functions of a model parameter θ . We also denote them simply by p_c instead of $p_c(\theta), c = 1, 2, 3, 4, 5$. In addition, suppose that the reader fails in F_c times with his c -th confidence, that is, the reader localized F_c false locations in radiographs with his c -th confidence. Then it is natural to assume that

$$F_5 \sim \text{Poisson}(q_5(\theta)N_X)$$

$$F_4 \sim \text{Poisson}(q_4(\theta)N_X)$$

$$F_3 \sim \text{Poisson}(q_3(\theta)N_X)$$

$$F_2 \sim \text{Poisson}(q_2(\theta)N_X)$$

$$F_1 \sim \text{Poisson}(q_1(\theta)N_X)$$

where, $N_X = N_I$ or N_L and we fix it for the duration of the paper.

The false rates $q_1(\theta)$, $q_2(\theta)$, $q_3(\theta)$, $q_4(\theta)$ and $q_5(\theta)$ are functions of a parameter of model.

The above model gives the probability law for the the random variables $H_c, F_c, c = 1, 2, \dots, C$, indicating the number of TP and the number of FP for each confidence level $c = 1, 2, \dots, C$.

We define $p_c(\theta)$ and $q_c(\theta)$ in terms of the model parameter $\mu, \sigma, \theta_c, c = 1, 2, \dots, C$.

$$p_c(\theta) = \int_{\theta_c}^{\theta_{c+1}} \text{Gaussian}(z|\mu, \sigma) dz$$

$$q_c(\theta) = \int_{\theta_c}^{\theta_{c+1}} \frac{d}{dz} \log \Phi(z) dz$$

We use the abbriviations p_c and q_c for $p_c(\theta)$ and $q_c(\theta)$.

For any given dataset, we will estimate the model parameter vector θ ;

$$\theta = (\theta_1, \theta_2, \dots, \theta_C; \mu, \sigma).$$

Intuitively, the reason why we choose such functions for $p_c(\theta)$ is the assumption that each lesion is equipped with i.i.d. latent variable, X distributed by $\text{Gaussian}(z|\mu, \sigma)$, and if X associated to some lesion falls into the interval $\theta_c < X < \theta_{c+1}$, then we consider that the reader marks this lesion with his c -th confidence level. In order to emphasize that each X is associated to some l -th lesion, $l = 1, 2, \dots, N_L$ we denote the latent variable by X_l for the l -th lesion instead the latent decision variable X . Here, we uses *latent* to means that the variable X cannot be observed. Since the latent variable relates decision of reader, and thus, in this context the latent variable is called a *decision* variable.

Similarly, suppose that each image (radiograph) is associated some latent variable Y distributed by $N_I \frac{d}{dz} \Phi(z)$ and if the Y associated to some image falls into interval the interval $\theta_c < Y < \theta_{c+1}$, then we consider that the reader will false decision with his c -th confidence level for the image.

Fundamental equations

The reason why we use the hit rates such as $\frac{p_2}{1-p_5-p_4-p_3}$ instead of p_c is that it ensures the equality $E[\frac{H_c}{N_L}] = p_c$. This equality is very important to establish Bayesian FROC theory so that it is compatible with the classical FROC theory. As an immediate consequence of the definition of hit rates, we have,

$$E\left[\frac{H_c}{N_L}\right] = p_c,$$

$$E\left[\frac{F_c}{N_X}\right] = q_c,$$

where E denotes the expectation and N_X is the number of lesion or the number of images and q_c is a false alarm rate, namely, $F_c \text{ Poisson}(N_X q_c)$.

More precisely or to express the above with model parameter explicitly, we should rewrite it as follows.

$$E_\theta\left[\frac{H_c}{N_L}\right] = p_c(\theta),$$

$$E_\theta\left[\frac{F_c}{N_X}\right] = q_c(\theta),$$

where $E_\theta[X]$ denotes the expectation of a random variable X with the likelihood $\pi(\omega|\theta)$ for data ω parameter θ , namely,

$$E_\theta[X] := \int X(\omega)P_\theta(d\omega) = \int x\pi(x|\theta)dx$$

So, the above two equations are rewritten as follows.

$$E_\theta\left[\frac{H_c}{N_L}\right] := \int \frac{H_c(\omega)}{N_L} P_\theta(d\omega) = \int \frac{h_c}{N_L} \pi(h, f|\theta) dhdf = p_c(\theta),$$

$$E_\theta\left[\frac{F_c}{N_X}\right] := \int \frac{F_c(\omega)}{N_X} P_\theta(d\omega) = \int \frac{f_c}{N_X} \pi(h, f|\theta) dhdf = q_c(\theta).$$

What redundant explanation!

These two family of equations are most important one, and the author made this model to satisfy this. Using these equations, we can define the FROC curve such that the curve can be interpreted as the points of expectations.

We call these equations the **fundamental equations** of FROC analysis. Using this, we can calculate the expectations of FPF and TPF in the later.

The new model by the author is a generative model The classical model can not synthesize dataset so that the total number of hits is bounded from above by the number of lesions.

Love The new model is made with great love of the author and poor condition and poor books (to tell the truth, I did not read any books when I made a prototype) without any support of money.

A details of model The formulation of hit rate differs from the classical theory.

The new model excludes the number of images The formulation of false rate differs from the classical theory and it allows us to exclude the number of images from modeling.

A multiple chemical sensitivity The author diseased the serious , so,,, the author is a patient of the chemical sensitivity, which make his life of quality much lower.

A multiple chemical sensitivity The author diseased the serious , so,,, the author is a patient of the chemical sensitivity, which make his life of quality much lower.

#' Using the above two equations, we can establish the alternative Bayesian FROC theory preserving classical notions and formulas.

To fit a model to any dataset, we use the code:

```
fit_Bayesian_FROC() Fit a model to data
dataList.Chakra.2 Example data in Chakraborty 1989 paper
dataList.Chakra.3 Example data in Chakraborty 1989 paper
dataList.Chakra.4 Example data in Chakraborty 1989 paper
```

Priors on the Model Parameter.

Recall that our model has the following parameter.

$$\theta = (\theta_1, \theta_2, \dots, \theta_C; \mu, \sigma).$$

In this section, we give priors on this parameter. Only one necessarily prior is to ensure the monotonicity on the thresholds parameters.

$$\theta_1 < \theta_2 < \dots < \theta_C.$$

To give this monotonicity, we have to assume UNDER CONSTRUCTION

Recall that the number of false alarms is distributed by Poisson with rate

$$q_c(\theta) = \log \frac{\Phi(\theta_{c+1})}{\Phi(\theta_c)}$$

Visualization of TP, FP by FPF, TPF

How to visualize our data constructed by hit and false alarms, that is, TP and FP? Traditionally, the so-called FPF;*False Positive Fraction* and TPT;*True Positive Fraction* are used. Recall that our data format:

A single reader and a single modality case auxiliary: number of images and lesions NI , NL ———

	confidence level	No. of false alarms (FP:False Positive)	No. of hits (TP:True Positive)
<i>definitely</i> present	5	F_5	H_5
<i>probably</i> present	4	F_4	H_4
equivocal	3	F_3	H_3
subtle	2	F_2	H_2
<i>very</i> subtle	1	F_1	H_1

In the above table, we introduce two kinds of random variables F_c H_c $c = 1, 2, 3, 4, 5$ which are non-negative integers and please keep in mind the notations because, from now on, we use them frequently throughout this paper.

Recall that *FPF* (*False Positive Fraction*) is defined as follows;

$$\begin{aligned} FPF(5) &:= \frac{F_5}{N_I}, \\ FPF(4) &:= \frac{F_4 + F_5}{N_I}, \\ FPF(3) &:= \frac{F_3 + F_4 + F_5}{N_I}, \\ FPF(2) &:= \frac{F_2 + F_3 + F_4 + F_5}{N_I}, \\ FPF(1) &:= \frac{F_1 + F_2 + F_3 + F_4 + F_5}{N_I}. \end{aligned}$$

Similarly, *TPF* (*True Positive Fraction*) is defined as follows;

$$\begin{aligned} TPF(5) &:= \frac{H_5}{N_L}, \\ TPF(4) &:= \frac{H_4 + H_5}{N_L}, \\ TPF(3) &:= \frac{H_3 + H_4 + H_5}{N_L}, \\ TPF(2) &:= \frac{H_2 + H_3 + H_4 + H_5}{N_L}, \\ TPF(1) &:= \frac{H_1 + H_2 + H_3 + H_4 + H_5}{N_L}. \end{aligned}$$

Combining TPF and FPF, we obtain the pairs.

$$\begin{aligned} &(FPF(1), TPF(1)), \\ &(FPF(2), TPF(2)), \\ &(FPF(3), TPF(3)), \\ &(FPF(4), TPF(4)), \\ &(FPF(5), TPF(5)). \end{aligned}$$

Plotting these five points in a two-dimensional plain, we can visualize our dataset..

In addition, connecting these points by lines, we obtain the so-called *empirical FROC curve*.

interpretation of the empirical FROC curve

In fact, if a reader (physician) has a high signal detection ability, namely, he can find more lesions in Radiographs (image), then the number of TPs denoted by H_1, H_2, H_3, H_4, H_5 will be more and more greater. Thus, the

$TPF(1), TPF(2), TPF(3), TPF(4), TPF(5)$

is also greater. Consequently, the points

$$(FPF(1), TPF(1)),$$

$$(FPF(2), TPF(2)),$$

$$(FPF(3), TPF(3)),$$

$$(FPF(4), TPF(4)),$$

$$(FPF(5), TPF(5)).$$

are located in upper positions. *This indicates that the high observer performance leads the empirical FROC curve to be more upper positions in the plane.*

Visualization of our model by curve

In this section, we provides the so-called *FROC curve* which is our desired visualization of estimated model. Roughly speaking, **an FROC curve is expected pairs of FPF and TPF**. Namely, the points of FPF and TPF will be on FROC curve if model is well fitting to data. So, comparing the FROC curve and the FPF and TPF, we can evaluate our goodness of fit.

In the above, ha,... I want to die.

Define $x(c), y(c), c = 1, 2, 3, 4, 5$ by the expectations of FPF and TPF, respectively, namely,

$$x(c) := E[FPF(c)],$$

$$y(c) := E[TPF(c)].$$

for $c = 1, 2, 3, 4, 5$.

Using the formulas $E_\theta[\frac{H_c}{N_L}] = p_c(\theta), E_\theta[\frac{F_c}{N_X}] = q_c(\theta)$, we can rewrite them in terms of the parameters μ, σ of the latent Gaussian, as follows.

$$x(c) = E[FPF(c)] = \int_{\theta_c}^{\infty} \frac{d}{dz} \log \Phi(z) dz = -\log \Phi(\theta_c),$$

$$y(c) = E[TPF(c)] = \int_{\theta_c}^{\infty} \text{Gaussian}(z|\mu, \sigma) dz = \Phi\left(\frac{\theta_c - \mu}{\sigma}\right).$$

From the first equation, we obtain that $\theta_c = \Phi^{-1}(\exp(-x(c)))$. Substituting this into the second equation, it follows that

$$y(c) = \Phi\left(\frac{\Phi^{-1}(\exp(-x(c))) - \mu}{\sigma}\right).$$

This implies that the set of points $(x(c), y(c))$, $c = 1, 2, 3, 4, 5$ consisting of all expectations for the pair of FPF and TPF is contained in the following set:

$$\{(x, y)|y = \Phi\left(\frac{\Phi^{-1}(\exp(-x) - \mu)}{\sigma}\right)\}.$$

We can regard this set as an image of smooth curves, Namely, here we define the so-called FROC curve as a map from 1-dimensional Euclidean space to 2-dimensional Euclidean space, mapping each $t > 0$ to

$$(x(t), y(t)) = \left(t, \Phi\left(\frac{\Phi^{-1}(\exp(-t)) - \mu}{\sigma}\right)\right)$$

Because $x(t) = t$, $t > 0$ is not bounded, the area under the FROC curve is infinity.

To calculate alternative notion of AUC in the ordinal ROC theory, we define the so-called AFROC curve:

$$(\xi(t), \eta(t)) = \left(1 - e^{-t}, \Phi\left(\frac{\Phi^{-1}(\exp(-t)) - \mu}{\sigma}\right)\right)$$

which contained in the rectangular space $[0, 1]^2$. The area Under the (AFROC) curve (briefly, we call it AUC) represents the observer performance. For example, if radiologist detects more lesions with small False Positives (FPs), then AUC would be high.

Using the parameter of the signal distribution, we express AUC as follows,

$$AUC = \int \eta d\xi = \frac{\mu/\sigma}{\sqrt{1 + 1/\sigma^2}}.$$

Introducing new parameter $a := \mu/\sigma$ and $b := 1/\sigma$, we can also write

$$AUC = \frac{a}{\sqrt{1 + b^2}}.$$

Generalized Model

Until now, we use the following two

$$p_c(\theta) = \int_{\theta_c}^{\theta_{c+1}} \text{Gaussian}(z|\mu, \sigma) dz$$

$$q_c(\theta) = \int_{\theta_c}^{\theta_{c+1}} \frac{d}{dz} \log \Phi(z) dz$$

for hit rates and false alarm rates.

However, the explicit representations of these integrands of $p_c(\theta)$, $q_c(\theta)$ are not determined in a prior manner. So, such explicit representations are redundant for a general theory. So, to simplify

our argument in the following, we use general notations $P(z|\theta_P)$, $Q(z|\theta_Q)$ instead of the above two integrands $Gaussian(z|\mu, \sigma)$ and $\frac{d}{dz} \log \Phi(z)$, and rewrite them as follows,

$$p_c(\theta) = \int_{\theta_c}^{\theta_{c+1}} P(z|\theta_P) dz,$$

$$q_c(\theta) = \int_{\theta_c}^{\theta_{c+1}} Q(z|\theta_Q) dz.$$

In the sequel, we assume that $P(z|\theta_P)$ is a **probability density** function (namely, its total integral is one) and $Q(z|\theta_Q)$ is a **positive** function (not necessarily to be a probability function). Namely,

$$\int P(z|\theta_P) dz = 1,$$

for all θ_P and

$$Q(z|\theta_Q) > 0,$$

for all z and θ_Q .

A single reader and a single modality

NI=63, NL=124 In R console ->	confidence level c	No. of false alarms f	No. of hits h
<i>definitely</i> present	c[1] = 5	f[1] = $F_5 = 1$	h[1] = $H_5 = 41$
<i>probably</i> present	c[2] = 4	f[2] = $F_4 = 2$	h[2] = $H_4 = 22$
equivocal	c[3] = 3	f[3] = $F_3 = 5$	h[3] = $H_3 = 14$
subtle	c[4] = 2	f[4] = $F_2 = 11$	h[4] = $H_2 = 8$
<i>very subtle</i>	c[5] = 1	f[5] = $F_1 = 13$	h[5] = $H_1 = 1$

We give a probability law for the random variables F_c $H_c, c = 1, \dots, 5$.

Suppose that there are N_L targets, and radiological context, each target is a lesion contained in some Radiograph as a shadow. Suppose that a radiologist try to find lesions for N_I radiographs. Suppose that now, the radiologist fined H_c lesions with his c -th confidence, then we assume that

$$H_5 \sim Binomial(p_5(\theta), N_L)$$

$$H_4 \sim Binomial\left(\frac{p_4(\theta)}{1 - p_5(\theta)}, N_L - H_5\right)$$

$$H_3 \sim Binomial\left(\frac{p_3(\theta)}{1 - p_5(\theta) - p_4(\theta)}, N_L - H_5 - H_4\right)$$

$$H_2 \sim \text{Binomial}\left(\frac{p_2(\theta)}{1 - p_5(\theta) - p_4(\theta) - p_3(\theta)}, N_L - H_5 - H_4 - H_3\right)$$

$$H_1 \sim \text{Binomial}\left(\frac{p_1(\theta)}{1 - p_5(\theta) - p_4(\theta) - p_3(\theta) - p_2(\theta)}, N_L - H_5 - H_4 - H_3 - H_2\right)$$

where, hit rates $p_1(\theta)$, $p_2(\theta)$, $p_3(\theta)$, $p_4(\theta)$ and $p_5(\theta)$ are functions of a model parameter θ . In addition, suppose that the reader fails F_c times with his c -th confidence, that is, the reader marked F_c false positives. Then it natural to assume that

$$F_5 \sim \text{Poisson}(q_5(\theta)N_X)$$

$$F_4 \sim \text{Poisson}(q_4(\theta)N_X)$$

$$F_3 \sim \text{Poisson}(q_3(\theta)N_X)$$

$$F_2 \sim \text{Poisson}(q_2(\theta)N_X)$$

$$F_1 \sim \text{Poisson}(q_1(\theta)N_X)$$

where, $N_X = N_I$ or N_L false rates $q_1(\theta)$, $q_2(\theta)$, $q_3(\theta)$, $q_4(\theta)$ and $q_5(\theta)$ are functions of a parameter of model.

The above model calculates the event of the data H_c , F_c , $c = 1, 2, \dots, C$ arises, indicating the number of TP and the number of FP.

We use Gaussian distributions for the functions $p_c(\theta)$ and $q_c(\theta)$ as follows.

$$p_c(\theta) = \int_{\theta_c}^{\theta_{c+1}} P(z|\theta_P) dz$$

$$q_c(\theta) = \int_{\theta_c}^{\theta_{c+1}} Q(z|\theta_Q) dz$$

where the model parameter vector is

$$\theta = (\theta_1, \theta_2, \dots, \theta_C; \theta_P, \theta_Q).$$

Recall that FPF is defined as follows;

$$FPF(5) := \frac{F_5}{N_I},$$

$$FPF(4) := \frac{F_4 + F_5}{N_I},$$

$$FPF(3) := \frac{F_3 + F_4 + F_5}{N_I},$$

$$FPF(2) := \frac{F_2 + F_3 + F_4 + F_5}{N_I},$$

$$FPF(1) := \frac{F_1 + F_2 + F_3 + F_4 + F_5}{N_I}.$$

Similarly, TPF is defined as follows;

$$TPF(5) := \frac{H_5}{N_L},$$

$$TPF(4) := \frac{H_4 + H_5}{N_L},$$

$$TPF(3) := \frac{H_3 + H_4 + H_5}{N_L},$$

$$TPF(2) := \frac{H_2 + H_3 + H_4 + H_5}{N_L},$$

$$TPF(1) := \frac{H_1 + H_2 + H_3 + H_4 + H_5}{N_L}.$$

Combining TPF and FPF, we obtain the pairs.

$$(FPF(1), TPF(1)),$$

$$(FPF(2), TPF(2)),$$

$$(FPF(3), TPF(3)),$$

$$(FPF(4), TPF(4)),$$

$$(FPF(5), TPF(5)).$$

Plotting these five points in a 2-dimensional plain, we can visualize our dataset.

Visualization of a generalized model by curve

In this section, we provide the so-called *FROC curve* which is our desired visualization of estimated model. Roughly speaking, **an FROC curve is expected pairs of FPF and TPF**. Namely, the points of FPF and TPF will be on FROC curve if model is well fitting to data. So, comparing the FROC curve and the FPF and TPF, we can evaluate our goodness of fit.

Let $c = 1, 2, 3, 4, 5$.

Define

$$x(c) := E[FPF(c)],$$

$$y(c) := E[TPF(c)].$$

Using the fundamental equations $E_\theta[\frac{H_c}{N_L}] = p_c(\theta)$, $E_\theta[\frac{F_c}{N_I}] = q_c(\theta)$,

$$y(c) = E[TPF(c)] = \int_{\theta_c}^{\infty} P(x|\theta_P)dx =: \Psi_P(\theta_c),$$

$$x(c) = E[FPF(c)] = \int_{\theta_c}^{\infty} Q(x|\theta_Q)dx =: \Psi_Q(\theta_c),$$

where Ψ_P and Ψ_Q denote the cumulative functions of the functions P and Q , respectively. (That is, $\Psi_P(x) := \int_x^{\infty} P(t)dt$ and $\Psi_Q(x) := \int_x^{\infty} Q(t)dt$.)

Note that we assume that P is a probability density function but Q is not. So, Ψ_P is a cumulative distribution function, but Ψ_Q is not a cumulative ‘distribution’ function.

This implies that all expectations for the pair of FPF and TPF, namely $(x(c), y(c)) = (E[FPF(c)], E[TPF(c)])$, is on the following set:

$$\{(x(t), y(t)) | x(t) = \Psi_Q(t), y(t) = \Psi_P(t), t > 0\}.$$

We can regard this set as the image of the smooth curve which is called *the generalized FROC curve* in this manuscript.

From the first equation, we obtain that $\theta_c = \Psi_Q^{-1}(x(c))$. Substituting this into the second equation, we obtain that

$$y(c) = \Psi_P(\Psi_Q^{-1}(x(c))).$$

This implies that all exceptions for the pair of FPF and TPF is on the set:

$$\{(x, y) | y = \Psi_P(\Psi_Q^{-1}(x))\}.$$

We can regard this set as an image of smooth curves.

$$(x(t), y(t)) = (t, \Psi_P(\Psi_Q^{-1}(t)))$$

Since $x(t) = t, t > 0$ is not bounded, the area under the FROC curve is infinity.

To calculate alternative notion of AUC in the ordinal ROC theory, we define the so-called AFROC curve:

$$(\xi(t), \eta(t)) = (1 - e^{-t}, \Psi_P(\Psi_Q^{-1}(x)))$$

MRMC Model for Multiple Readers and Multiple Modalities (MRMC)

NI=63, NL=124 In R console ->	modality ID m	reader ID q	confidence c	No. of FPs f	No. of TP h
<i>definitely present</i>	1	1	c[1] = 5	f[1] = $F_{1,1,5}$	h[1] = $H_{1,1,5}$
<i>probably present</i>	1	1	c[2] = 4	f[2] = $F_{1,1,4}$	h[2] = $H_{1,1,4}$
equivocal	1	1	c[3] = 3	f[3] = $F_{1,1,3}$	h[3] = $H_{1,1,3}$
subtle	1	1	c[4] = 2	f[4] = $F_{1,1,2}$	h[4] = $H_{1,1,2}$
very subtle	1	1	c[5] = 1	f[5] = $F_{1,1,1}$	h[5] = $H_{1,1,1}$
<i>definitely present</i>	1	2	c[6] = 5	f[6] = $F_{1,2,5}$	h[6] = $H_{1,2,5}$
<i>probably present</i>	1	2	c[7] = 4	f[7] = $F_{1,2,4}$	h[7] = $H_{1,2,4}$

equivocal	1	2	c[8] = 3	f[8] = $F_{1,2,3}$	h[8] = $H_{1,2,3}$
subtle	1	2	c[9] = 2	f[9] = $F_{1,2,2}$	h[9] = $H_{1,2,2}$
very subtle	1	2	c[10] = 1	f[10] = $F_{1,2,1}$	h[10] = $H_{1,2,1}$
definitely present	2	1	c[11] = 5	f[11] = $F_{2,1,5}$	h[11] = $H_{2,1,5}$
probably present	2	1	c[12] = 4	f[12] = $F_{2,1,4}$	h[12] = $H_{2,1,4}$
equivocal	2	1	c[13] = 3	f[13] = $F_{2,1,3}$	h[13] = $H_{2,1,3}$
subtle	2	1	c[14] = 2	f[14] = $F_{2,1,2}$	h[14] = $H_{2,1,2}$
very subtle	2	1	c[15] = 1	f[15] = $F_{2,1,1}$	h[15] = $H_{2,1,1}$
definitely present	2	2	c[16] = 5	f[16] = $F_{2,2,5}$	h[16] = $H_{2,2,5}$
probably present	2	2	c[17] = 4	f[17] = $F_{2,2,4}$	h[17] = $H_{2,2,4}$
equivocal	2	2	c[18] = 3	f[18] = $F_{2,2,3}$	h[18] = $H_{2,2,3}$
subtle	2	2	c[19] = 2	f[19] = $F_{2,2,2}$	h[19] = $H_{2,2,2}$
very subtle	2	2	c[20] = 1	f[20] = $F_{2,2,1}$	h[20] = $H_{2,2,1}$

An example data in this package

R codes

R object named `dd` is an example data, and to show the above table format, execute the following codes

```
library(BayesianFROC);viewdata(dd)
```

In this section we use the abbreviation *MRMC* which means *Multiple Readers and Multiple Modalities*. In MRMC, Observer performance ability has *individualities* caused by readers and modalities. Once we includes these individual differences in our Bayesian model, such model will give us an answer for the modality comparison issues.

The author implements several models for MRMC.

- 1) Non hierarchical MRMC model
- 2) hierarchical MRMC model
- 3) A Single reader and multiple modalities model

I am a patient of Multiple Chemical Sensitivity (CS) which cause inflammations in the brain and it makes me hard to write this. I know there are many mistakes. When I read my writing, I always find and fix. Please forgive me, because CS makes me foolish.

MRMC model Without hyper parameter

To include heterogeneity caused by readers and modalities, the author first made a hierarchical model. However, the model has divergent transitions in MCMC iterations. Thus the author also made a non-hierarchical model in which the author removed the hyper parameters to get more stable MCMC simulation and he confirmed that the new model is divergent free with my fake data.

In MRMC models, the model parameter is a vector denoted by

$$\theta = (\theta_1, \theta_2, \dots, \theta_C; \mu, \sigma),$$

where each $\theta_i (i = 1, 2, \dots, C)$ is a real number and μ, σ are (M, R) -matrices whose components are denoted by

$$\begin{aligned}
&\mu_{1,1}, \mu_{1,2}, \mu_{1,3}, \dots, \mu_{1,r}, \dots, \mu_{1,R}, \\
&\mu_{2,1}, \mu_{2,2}, \mu_{2,3}, \dots, \mu_{2,r}, \dots, \mu_{2,R}, \\
&\mu_{3,1}, \mu_{3,2}, \mu_{3,3}, \dots, \mu_{3,r}, \dots, \mu_{3,R}, \\
&\dots, \\
&\mu_{m,1}, \mu_{m,2}, \mu_{m,3}, \dots, \mu_{m,r}, \dots, \mu_{m,R}, \\
&\dots, \\
&\mu_{M,1}, \mu_{M,2}, \mu_{M,3}, \dots, \mu_{M,r}, \dots, \mu_{M,R},
\end{aligned}$$

and

$$\begin{aligned}
&\sigma_{1,1}, \sigma_{1,2}, \sigma_{1,3}, \dots, \sigma_{1,r}, \dots, \sigma_{1,R}, \\
&\sigma_{2,1}, \sigma_{2,2}, \sigma_{2,3}, \dots, \sigma_{2,r}, \dots, \sigma_{2,R}, \\
&\sigma_{3,1}, \sigma_{3,2}, \sigma_{3,3}, \dots, \sigma_{3,r}, \dots, \sigma_{3,R}, \\
&\dots, \\
&\sigma_{m,1}, \sigma_{m,2}, \sigma_{m,3}, \dots, \sigma_{m,r}, \dots, \sigma_{m,R}, \\
&\dots, \\
&\sigma_{M,1}, \sigma_{M,2}, \sigma_{M,3}, \dots, \sigma_{M,r}, \dots, \sigma_{M,R},
\end{aligned}$$

where the subscripts m and r indicate the m -th modality and the r -th reader, respectively.

Note that we use the notation θ for

$$\theta = (\theta_1, \theta_2, \dots, \theta_C; \mu, \sigma),$$

and do not confuse it with

$$(\theta_1, \theta_2, \dots, \theta_C).$$

Using the model parameter θ , we can define AUC associated with each pair of reader and modality as follows.

$$AUC_{m,r} = \frac{\mu_{m,r}/\sigma_{m,r}}{\sqrt{1 + 1/\sigma_{m,r}^2}}.$$

Furthermore, we can extract the efficacy of modality.

$$AUC_m = \frac{1}{R} \sum_{r=1}^R AUC_{m,r},$$

which is also denoted by $A[m], m=1, 2, \dots, M$ in the R console (or R studio console) and retained in the \mathbf{R} object of the $S4$ class (the so-called *stanfit* or its extended class).

Using $A[m], m=1, 2, \dots, M$, we can compare modalities such as MRI, CT, PET, etc. Note that if our trial use x-ray films taken by MRI and CT, then $M=2$. If images are taken by MRI, CT, PET, then $M=3$. So, $A[m], m=1, 2, \dots, M$ is a function of the model parameter. In Bayesian sense, the estimates are posterior samples and thus, $A[m], m=1, 2, \dots, M$ are obtained as MCMC samples. Using these, we can calculate posterior probabilities of any events. This is the author's main scheme. Ha,, I want to

Of course, these AUCs are defined as the area under the AFROC curve for the r th reader and the m th modality. The so-called FROC curve for the r th reader and the m th modality is a map from 1-dimensional Euclidean space to 2-dimensional Euclidean space, mapping each $t > 0$ to

$$(x_{m,r}(t), y_{m,r}(t)) = (t, \Phi(\frac{\Phi^{-1}(\exp(-t)) - \mu_{m,r}}{\sigma_{m,r}}))$$

Because $x(t) = t, t > 0$ is not bounded, the area under the FROC curve is infinity.

To calculates alternative notion of AUC in the ordinal ROC theory, we define the so-called AFROC curve:

$$(\xi_{m,r}(t), \eta_{m,r}(t)) = (1 - e^{-t}, \Phi(\frac{\Phi^{-1}(\exp(-t)) - \mu_{m,r}}{\sigma_{m,r}}))$$

which contained in the rectangular space $[0, 1]^2$.

Probability law of hits

In the sequel, the subscripts m, r mean the m -th modality and the r -th reader, respectively.

Random variables of hits are distributed as follows.

$$H_{5,m,r} \sim Binomial(p_{5,m,r}(\theta), N_L),$$

where the notation $H_{5,m,r}$ denotes the number of hits (TPs) with confidence level 5 of the m -th modality for the r th reader.

Now, the $H_{5,m,r}$ targets (signals, lesions) are found by the reader (radiologist), and the residue of targes, i.e., number of remaining targets is $N_L - H_{5,m,r}$.

Thus, the number of hits with the 4-th confidence level $H_{4,m,r}$ should be drawn from the binomial distribution with remaining targets whose number is $N_L - H_{5,m,r}$ and thus

$$H_{4,m,r} \sim Binomial(\frac{p_{4,m,r}(\theta)}{1 - p_{5,m,r}(\theta)}, N_L - H_{5,m,r}).$$

Similarly,

$$H_{3,m,r} \sim Binomial(\frac{p_{3,m,r}(\theta)}{1 - p_{5,m,r}(\theta) - p_{4,m,r}(\theta)}, N_L - H_{5,m,r} - H_{4,m,r}).$$

$$H_{2,m,r} \sim Binomial(\frac{p_{2,m,r}(\theta)}{1 - p_{5,m,r}(\theta) - p_{4,m,r}(\theta) - p_{3,m,r}(\theta)}, N_L - H_{5,m,r} - H_{4,m,r} - H_{3,m,r}).$$

$$H_{1,m,r} \sim \text{Binomial}\left(\frac{p_{1,m,r}(\theta)}{1 - p_{5,m,r}(\theta) - p_{4,m,r}(\theta) - p_{3,m,r}(\theta) - p_{2,m,r}(\theta)}, N_L - H_{5,m,r} - H_{4,m,r} - H_{3,m,r} - H_{2,m,r}\right).$$

Probability law of false alarms

Let N_X be the one of the followings and fix it.

- 1) $N_X = N_L$ (The number of lesions), if `ModifiedPoisson = TRUE`.
- 2) $N_X = N_I$ (The number of images), if `ModifiedPoisson = FALSE`.

Using N_X , we assume the following,

$$F_{5,m,r} \sim \text{Poisson}(q_5(\theta)N_X),$$

$$F_{4,m,r} \sim \text{Poisson}(q_4(\theta)N_X),$$

$$F_{3,m,r} \sim \text{Poisson}(q_3(\theta)N_X),$$

$$F_{2,m,r} \sim \text{Poisson}(q_2(\theta)N_X),$$

$$F_{1,m,r} \sim \text{Poisson}(q_1(\theta)N_X),$$

where subscripts m, r mean the m -th modality and the r -th reader, respectively.

The rate $p_{c,m,r}(\theta)$ and $q_c(\theta)$ are calculated from the model parameter θ .

We use a Gaussian distribution and the cumulative distribution function $\Phi(\cdot)$ of the standard Gaussian for the functions $p_{c,m,r}(\theta)$ and $q_c(\theta)$ as following manner.

$$p_{c,m,r}(\theta) = \int_{\theta_c}^{\theta_{c+1}} \text{Normal}(z | \mu_{c,m,r}, v_{c,m,r}) dz$$

$$q_c(\theta) = \int_{\theta_c}^{\theta_{c+1}} \frac{d}{dz} \log \Phi(z) dz$$

where the model parameter vector is

$$\theta = (\theta_1, \theta_2, \dots, \theta_C; \theta_P, \theta_Q).$$

By specifying a model parameter $\theta = (\theta_1, \theta_2, \dots, \theta_C; \theta_P, \theta_Q)$. we can make a fake dataset consisting of hit data $H_{c,m,r}$ false alarm data $F_{c,m,r}$ for each c, m, r . So, our model is a generative model and this is a crucial difference between our model and the classical one.

Without hyper parameter MRMC model

A Non-Centered Implementation

$AA[md, qd] \sim \text{Normal}(A[md], \text{hyper_v}[qd])$

Non centered version is the following:

$AA_tilde[md, qd] \sim \text{Normal}(0, 1)$

$AA[md, qd] = A[md] + \text{hyper_v}[qd] * AA_tilde$

But, the $AA[md, qd]$ is already defined as follows.

$AA[md, qd] = \text{Phi}((\mu[md, qd] / \sqrt{v[md, qd]}) / \sqrt{(1 / v[md, qd])^2 + 1})$;

Thus usual non centered model **cannot be implemented**.

The assumption

$AA[md, qd] \sim \text{Normal}(A[md], \text{hyper_v}[qd])$

is an approximation. So, this model is not correct. I am not sure whether the approximation worsen my model.

The hyper parameters have been in use for more than 2 years in this package. However it caused divergent transitions. Thus the author made a new model without these hyper parameters.

Example dataset is `dd` and `ddd` and `dddd` and `ddddd` and ...etc. _____

Validation of model via SBC

SBC tests the Null hypothesis that the MCMC sampling is correct by using some rank statistic which synthesizes a histogram. If this histogram is not uniformly distributed, then we reject the null hypothesis, and we conclude that our MCMC sampling contains bias.

Talts, S., Betancourt, M., Simpson, D., Vehtari, A., and Gelman, A. (2018). *Validating Bayesian Inference Algorithms with Simulation-Based Calibration*. arXiv preprint arXiv:1804.06788. <https://arxiv.org/abs/1804.06788>

Validation of model via Posterior Predictive p value

See `ppp()`.

Let $\theta_1, \theta_2, \dots, \theta_n$ be MCMC samples from a posterior distribution $\pi(\cdot|D)$ for a given dataset D . Let $L(y|\theta_i)$ be a likelihood function for a dataset y and model parameter θ . Let

$$y_j^i \sim L(\cdot|\theta_i).$$

For any real-valued function $\phi = \phi(y, \theta)$, we can calculate its integral with the posterior predictive measure as the approximation of two steps Monte Carlo integral as follows.

$$\begin{aligned} & \int \int \phi(y, \theta) L(y|\theta) \pi(\theta|y) dy d\theta \\ &= \int \sum_i \phi(y, \theta_i) L(y|\theta_i) dy \\ &= \sum_j \sum_i \phi(y_j^i, \theta_i) L(y_j^i|\theta_i). \end{aligned}$$

Using $\phi = 1(T(y, \theta) > T(y, \theta_{observed}))$, we obtain the so-called *posterior predictive p value*. (The author hates this notion.)

In my opinion, this criteria is not clear whether it is reliable quantities for evaluations.

Validation of model; Comparison between truth and estimates of fake data-sets which are drawn using the truth.

I think this is the most fundamental and intuitive validation.

Under Construction

Appendix: — Terminology —

hit which is also called True Positive: TP, which is denoted with each confidence level, $c = 1, 2, 3, \dots, C$ as follows: H_1, H_2, \dots, H_C or $h=c(h[1], h[2], \dots, h[C])$, where $h[1]=H_C$ corresponds a number of hit with most high confidence level

False alarm which is also called False Positive: FP, which is denoted with each confidence, $c = 1, 2, 3, \dots, C$ levels as follows: F_1, F_2, \dots, F_C or $f=c(f[1], f[2], \dots, f[C])$, where $f[1]=F_C$ corresponds a number of false alarms with most high confidence level

Modality Imaging methods, such as MRI, CT, PET,...etc. In another context, it means efficacy of treatment.

Reader is a radiologist, physician, who try to detect lesions from radiographs. For a single image, reader can answer multiple suspicious shadows and he assigns to each suspicious shadows his or her confidence level. So, the reader localizes and rates for each suspicious shadows. A data analyst evaluates whether each reader's localization of lesion is true or false. Note that a single image can synthesize multiple-false positives or multiple true positives. Such a multiplicity distincts FROC analysis with ordinal ROC analysis.

Image is a radiograph taken by MRI, CT, PET, etc.

Modality comparison The question that which modality (MRI, CT, PET, ... etc) is best to detect lesions in radiographs? In order to answer this question, the FROC analysis exists.

hit rate Each lesion can synthesize a hit of confidence level c according to Bernoulli distribution with probability of p_c , which call hit rate (of c)

false alarm rate Each image synthesize a false alarm (False Positive: FP) of confidence level c according to Poisson distribution with probability of λ_c , which call *false alarm rate (of c)* or *simply false rate*.

Number of images which is denoted by N_I . An image means a radiograph or an X ray film, including shadows, each of which is caused by lesions or noise. Namely, each radiograph does not necessarily includes lesions.

Number of lesions Suppose that there are N_I radiographs. Then by summing the number of lesions over all radiographs, we obtain the number of lesion N_L .

FROC curve alternative notion of ROC curve in FROC context.

AFROC curve Alternative-FROC curve, whose area under the curve indicates observer performance. Since area under the FROC curve is infinity, we use this area under the AFROC curve instead of the area under the FROC curve.

AUC A real number between 0 and 1, indicating how many lesions radiologist can detect from radiographs. It is the area under the AFROC curve. In ROC context, AUC should be greater than 0.5, but in FROC context, the interpretation of AUC is not same as that in ROC context. For example, $AUC=0.5$ does not means that it is same as the most bad observer performance.

Chi square The difference of expectation minus observation, namely it is estimates minus actual observed data. Smaller is better.

Posterior Predictive P value (PPP) This is a posterior predictive probability of the event that a test statistic is greater than its observed value. The author implements the χ^2 goodness of fit as a test statistic and in this context, if the PPP is small then we reject the null hypothesis that the model is well fit to data. The author hates this traditional bitch.

FPF:False Positive Fraction Cumulative sum of false alarms (FPs) divided by the number of Images or the number of lesions. Using FPFs as x and TPFs as y, we can visualize FPs and TPs.

TPF:True Positive Fraction Cumulative sum of hits (TPs) decided by the number of Lesions (signals, targets). Using FPFs as x and TPFs as y, we can visualize FPs and TPs.

Now, I am in very serious condition both money and employment. I cannot get any job, this package development cannot save my life.

I am a chemical sensitivity patient. I cannot overcome this serious disease.

When I made this package, I hoped this makes my life safe, but it cannot.

I really Despair my life.

I do not study Statistics, but geometry, differential geometry.

check_hit_is_less_than_NL

Check total hit is less than NL for each reader and each modality

Description

This check a give dataset consisting of MRMC data satisfies the condition that the number hits is less than the number of lesions for each reader and each modality.

Usage

```
check_hit_is_less_than_NL(dataList)
```

Arguments

dataList A list, specifying an FROC data to be fitted a model. It consists of data of numbers of TPs, FPs, lesions, images. .In addition, if in case of mutiple readers or mutiple modalities, then modaity ID and reader ID are included also.

The **dataList** will be passed to the function `rstan::sampling()` of **rstan**. This is a variable in the function `rstan::sampling()` in which it is named **data**.

For the single reader and a single modality data, the **dataList** is made by the following manner:

```
dataList.Example <-list(
  h = c(41,22,14,8,1),# number of hits for each confidence level
  f = c(1,2,5,11,13),# number of false alarms for each confidence level

  NL = 124,# number of lesions (signals)
```


NI = 63, # number of images (trials)
 C = 5) # number of confidence, .. the author thinks it can be calculated as the length of h or f ...? ha, why I included this. ha .. should be omitted.

Using this object `dataList.Example`, we can apply `fit_Bayesian_FROC()` such as `fit_Bayesian_FROC(dataList.Example)`.

To make this R object `dataList` representing FROC data, this package provides three functions:

`convertFromJafroc()` If data is a **JAFROC xlsx** formulation.
`dataset_creator_new_version()` Enter TP and FP data **by table** .
`create_dataset()` Enter TP and FP data by **interactive** manner.

Before fitting a model, we can confirm our dataset is correctly formulated by using the function `viewdata()`.

A Single reader and a single modality (SRSC) case.

In a single reader and a single modality case (`srsc`), `dataList` is a list consisting of `f, h, NL, NI, C` where `f, h` are numeric vectors and `NL, NI, C` are positive integers.

- f Non-negative integer vector specifying number of false alarms associated with each confidence level. The first component corresponding to the highest confidence level.
- h Non-negative integer vector specifying number of Hits associated with each confidence level. The first component corresponding to the highest confidence level.
- NL A positive integer, representing Number of Lesions.
- NI A positive integer, representing Number of Images.
- C A positive integer, representing Number of Confidence level.

The detail of these dataset, see the datasets endowed with this package. 'Note that the maximal number of confidence level, denoted by `C`, are included, however, Note that confidence level vector `c` should not be specified. If specified, will be ignored, since it is created by `c <- c(rep(C:1))` in the program and do not refer from user input data, where `C` is the highest number of confidence levels. So, you should write down your hits and false alarms vector so that it is compatible with this automatically created `c` vector.

data Format:

A single reader and a single modality case

NI=63, NL=124 In R console ->	confidence level c	No. of false alarms f	No. of hits h
definitely present	$c[1] = 5$	$f[1] = F_5 = 1$	$h[1] = H_5 = 41$
probably present	$c[2] = 4$	$f[2] = F_4 = 2$	$h[2] = H_4 = 22$

equivocal	$c[3] = 3$	$f[3] = F_3 = 5$	$h[3] = H_3 = 14$
subtle	$c[4] = 2$	$f[4] = F_2 = 11$	$h[4] = H_2 = 8$
very subtle	$c[5] = 1$	$f[5] = F_1 = 13$	$h[5] = H_1 = 1$

* *false alarms* = False Positives = FP

* *hits* = True Positives = TP

Note that in FROC data, all confidence level means *present* (*diseased, lesion*) case only, no confidence level indicating absent. Since each reader marks his suspicious location only if he thinks lesions are *present*, and marked positions generates the hits or false alarms, *thus* each confidence level represents that lesion is *present*. In the absent case, reader dose not mark any locations and hence, the absent confidence level does not relate this dataset. So, if reader think it is no lesion, then in such case confidence level is not needed.

Note that the first column of confidence level vector c should not be specified. If specified, will be ignored, since it is created by $c \leftarrow c(\text{rep}(C:1))$ automatically in the program and do not refer from user input data even if it is specified explicitly, where C is the highest number of confidence levels. So you should check the compatibility of your data and the confidence level vector $c \leftarrow c(\text{rep}(C:1))$ via a table which can be displayed by the function `viewdata()`.

Multiple readers and multiple modalities case, i.e., MRMC case

In case of multiple readers and multiple modalities, i.e., MRMC case, in order to apply the function `fit_Bayesian_FROC()`, dataset represented by an R list object representing FROC data must contain components $m, q, c, h, f, NL, C, M, Q$.

- C A positive integer, representing the **highest** number of confidence level, this is a scalar.
- M A positive integer vector, representing the number of **modalities**.
- Q A positive integer, representing the number of **readers**.
- m A vector of positive integers, representing the **modality ID** vector.
- q A vector of positive integers, representing the **reader ID** vector.
- c A vector of positive integers, representing the **confidence level**. This vector must be made by `rep(rep(C:1), M*Q)`
- h A vector of non-negative integers, representing the number of **hits**.
- f A vector of non-negative integers, representing the number of **false alarms**.
- NL A positive integer, representing the Total number of **lesions** for all images, this is a scalar.

Note that the maximal number of confidence level (denoted by C) are included in the above R object. However, each confidence level vector is not included in the data, because it is created automatically from C . To confirm false positives and hits are correctly ordered with respect to the automatically generated confidence vector,

the function `viewdata()` shows the table. Revised 2019 Nov 27 Revised 2019 Dec 5

Example data.

Multiple readers and multiple modalities (i.e., MRMC)

Modality ID	Reader ID	Confidence levels	No. of false alarms	No. of hits.
m	q	c	f	h
1	1	3	20	111
1	1	2	29	55
1	1	1	21	22
1	2	3	6	100
1	2	2	15	44
1	2	1	22	11
2	1	3	6	66
2	1	2	24	55
2	1	1	23	1
2	2	3	5	66
2	2	2	30	55
2	2	1	40	44

* *false alarms* = False Positives = FP

* *hits* = True Positives = TP

Value

Logical, TRUE or FALSE. If TRUE, then the format of dataset is correct. If not, then the dataset is incorrect in the sense that the number of hits is greater than the number of lesions for some reader and some imaging modality.

Examples

```
logical <- check_hit_is_less_than_NL(BayesianFROC::dd)
```

Description

This function evaluate R hat statistics for any fitted model object of class `stanfit`.

Usage

```
check_rhat(StanS4class)
```

Arguments

`StanS4class` An S4 object of class `stanfitExtended` which is an inherited class from the S4 class `stanfit`. This R object is a fitted model object as a return value of the function `fit_Bayesian_FROC()`.
It can be passed to `DrawCurves()`, `ppp()` and ... etc

Details

It evaluate whether or not r hat statistics are all near 1.

Value

Logical, that is TRUE or FALSE. If model converges then TRUE, and if not FALSE.

Author(s)

betanalpha, so not my function. But I modified it. So, alphanbetan is one of the standeveloper, so his function will has consensus, thus I use it.

References

Gelman A. \& Rubin, D.B. (1992). Inference from Iterative Simulation Using Multiple Sequences, Statistical Science, Volume 7, Number 4, 457-472.

chi_square_at_replicated_data_and_MCMC_samples_MRMC

chi square at replicated data drawn (only one time) from model with each MCMC samples.

Description

To pass the return value to the calculator of the posterior predictive p value.

Usage

```
chi_square_at_replicated_data_and_MCMC_samples_MRMC(  
  StanS4class,  
  summary = TRUE,  
  seed = NA,  
  serial.number = NA  
)
```

Arguments

StanS4class	An S4 object of class <code>stanfitExtended</code> which is an inherited class from the S4 class <code>stanfit</code> . This R object is a fitted model object as a return value of the function <code>fit_Bayesian_FROC()</code> . It can be passed to <code>DrawCurves()</code> , <code>ppp()</code> and ... etc
summary	Logical: TRUE or FALSE. Whether to print the verbose summary. If TRUE then verbose summary is printed in the R console. If FALSE, the output is minimal. I regret, this variable name should be verbose.
seed	This is used only in programming phase. If seed is passed, then, in procedure indicator the seed is printed. This parameter is only for package development.
serial.number	An positive integer or Character. This is for programming perspective. The author use this to print the serial numbre of validation. This will be used in the validation function.

Details

For a given dataset D_0 , let $\pi(.|D_0)$ be a posterior of the given data D_0 .

Now, we draw poterior samples.

$$\theta_1 \sim \pi(.|D_0),$$

$$\theta_2 \sim \pi(.|D_0),$$

$$\theta_3 \sim \pi(.|D_0),$$

....,

$$\theta_n \sim \pi(.|D_0).$$

We let $L(|\theta)$ be a likelihood function, which is also denoted by $L(y|\theta)$ for a given data y . But, the specification of a data y is somehow coversome, thus, to denote the function sending each y into $L(y|\theta)$, we use the notation $L(|\theta)$.

Now, we synthesize data-samples $(y_i; i = 1, 2, \dots, n)$ in **only one time drawing** from the collection of likelihoods $L(|\theta_1), L(|\theta_2), \dots, L(|\theta_n)$.

$$y_1 \sim L(.|\theta_1),$$

$$y_2 \sim L(.|\theta_2),$$

$$y_3 \sim L(.|\theta_3),$$

....,

$$y_n \sim L(.|\theta_n).$$

Altogether, using these pair of samples $(y_i, \theta_i), i = 1, 2, \dots, n$, we calculates the **return value** of this function. That is,

$$\chi(y_1|\theta_1),$$

$$\begin{aligned} &\chi(y_2|\theta_2), \\ &\chi(y_3|\theta_3), \\ &\dots, \\ &\chi(y_n|\theta_n). \end{aligned}$$

This is contained in a return value,

so the return value is a vector whose length is the number of MCMC iterations except the burn-in period.

Application of this return value to calculate the so-called *Posterior Predictive P value*.

In other functions, the author use this function with many seeds. Namely, changing seed, we can obtain

$$\begin{aligned} &y_{1,1}, y_{1,2}, y_{1,3}, \dots, y_{1,j}, \dots, y_{1,J} \sim L(\cdot|\theta_1), \\ &y_{2,1}, y_{2,2}, y_{2,3}, \dots, y_{2,j}, \dots, y_{2,J} \sim L(\cdot|\theta_2), \\ &y_{3,1}, y_{3,2}, y_{3,3}, \dots, y_{3,j}, \dots, y_{3,J} \sim L(\cdot|\theta_3), \\ &\dots, \\ &y_{i,1}, y_{i,2}, y_{i,3}, \dots, y_{i,j}, \dots, y_{i,J} \sim L(\cdot|\theta_i), \\ &\dots, \\ &y_{I,1}, y_{I,2}, y_{I,3}, \dots, y_{I,j}, \dots, y_{I,J} \sim L(\cdot|\theta_I). \end{aligned}$$

where $L(\cdot|\theta_i)$ is a likelihood function for a model parameter θ_i . And thus, we calculate the chi square statistics.

$$\begin{aligned} &\chi(y_{1,1}|\theta_1), \chi(y_{1,2}|\theta_1), \chi(y_{1,3}|\theta_1), \dots, \chi(y_{1,j}|\theta_1), \dots, \chi(y_{1,J}|\theta_1), \\ &\chi(y_{2,1}|\theta_2), \chi(y_{2,2}|\theta_2), \chi(y_{2,3}|\theta_2), \dots, \chi(y_{2,j}|\theta_2), \dots, \chi(y_{2,J}|\theta_2), \\ &\chi(y_{3,1}|\theta_3), \chi(y_{3,2}|\theta_3), \chi(y_{3,3}|\theta_3), \dots, \chi(y_{3,j}|\theta_3), \dots, \chi(y_{3,J}|\theta_3), \\ &\dots, \\ &\chi(y_{i,1}|\theta_i), \chi(y_{i,2}|\theta_i), \chi(y_{i,3}|\theta_i), \dots, \chi(y_{i,j}|\theta_i), \dots, \chi(y_{i,J}|\theta_i), \\ &\dots, \\ &\chi(y_{I,1}|\theta_I), \chi(y_{I,2}|\theta_I), \chi(y_{I,3}|\theta_I), \dots, \chi(y_{I,j}|\theta_I), \dots, \chi(y_{I,J}|\theta_I). \end{aligned}$$

which are used when we calculate the so-called *Posterior Predictive P value* to test the *null hypothesis* that our model is fitted a data well.

Revised 2019 Sept. 8 Revised 2019 Dec. 2

Revised 2020 March

Value

From any given posterior MCMC samples $\theta_1, \theta_2, \dots, \theta_i, \dots, \theta_n$ (provided by stanfitExtended object), it calculates a return value as a vector of the form $\chi(y_i|\theta_i), i = 1, 2, \dots$, where each dataset y_i is drawn from the corresponding likelihood $likelihood(.|\theta_i), i = 1, 2, \dots$, namely,

$$y_i \sim likelihood(.|\theta_i).$$

The return value also retains these $y_i, i = 1, 2, \dots$

Revised 2019 Dec. 2

Examples

```
## Not run:

fit <- fit_Bayesian_FROC( ite = 1111, dataList = ddd )
a <- chi_square_at_replicated_data_and_MCMC_samples_MRMC(fit)

b<-a$List_of_dataList
lapply(b, plot_FPF_and_TPF_from_a_dataset)

## End(Not run)
```

chi_square_goodness_of_fit

Chi square goodness of fit statistics at each MCMC sample w.r.t. a given dataset.

Description

Calculates a vector, consisting of **the Goodness of Fit (Chi Square)** for a given dataset D and each posterior MCMC samples $\theta_i = \theta_i(D), i = 1, 2, 3, \dots$, namely,

$$\chi^2(D|\theta_i)$$

for $i = 1, 2, 3, \dots$ and thus its dimension is the number of MCMC iterations..

Note that In MRMC cases, it is defined as follows.

$$\chi^2(D|\theta) := \sum_{r=1}^R \sum_{m=1}^M \sum_{c=1}^C \left(\frac{[H_{c,m,r} - N_L \times p_{c,m,r}(\theta)]^2}{N_L \times p_{c,m,r}(\theta)} + \frac{[F_{c,m,r} - (\lambda_c - \lambda_{c+1}) \times N_L]^2}{(\lambda_c(\theta) - \lambda_{c+1}(\theta)) \times N_L} \right).$$

where a dataset D consists of the pairs of the number of False Positives and the number of True Positives ($F_{c,m,r}, H_{c,m,r}$) together with the number of lesions N_L and the number of images N_I and θ denotes the model parameter.

Usage

```
chi_square_goodness_of_fit(
  StanS4class,
  dig = 3,
  h = StanS4class@dataList$h,
  f = StanS4class@dataList$f
)
```

Arguments

- | | |
|-------------|---|
| StanS4class | An S4 object of class <code>stanfitExtended</code> which is an inherited class from the S4 class <code>stanfit</code> . This R object is a fitted model object as a return value of the function <code>fit_Bayesian_FROC()</code> .
It can be passed to <code>DrawCurves()</code> , <code>ppp()</code> and ... etc |
| dig | A variable to be passed to the function <code>rstan::sampling()</code> of rstan in which it is named <code>...</code> ?. A positive integer representing the Significant digits, used in stan Cancellation. Default = 5, |
| h | A vector of positive integers, representing the number of hits. This variable was made in order to substitute the hits data drawn from the posterior predictive distributions. In famous Gelman's book, he explain how to use the test statistics in the Bayesian context. In this context I need to substitute the replication data from the posterior predictive distributions. |
| f | A vector of positive integers, representing the number of false alarms. This variable was made in order to substitute the false alarms data drawn from the posterior predictive distributions. In famous Gelman's book, he explain how to use the test statistics in the Bayesian context. In this context I need to substitute the replication data from the posterior predictive distributions. |

Details

To calculate the chi square (goodness of fit) $\chi^2(y|\theta)$ test statistics, the two variables are required; one is an observed dataset y and the other is an estimated parameter θ . In the classical chi square values, MLE(maximal likelihood estimator) is used for an estimated parameter θ in $\chi^2(y|\theta)$. However, in the Bayesian context, the parameter is not deterministic and we consider it is a random variable such as samples from the posterior distribution. And such samples are obtained in the Hamiltonian Monte Carlo Simulation. Thus we can calculate chi square values for each MCMC sample.

Value

Chi squares for each MCMC sample.

$$\chi^2 = \chi^2(D|\theta_i), i = 1, 2, \dots, N$$

So, the return values is a vector of length N which denotes the number of MCMC iterations except the warming up period. Of course if MCMC is not only one chain, then all samples of chains are used to calculate the chi square.

In the sequel, we use the notations

for a prior $\pi(\theta)$,
 posterior $\pi(\theta|D)$,
 likelihood $f(D|\theta)$,
 parameter θ ,
 datasets D , for example, we can write as follows;

$$\pi(\theta|D) \propto f(D|\theta)\pi(\theta).$$

Let us denote the **posterior MCMC samples** of size N for a given data-set D by

$$\theta_1, \theta_2, \theta_3, \dots, \theta_N$$

which are drawn from posterior $\pi(\theta|D)$ of given data D .

Recall that the chi square goodness of fit statistics χ depends on the model parameter θ and data D , namely,

$$\chi^2 = \chi^2(D|\theta)$$

.

The function calculates a vector of length N whose components is given by:

$$\chi^2(D|\theta_1), \chi^2(D|\theta_2), \chi^2(D|\theta_3), \dots, \chi^2(D|\theta_N),$$

So, the return value is a vector of size N .

As an application of this return value ($\chi^2(D|\theta_i); i = 1, \dots, N$), we can calculate the posterior mean of $\chi = \chi(D|\theta)$, namely, we get

$$\chi^2(D) = \int \chi^2(D|\theta)\pi(\theta|D)d\theta.$$

as its Monte Carlo integral

$$\frac{1}{N} \sum_{i=1}^N \chi^2(D|\theta_i),$$

In my model, almost all example, result of calculation shows that

$$\int \chi^2(D|\theta)\pi(\theta|D)d\theta > \chi^2(D) \int \theta\pi(\theta|D)d\theta$$

The above inequality is true for all D ? I conjecture it.

Revised 2019 August 18 Revised 2019 Sept. 1 Revised 2019 Nov 28

Our data is **2C categories**, that is,

the number of hits :h[1], h[2], h[3],...,h[C] and

the number of false alarms: $f[1], f[2], f[3], \dots, f[C]$.

Our model has **C+2 parameters**, that is,

the thresholds of the bi normal assumption $z[1], z[2], z[3], \dots, z[C]$ and

the mean and standard deviation of the signal distribution.

So, the degree of freedom of this statistics is calculated by

No. of categories - No. of parameters - 1 = $2C - (C+2) - 1 = C - 3$.

This differ from Chakraborty's result $C-2$. Why ?

Examples

```
## Not run:
#=====
#                               Synthesize the MCMC samples from a dataset.
#=====

fit <- fit_Bayesian_FROC(BayesianFROC::dataList.Chakra.1,
                        ite = 1111,
                        summary =FALSE,
                        cha = 2)

#=====
# The chi square discrepancies are calculated by the following code
#=====

Chi.Square.for.each.MCMC.samples <- chi_square_goodness_of_fit(fit)

#=====
# With Warning
#=====

chi_square_goodness_of_fit(fit)

#=====
# Without warning
#=====

chi_square_goodness_of_fit(fit,
                          h=fit@dataList$h,
                          f=fit@dataList$f)
```

```

=====
# Get posterior mean of the chi square discrepancy.
=====

m<- mean(Chi.Square.for.each.MCMC.samples)

=====
# The author read at 2019 Sept. 1, it helps him. Thanks me!!
#
# Calculate the p-value for the posterior mean of the chi square discrepancy.
=====

stats::pchisq(m,df=1)

=====
# Difference between chi sq. at EAP and EAP of chi sq.
=====

mean( fit@chisquare - chi_square_goodness_of_fit(fit))

## End(Not run)# dottest

```

chi_square_goodness_of_fit_from_input_all_param

Not vector: The Goodness of Fit (Chi Square) Calculator

Description

Chi square goodness of fit statistics for each MCMC sample with a fixed dataset.

Our data is $2C$ categories, that is,

the number of hits : $h[1], h[2], h[3], \dots, h[C]$ and

the number of false alarms: $f[1], f[2], f[3], \dots, f[C]$.

Our model has $C+2$ parameters, that is,

the thresholds of the bi normal assumption $z[1], z[2], z[3], \dots, z[C]$ and

the mean and standard deviation of the signal distribution.

So, the degree of freedom of this statistics is calculated by

$2C-(C+2)-1 = C - 3$.

This differ from Chakraborty's result $C-2$. Why ?

Usage

```
chi_square_goodness_of_fit_from_input_all_param(
  h,
  f,
  p,
  lambda,
  NL,
  NI,
  ModifiedPoisson = FALSE,
  dig = 3
)
```

Arguments

- h** A vector of non-negative integers, indicating the number of hits. The reason why the author includes this variable is to substitute the false alarms from the posterior predictive distribution. In famous Gelman's book, he explain how to make test statistics in the Bayesian context, and it require the samples from posterior predictive distribution. So, in this variable author substitute the replication data from the posterior predictive distributions.
- f** A vector of non-negative integers, indicating the number of false alarms. The reason why the author includes this variable is to substitute the false alarms from the posterior predictive distribution. In famous Gelman's book, he explain how to make test statistics in the Bayesian context, and it require the samples from posterior predictive distribution. So, in this variable author substitute the replication data from the posterior predictive distributions.
- p** A vector of non-negative integers, indicating hit rate. A vector whose length is number of confidence levels.
- lambda** A vector of non-negative integers, indicating False alarm rate. A vector whose length is number of confidence levels.
- NL** An integer, representing Number of Lesions
- NI** An integer, representing Number of Images
- ModifiedPoisson** Logical, that is TRUE or FALSE.
 If ModifiedPoisson = TRUE, then Poisson rate of false alarm is calculated *per lesion*, and model is fitted so that the FROC curve is an expected curve of points consisting of the pairs of TPF per lesion and FPF *per lesion*.
 Similarly,
 If ModifiedPoisson = TRUE, then Poisson rate of false alarm is calculated *per image*, and model is fitted so that the FROC curve is an expected curve of points consisting of the pair of TPF per lesion and FPF *per image*.
 For more details, see the author's paper in which I explained *per image* and *per lesion*. (for details of models, see [vignettes](#) , now, it is omitted from this package, because the size of vignettes are large.)
 If ModifiedPoisson = TRUE, then the *False Positive Fraction (FPF)* is defined as follows (F_c denotes the number of false alarms with confidence level c)

$$\frac{F_1 + F_2 + F_3 + F_4 + F_5}{N_L},$$

$$\frac{F_2 + F_3 + F_4 + F_5}{N_L},$$

$$\frac{F_3 + F_4 + F_5}{N_L},$$

$$\frac{F_4 + F_5}{N_L},$$

$$\frac{F_5}{N_L},$$

where N_L is a number of lesions (signal). To emphasize its denominator N_L , we also call it the *False Positive Fraction (FPF) per lesion*.

On the other hand,

if ModifiedPoisson = FALSE (Default), then *False Positive Fraction (FPF)* is given by

$$\frac{F_1 + F_2 + F_3 + F_4 + F_5}{N_I},$$

$$\frac{F_2 + F_3 + F_4 + F_5}{N_I},$$

$$\frac{F_3 + F_4 + F_5}{N_I},$$

$$\frac{F_4 + F_5}{N_I},$$

$$\frac{F_5}{N_I},$$

where N_I is the number of images (trial). To emphasize its denominator N_I , we also call it the *False Positive Fraction (FPF) per image*.

The model is fitted so that the estimated FROC curve can be regarded as the expected pairs of FPF per image and TPF per lesion (ModifiedPoisson = FALSE)

or as the expected pairs of FPF per image and TPF per lesion (ModifiedPoisson = TRUE)

If ModifiedPoisson = TRUE, then FROC curve means the expected pair of FPF **per lesion** and TPF.

On the other hand, if ModifiedPoisson = FALSE, then FROC curve means the expected pair of **FPF per image** and TPF.

So, data of FPF and TPF are changed thus, a fitted model is also changed whether ModifiedPoisson = TRUE or FALSE. In traditional FROC analysis, it uses only per images (trial). Since we can divide one image into two images or more images, number of trial is not important. And more important is per signal. So, the author also developed FROC theory to consider FROC analysis under per signal. One can see that the FROC curve is rigid with respect to change of a number of images, so, it does not matter whether ModifiedPoisson = TRUE or FALSE. This rigidity of curves means that the number of images is redundant parameter for the FROC trial and thus the author try to exclude it.

Revised 2019 Dec 8 Revised 2019 Nov 25 Revised 2019 August 28

dig A variable to be passed to the function `rstan::sampling()` of **rstan** in which it is named `...`?. A positive integer representing the Significant digits, used in stan Cancellation. Default = 5,

Details

To calculate the chi square test statistics, the two quantities are needed, that is, data and parameter. In the classical (frequentists) chi square values, as the estimates of parameter, for example, MLE (maximal likelihood estimator) is chosen. In Bayesian sense, the parameter can be taken for all MCMC iterations, that is, parameter is not deterministic and we consider it is a random variable or samples from the posterior distribution. And such samples are obtained in the Hamiltonian Monte Carlo Simulation with the author's Bayesian Model. Thus we can calculate chi square values with MCMC samples.

Value

A number !! Not list nor dataframe nor vector !! Only A number represent the chi square for your input data.

Examples

```
## Not run:

# Make a stanfit object (more precisely its inherited S4 class object)

fit <- fit_Bayesian_FROC(BayesianFROC::dataList.Chakra.1,
                        ite = 1111,
                        summary =FALSE,
                        cha = 2)

# The chi square discrepancies (Goodness of Fit) are calculated
# by the following code with the posterior mean as a parameter.#
```

```

NI          <- fit@dataList$NI
NL          <- fit@dataList$NL
f.observed <- fit@dataList$f
h.observed <- fit@dataList$h
C           <- fit@dataList$C

# p <- rstan::get_posterior_mean(fit, par=c("p"))
# lambda <- rstan::get_posterior_mean(fit, par=c("l"))
# Note that get_posterior_mean is not a number but a matrix when
# Chains is not 1.
# So, instead of it, we use
#
e   <- extract_EAP_CI(fit,"l",fit@dataList$C )
lambda <- e$l.EAP

e   <- extract_EAP_CI(fit,"p",fit@dataList$C )
p   <- e$p.EAP

Chi.Square <- chi_square_goodness_of_fit_from_input_all_param(
    h = h.observed,
    f = f.observed,
    p = p,
    lambda = lambda,
    NL = NL,
    NI = NI
)

# Get posterior mean of the chi square discrepancy.

Chi.Square

# Calculate the p-value for the posterior mean of the chi square discrepancy.

stats::pchisq(Chi.Square,df=1)

## End(Not run)# dottest

```

chi_square_goodness_of_fit_from_input_all_param_MRMC

Chi square in the case of MRMC at a given dataset and a given parameter.

Description

Given parameter and data, the chi square is calculated.

Usage

```
chi_square_goodness_of_fit_from_input_all_param_MRMC(
  ppp,
  dl,
  dataList,
  summary = TRUE
)
```

Arguments

- | | |
|----------|--|
| ppp | An array of [C, M, Q], representing hit rate, where C, M, Q denotes the number of confidences, modalities, readers, respectively. |
| dl | An vector of length C M Q representing false alarm rate, where C, M, Q denotes the number of confidences, modalities, readers, respectively. |
| dataList | <p>A list, specifying an FROC data to be fitted a model. It consists of data of numbers of TPs, FPs, lesions, images. .In addition, if in case of mutple readers or mutple modalities, then modaity ID and reader ID are included also.</p> <p>The dataList will be passed to the function <code>rstan::sampling()</code> of rstan. This is a variable in the function <code>rstan::sampling()</code> in which it is named <code>data</code>.</p> <p>For the single reader and a single modality data, the dataList is made by the following manner:</p> <pre>dataList.Example <-list(h = c(41,22,14,8,1),# number of hits for each confidence level f = c(1,2,5,11,13),# number of false alarms for each confidence level NL = 124,# number of lesions (signals) NI = 63,# number of images (trials) C = 5) # number of confidence,.. the author thinks it can be calculated as the length of h or f ...? ha,why I included this. ha .. should be omitted.</pre> <p>Using this object <code>dataList.Example</code>, we can apply <code>fit_Bayesian_FROC()</code> such as <code>fit_Bayesian_FROC(dataList.Example)</code>.</p> <p>To make this R object <code>dataList</code> representing FROC data, this package provides three functions:</p> <ul style="list-style-type: none"> convertFromJafroc() If data is a JAFROC xlsx formulation. dataset_creator_new_version() Enter TP and FP data by table . |

`create_dataset()` Enter TP and FP data by **interactive** manner.

Before fitting a model, we can confirm our dataset is correctly formulated by using the function `viewdata()`.

A Single reader and a single modality (SRSC) case.

In a single reader and a single modality case (srsc), `dataList` is a list consisting of `f, h, NL, NI, C` where `f, h` are numeric vectors and `NL, NI, C` are positive integers.

- `f` Non-negative integer vector specifying number of false alarms associated with each confidence level. The first component corresponding to the highest confidence level.
- `h` Non-negative integer vector specifying number of Hits associated with each confidence level. The first component corresponding to the highest confidence level.
- `NL` A positive integer, representing Number of Lesions.
- `NI` A positive integer, representing Number of Images.
- `C` A positive integer, representing Number of Confidence level.

The detail of these dataset, see the datasets endowed with this package. 'Note that the maximal number of confidence level, denoted by `C`, are included, however, Note that confidence level vector `c` should not be specified. If specified, will be ignored, since it is created by `c <- c(rep(C:1))` in the program and do not refer from user input data, where `C` is the highest number of confidence levels. So, you should write down your hits and false alarms vector so that it is compatible with this automatically created `c` vector.

data Format:

A single reader and a single modality case

NI=63, NL=124 In R console ->	confidence level c	No. of false alarms f	No. of hits h
definitely present	<code>c[1] = 5</code>	<code>f[1] = F₅ = 1</code>	<code>h[1] = H₅ = 41</code>
probably present	<code>c[2] = 4</code>	<code>f[2] = F₄ = 2</code>	<code>h[2] = H₄ = 22</code>
equivocal	<code>c[3] = 3</code>	<code>f[3] = F₃ = 5</code>	<code>h[3] = H₃ = 14</code>
subtle	<code>c[4] = 2</code>	<code>f[4] = F₂ = 11</code>	<code>h[4] = H₂ = 8</code>
very subtle	<code>c[5] = 1</code>	<code>f[5] = F₁ = 13</code>	<code>h[5] = H₁ = 1</code>

* *false alarms* = False Positives = FP

* *hits* = True Positives = TP

Note that in FROC data, all confidence level means *present (diseased, lesion)*

case only, no confidence level indicating absent. Since each reader marks his suspicious location only if he thinks lesions are *present*, and marked positions generates the hits or false alarms, *thus* each confidence level represents that lesion is *present*. In the absent case, reader dose not mark any locations and hence, the absent confidence level does not relate this dataset. So, if reader think it is no lesion, then in such case confidence level is not needed.

Note that the first column of confidence level vector c should not be specified. If specified, will be ignored, since it is created by $c \leftarrow c(\text{rep}(C:1))$ automatically in the program and do not refer from user input data even if it is specified explicitly, where C is the highest number of confidence levels. So you should check the compatibility of your data and the confidence level vector $c \leftarrow c(\text{rep}(C:1))$ via a table which can be displayed by the function `viewdata()`.

Multiple readers and multiple modalities case, i.e., MRMC case

In case of multiple readers and multiple modalities, i.e., MRMC case, in order to apply the function `fit_Bayesian_FROC()`, dataset represented by an R list object representing FROC data must contain components $m, q, c, h, f, NL, C, M, Q$.

- C A positive integer, representing the **highest** number of confidence level, this is a scalar.
- M A positive integer vector, representing the number of **modalities**.
- Q A positive integer, representing the number of **readers**.
- m A vector of positive integers, representing the **modality** ID vector.
- q A vector of positive integers, representing the **reader** ID vector.
- c A vector of positive integers, representing the **confidence level**. This vector must be made by `rep(rep(C:1), M*Q)`
- h A vector of non-negative integers, representing the number of **hits**.
- f A vector of non-negative integers, representing the number of **false alarms**.
- NL A positive integer, representing the Total number of **lesions** for all images, this is a scalar.

Note that the maximal number of confidence level (denoted by C) are included in the above R object. However, each confidence level vector is not included in the data, because it is created automatically from C . To confirm false positives and hits are correctly ordered with respect to the automatically generated confidence vector,

the function `viewdata()` shows the table. Revised 2019 Nov 27 Revised 2019 Dec 5

Example data.

Multiple readers and multiple modalities (i.e., MRMC)

Modality ID	Reader ID	Confidence levels	No. of false alarms	No. of hits.
m	q	c	f	h
1	1	3	20	111

1	1	2	29	55
1	1	1	21	22
1	2	3	6	100
1	2	2	15	44
1	2	1	22	11
2	1	3	6	66
2	1	2	24	55
2	1	1	23	1
2	2	3	5	66
2	2	2	30	55
2	2	1	40	44

```

summary      * false alarms = False Positives = FP
              * hits = True Positives = TP
              Logical: TRUE of FALSE. Whether to print the verbose summary. If TRUE then
              verbose summary is printed in the R console. If FALSE, the output is minimal. I
              regret, this variable name should be verbose.

```

Value

A list, contains $\chi^2(Data|\theta)$, where *Data* and θ are specified by user.

Examples

```

## Not run:
#=====
# 0)
#=====

#      Chi square depends on data and model parameter, thus what we have to do is:
#      prepare data and parameter

#      In the follwoing, we use data named ddd as a dataset to be fitted a model,
#      and use posterior mean estimates as model parameter
#      To do so, we first prepare MCMC samples under the given data named ddd

fit <- fit_Bayesian_FROC( dataList = ddd, ite = 1111 )

#=====
# 1) hit rate and false alarm rate
#=====

```

```

e <- extract_estimates_MRMC(fit);
dl <- e$dl.EAP;
ppp <- e$ppp.EAP;

#=====
# 2) Calculates chi square using above hit rate and false alarm rate and data named ddd
#=====

chi_square_goodness_of_fit_from_input_all_param_MRMC(ppp,dl,ddd)

## End(Not run)# dontrun

```

Chi_square_goodness_of_fit_in_case_of_MRMC_Posterior_Mean

Chi square statistic (goodness of fit) in the case of MRMC at the pair of given data and each MCMC sample

Description

Revised 2019 Oct 16. Revised 2019 Nov 1. Revised 2019 Nov 27. Revised 2019 Dec 1.

In the following, we explain what this function calculates.

Let $\chi^2(y|\theta)$ be a *chi square goodness of fit* statistic which is defined by

(Observed data - Expectation)²/Expectation.

In MRMC cases, it is defined as follows.

$$\chi^2(D|\theta) := \sum_{r=1}^R \sum_{m=1}^M \sum_{c=1}^C \left(\frac{[H_{c,m,r} - N_L \times p_{c,m,r}(\theta)]^2}{N_L \times p_{c,m,r}(\theta)} + \frac{[F_{c,m,r} - (\lambda_c - \lambda_{c+1}) \times N_L]^2}{(\lambda_c(\theta) - \lambda_{c+1}(\theta)) \times N_L} \right).$$

where a dataset D consists of the pairs of the number of False Positives and the number of True Positives ($F_{c,m,r}, H_{c,m,r}$) together with the number of lesions N_L and the number of images N_I and θ denotes the model parameter.

Note that we can rewrite the chi square as follows.

$$\chi^2(D|\theta) := \sum_{r=1}^R \sum_{m=1}^M \sum_{c=1}^C \left(\frac{[H_{c,m,r} - E_{\theta}[H_{c,m,r}]]^2}{E_{\theta}[H_{c,m,r}]} + \frac{[F_{c,m,r} - E_{\theta}[F_{c,m,r}]]^2}{E_{\theta}[F_{c,m,r}]} \right).$$

So, the chi square has two terms.

1) The first term is the difference of hit and its expectation.

2) The second term is the differences of observed false alarms and its expectations.

In this function, we calculate each term, separately. So, return values retain these two terms, separately.

In this function, we calculate the following (I) and (II):

(I) A vector —————

Let us denote a collection of posterior MPMC samples for a given dataset D by

$$\theta_1, \theta_2, \dots, \theta_i, \dots, \theta_N,$$

namely, each θ_i is synthesized from posterior $\pi(\theta|D)$, $\theta_i \sim \pi(\theta|D)$.

Substituting these MPMC samples into the above definition of the chi square, we obtain the following vector as a return value of this function.

$$\begin{aligned} &\chi^2(D|\theta_1), \\ &\chi^2(D|\theta_2), \\ &\chi^2(D|\theta_3), \\ &\quad \vdots \\ &\quad \vdots \\ &\chi^2(D|\theta_N). \end{aligned}$$

(II) A mean of the above vector, namely, the posterior mean of the chi square over all MPMC samples —————

Using the set of chi squares ($\chi^2(D|\theta_i); i = 1, \dots, N$) calculated for each posterior MPMC samples $\theta_i \sim \pi(\theta|D)$, the function also calculates the posterior mean of the chi square statistic, namely,

$$\int \chi^2(D|\theta)\pi(\theta|D)d\theta,$$

by approximating it as

$$\frac{1}{N} \sum_{i=1}^N \chi^2(D|\theta_i),$$

where $\pi(\theta|D)$ denotes the posterior probability density under the given data D .

Do not confuse it with the following

$$\chi^2(D|\theta^*).$$

where θ^* denotes the posterior estimates, i.e., $\theta^* := \int \theta\pi(\theta|D)d\theta$.

Usage

```
Chi_square_goodness_of_fit_in_case_of_MRMC_Posterior_Mean(
  StanS4class,
  summary = TRUE,
  dl_is_an_array_of_C_only_and_not_C_M_Q = TRUE
)
```

Arguments

StanS4class An S4 object of class `stanfitExtended` which is an inherited class from the S4 class `stanfit`. This R object is a fitted model object as a return value of the function `fit_Bayesian_FROC()`.
It can be passed to `DrawCurves()`, `ppp()` and ... etc

summary Logical: TRUE or FALSE. Whether to print the verbose summary. If TRUE then verbose summary is printed in the R console. If FALSE, the output is minimal. I regret, this variable name should be verbose.

dl_is_an_array_of_C_only_and_not_C_M_Q
A Boolean, if TRUE, then false rate lambda simply denoted by l in R script (λ) is an vector $l[C]$. If false, then the false alarm rate is an array $l[C, M, Q]$.

Details

This function is implemented by vectorizations and further technics. When the author review this, I find my past work is great,... I forget that I made this. But this function is great.

Revised 2019 Nov 1

Value

A list, calculated by each modality reader and cofidence level, and MCMC samples. A one the component of list contains $\{\chi^2(Data|\theta_i); i=1,2,3,...n\}$, where n is the number of MCMC iterations. Each component of list is an array whose index indicats `[MCMC, Confidence, Modality, Reader]`. Each component of list is an array whose index indicats `[MCMC, C, M, Q]`.

To be passed to the calculation of Posterior predictive p value, I need the sum of return value, that is, sum of C,M,Q and resulting quantities construct a vetor whose length is a same as the number of MCMC iterations. I love you. I need you. So, to calculate such quantites, the author will make a new function.

Also, it retains the posterior mean of chi square statistic for an assumed occurrence of the data D :

$$\chi^2(Data) = \int \chi^2(Data|\theta)\pi(\theta|D)d\theta$$

Examples

```
## Not run:
```

```
#####  
#           1) Create a fitted model object for data named dd  
#####  
  
fit <- fit_Bayesian_FROC(  ite = 1111, # Number of MCMC iterations  
                          cha = 1,  
                          dataList = BayesianFROC::dd # This is a MRMC dataset.  
                          )  
  
#####  
#           2) Calculate a chi square and meta data  
#####  
  
a <- Chi_square_goodness_of_fit_in_case_of_MRMC_Posterior_Mean(fit)  
  
#####  
#           3) Extract a chi square  
#####  
  
chi.square <- a$chi.square  
  
#####  
#   A case of single reader is special in the programming perspective  
#                                           2020 Feb 24  
#####  
  
f <- fit_Bayesian_FROC( ite = 1111,  
                      cha = 1,  
                      summary = TRUE,  
                      dataList = dddd,  
                      see = 123)  
  
Chi_square_goodness_of_fit_in_case_of_MRMC_Posterior_Mean(f)
```

```
# Revised 2019 August 19
#      2019 Nov 1
```

```
## End(Not run)# dontrun
```

clearWorkspace *Clear Work Space*

Description

If functions are masked in global environment, I use this. this function has no variables.

Usage

```
clearWorkspace()
```

Author(s)

Issei Tsunoda

Close_all_graphic_devices
 Close the Graphic Device

Description

Close the graphic device to avoid errors in R CMD check.

Usage

```
Close_all_graphic_devices()
```

Examples

```
## Not run:
#   Open the graphic devices

grDevices::dev.new();plot(stats::runif(100),stats::runif(100))
grDevices::dev.new();plot(stats::runif(100),stats::runif(100))
grDevices::dev.new();plot(stats::runif(100),stats::runif(100))
grDevices::dev.new();plot(stats::runif(100),stats::runif(100))
grDevices::dev.new();plot(stats::runif(100),stats::runif(100))
```



```

grDevices::dev.new();plot(stats::runif(100),stats::runif(100))

#   Close the graphic device

##   Close_all_graphic_devices()

#'
## End(Not run)# dottest

```

```
compare           model comparison
```

Description

This is a model comparison.

Usage

```
compare(NI, ite = 1111)
```

Arguments

NI	images
ite	iteration #####1##### ##2##### ##3##### ##4##### ##5##### ##6##### #####7##### ##8##### ##9#####

```
comparison       model comparison
```

Description

This is a model comparison.

Usage

```

comparison(
  Number.of.variation.of.NL,
  Number.of.images,
  ite = 1111,
  DrawCurve = FALSE,
  dig = 3,
  e = 0
)

```

Arguments

Number.of.variation.of.NL	Lesion
Number.of.images	images
ite	iteration
DrawCurve	Logical: TRUE of FALSE. Whether the curve is to be drawn. TRUE or FALSE. If you want to draw the FROC and AFROC curves, then you set DrawCurve =TRUE, if not then DrawCurve =FALSE. The reason why the author make this variable DrawCurve is that it takes long time in MRMC case to draw curves, and thus Default value is FALSE in the case of MRMC data.
dig	A variable to be passed to the function <code>rstan::sampling()</code> of rstan in which it is named <code>...</code> . A positive integer representing the Significant digits, used in stan Cancellation. Default = 5,
e	exp for false alarms

ConfirmConvergence *Check R hat criterion*

Description

Calculates the maximum and the minimal values of R hat over all parameters. In addition, it returns a logical R object whether R hat is good (TRUE) or bad (FALSE).

Usage

```
ConfirmConvergence(StanS4class, summary = TRUE, digits = 2)
```

Arguments

StanS4class	An S4 object of the class <code>stanfit</code> . No need that it is the S4 class <code>stanfitExtended</code> .
summary	Logical: TRUE of FALSE. Whether to print the verbose summary. If TRUE then verbose summary is printed in the R console. If FALSE, the output is minimal. I regret, this variable name should be verbose.
digits	A positive integer, indicating digits for R hat statistics.

Details

Evaluates convergence criterion based on only the R hat statistics for a fitted model object. Revised Nov 23.

Value

Logical: TRUE of FALSE. If model converges (all R hat are closed to 1) then it is TRUE, and if not(some R hat is far from 1), then FALSE.

References

Gelman A. & Rubin, D.B. (1992). Inference from Iterative Simulation Using Multiple Sequences, *Statistical Science*, Volume 7, Number 4, 457-472.

See Also

check_rhat(), which is made by Betanalpha.

Examples

```
## Not run:
#=====The first example=====

      #((Primitive way)).
#1) Build the data for a singler reader and a single modality case.

dat <- list(c=c(3,2,1),      #Confidence level
           h=c(97,32,31), #Number of hits for each confidence level
           f=c(1,14,74),  #Number of false alarms for each confidence level

           NL=259,        #Number of lesions
           NI=57,        #Number of images
           C=3)          #Number of confidence level

# where, c denotes Confidence level,
#       h denotes number of Hits for each confidence level,
#       f denotes number of False alarms for each confidence level,
#       NL denotes Number of Lesions,
#       NI denotes Number of Images,

#2) Fit the FROC model.
#Since the above dataset "dat" are single reader and single modality,
#the following function fit the non hierarchical model.

fit <- BayesianFROC::fit_Bayesian_FROC(dat,ite=1111)

# Where, the variable "ite" specifies the iteration of MCMC samplings.
# Larger iteration is better.

#3.1) Confirm whether our estimates converge.
```

```

ConfirmConvergence(fit)

# By the above R script,
# the diagnosis of convergence will be printed in the R (R-studio) console.
# The diagnosis is based on only the R hat statistic.
# It also return the logical vector indicating whether or not the MCMC converge,
# if MCMC converges, then the return value is TRUE and if not, then FALSE.

# This logical return value is used in this package development
# and the user should not be interested.

# The following was useful for programming.
#3.2) The return value is TRUE or FALSE.

x <- ConfirmConvergence(fit)

#3.3) If you do not want to print the results in the R (Studio) console, then

x <- ConfirmConvergence(fit,summary=FALSE)

# 2019.05.21 Revised.
# 2019.12.02 Revised.

## End(Not run)# dontrun

```

Confirm_hit_rates_are_correctly_made_in_case_of_MRMC
Check hit rate is defined correctly

Description

Each hit rate is defined by dividing the area under the probability density function into C+1 regions. Thus, the sum of hit rates over all confidence level must be less than 1 which is checked by this function..

This function checks the sum of all hit rate over all confidence levels are less than 1 in case of MRMC

This code confirm the following inequality:

$$\sum_{cd} ppp[cd, md, qd] < 1$$

for each cd, md ($cd = 1, 2, \dots, C, md = 1, 2, \dots, M$).

The return value is an array consisting of logical R objects indicating whether the above inequality is TRUE or FALSE.

2020 Jan

Usage

```
Confirm_hit_rates_are_correctly_made_in_case_of_MRMC(
  StanS4class.or.An.array.of.ppp
)
```

Arguments

StanS4class.or.An.array.of.ppp
A stanfitExtended object or an array of component of hit rate namely ppp

Value

A array with logical components. Its dimension constructed by number of readers and modalities.

Examples

```
#####
#                               array: ppp
#####

p.truth.array <- hits_rate_creator()

Confirm_hit_rates_are_correctly_made_in_case_of_MRMC(p.truth.array)

## Not run:
#####
#                               fitted model object
#####

f <- fit_Bayesian_FROC(dd,ite = 1111)

Confirm_hit_rates_are_correctly_made_in_case_of_MRMC(f)

## End(Not run)
```

convertFromJafroc *Convert .xlsx File of **Jafroc** into R Object*

Description

Convert an FROC dataset

from .xlsx file of **Jafroc**

into R object

Usage

```
convertFromJafroc(No.of.Modalities, No.of.readers, No.of.confidence.levels)
```

Arguments

No.of.Modalities

A positive integer, indicating the number of *modalities* which is used in an .xlsx file.

No.of.readers

A positive integer, indicating the number of *readers* which is used in an .xlsx file.

No.of.confidence.levels

A positive integer, indicating the number of *confidence levels* which is used in an .xlsx file.

Format

The .xlsx file of Jafroc consists of three sheets named ***TP, FP, Truth, precisely! Correctly!*** (other names never be permitted !!)

————— ***TP*** —————

A sheet named ***TP*** consists of five columns ***precisely*** named from the right hand side:

ReaderID, ModalityID, CaseID, LesionID, TP_Rating.

NOTE.

CaseID Note that the above word ***CaseID*** means the Image ID vectors indicating the ID of radiographs. That is "case = image = radiograph".

the first row Note that the first row of each sheet of .xlsx file is constructed by the names of column as follows:

An Example of the sheet named ***TP*** in a .xlsx file for the ***Jafroc*** software

Interpretation of table

Throughout this explanation, we follow the convention that readers are male.

For example, the first row means the first reader (ReaderID=1) correctly find the first lesion (LesionID = 1) in the first image (CaseID = 1) taken by the first modality (ModalityID = 1) with his rating 5 (TP_Rating =5).

Similarly the second row means the first reader (ReaderID=1) correctly find the 4-th lesion (LesionID = 4) in the second image (CaseID = 2) taken by the 2-nd modality (ModalityID = 2) with his rating 4 (TP_Rating = 4).

ReaderID	ModalityID	CaseID	LesionID	TP_Rating.
1	1	1	1	5
1	2	2	1	4
1	3	4	1	5
1	1	8	1	3
1	2	8	2	4
1	3	9	1	4
1	1	9	2	3
1	2	9	3	5
1	3	11	1	3
2	1	1	1	4
2	2	4	1	4
2	3	5	1	4
2	1	8	1	1
2	2	8	2	2
2	3	8	3	2
2	1	10	1	3
2	2	10	2	2
2	3	11	1	2
:	:	:	:	:
:	:	:	:	:

FP

A sheet named **FP** consists of four columns *precisely* named from the right hand side: **ReaderID**, **ModalityID**, **CaseID**, **FP_Rating** An Example of a sheet named FP in a .xlsx file for the Jafroc software

Interpretation of table

For example, the first row means the first reader (ReaderID=1) makes a false alarm location in the first image (CaseID = 1) taken by the first modality (ModalityID = 1) with his rating 2 (TP_Rating =2).

Similarly the second row means the first reader (ReaderID=1) makes a false alarm location in the second image (CaseID = 2) taken by the 2-nd modality (ModalityID = 2) with his rating 1 (TP_Rating = 1).

Similarly the 6-th and 7-th rows mean that the first reader (ReaderID=1) makes two false alarm location in the second patient (CaseID = 2). The first false alarm is in the image taken by the 1-st modality (ModalityID = 1) with his rating 1 (TP_Rating = 1). The second false alarm is in the image taken by the 3-rd modality (ModalityID = 3) with his rating 2 (TP_Rating = 2).

ReaderID	ModalityID	CaseID	FP_Rating.
1	1	1	2

1	2	2	1
1	3	3	1
1	1	5	2
1	2	7	1
1	3	7	2
1	1	9	3
1	2	9	4
1	3	10	1
2	1	1	2
2	2	2	3
2	3	3	4
2	1	8	1
2	2	9	1
2	3	11	1
2	1	14	1
2	2	15	1
2	3	21	2
:	:	:	:
:	:	:	:

Truth

A sheet named **Truth** consists of three columns *precisely* named from the right hand side: **CaseID**, **LesionID**, **Weight** .

An Example of a sheet named Truth in a .xlsx file for the Jafroc software

Interpretation of table

For example, the first image (CaseID = 1) contains three lesions each of which is named 1,2,3, namely LesionID = 1,2,3. For example, the second image (CaseID = 2) contains two lesions each of which is named 1,2, namely LesionID = 1,2. For example, the third image (CaseID = 3) contains a single lesion named 1, namely LesionID = 1.

CaseID	LesionID	Weight
1	1	0.3333...
1	2	0.3333...
1	3	0.3333...
2	1	0.5
2	2	0.5
3	1	1
4	1	0.25
4	2	0.25
4	3	0.25
4	4	0.25
5	1	0.5
5	2	0.5
6	1	0.3333...
6	2	0.3333...

6	3	0.3333...
7	1	0.3333...
7	2	0.3333...
7	3	0.3333...
8	1	0.25
8	2	0.25
8	3	0.25
8	4	0.25
:	:	:
:	:	:

Note that the weight are used such that each image influences a same effect on the estimates. Without weight, the images including many targets (lesions) will have very strong effect on the estimates. To avoid such bias, Jafroc uses weight. In another context, weight would be used to specify more important lesions in each image.

Revised 2019 Dec 13; 2020 May 27

However, in this package, we do not use the information of weight. Since the theory of the author of this package did not consider such weight. In the future I have to include the notion of weight. Jafroc use the notion of figure of merit as non parametric manner. So, it seems difficult to include it in the Bayesian model, since generally speaking, Bayesian methodology is parametric.

Details

Create a dataset to be passed into the function `fit_Bayesian_FROC`. Convert an Excel file whose extension is `.xlsx` of Jafroc format to an R object representing FROC data to which we will apply functions in this package such as `fit_Bayesian_FROC()`.

Revised 2019 Jun 19 Revised 2019 Dec 13

The return values include a list which can be passed to the function `fit_Bayesian_FROC`. For data of Jafroc, running this function, we immediately can fit the author's Bayesian FROC model to this return value.

The Jafroc software's format consists of suspicious locations marked by readers and true locations. Such data is *redundant* for our Bayesian statistical models. So, we reduce the information of data to the number of false positives and number of hits for each confidence levels by this function.

Data can be calculated from the following Jafroc data, in which there are more information than TP and FP. In fact, in the Jafroc data, the FP and TP are counted for each images, each lesions etc. So, it has more information.

It causes limitation of our model. So, our model start to fit a model to the reduced data from Jafroc. So, the reduction will cause the non accuracy evaluation of the observer performance. The future research I should start the Jafroc formulation.

Value

A list, representing FROC data.

References

Bayesian Models for Free-response Receiver Operating Characteristic Analysis, pre-print

See Also

Rjafroc, which is unfortunately not on CRAN, now 2019 Jun 19. Or JAFROC software in the Chakarboty's Web page. Unfortunately, this software is no longer supported.

Examples

```
## Not run:
## Only run examples in interactive R sessions
if (interactive()) {
#=====
#           Example for convert the Jafroc data to the BayesianFROC
#=====

# Work Flow of this example

# step 0) Prepare Jafroc .xlsx file contained in this package
# step 1) Convert the .xlsx file obtained in step 0)
# step 2) Fit a model to data object obtained in step 1)

#=====
#           step 0)      Make a Jafroc data as an example dataset
#=====

# If you can search the xlsx file named JAFROC_data.xlsx
# in the director "inst/extdata" of this package,
# Then this step 0) is redundant. The author prepare this example for the people who
# cannot search the xlsx file in the "inst/extdata" of this package.

# By an xlsx file named JAFROC_data.xlsx in the director "inst/extdata" of this package,
# we can reconstruct it as follows:(If someone can obtain the Excel file
# from the path BayesianFROC/inst/extdata/JAFROC_data.xlsx, then the following code
# is not required to run. If searching bother you, then run the R script to obtain the
# Excel file.)
```

```

# I do not know how to users refer the JAFROC_data.xlsx in this package,
# so I provide it by making the same xlsx file as the JAFROC_data.xlsx.

# Note that JAFROC_data.xlsx cannot remove,
# if it is removed, then devtools::run_examples() make an error.

Truth <- readxl::read_excel(system.file("extdata",
  "JAFROC_data.xlsx",
  package="BayesianFROC"),
  sheet = "Truth")
##### utils::View(T Truth)

TP <- readxl::read_excel( system.file("extdata",
  "JAFROC_data.xlsx",
  package="BayesianFROC"),
  sheet = "TP")
#### utils::View(TP)

FP <- readxl::read_excel( system.file("extdata",
  "JAFROC_data.xlsx",
  package="BayesianFROC"),
  sheet = "FP")
#### utils::View(FP)

sample <- list(TP=TP,FP=FP,Truth=Truth)
openxlsx::write.xlsx(sample,"JafrocDatasetExample.xlsx")

tcltk::tkmessageBox(
  message="A file named

  JafrocDatasetExample.xlsx

  is created in the working directory")

# Now, we obtain an excel file named "JafrocDatasetExample.xlsx", which is same as
# the JAFROC_data.xlsx.
# whose format is available in the Jafroc software developed by Chakraborty.
# If you use your data, your data must has same format of "JafrocDatasetExample.xlsx".
# Note that other excel data must comply with the above format.

# Note that if you have an excel file
# which is formulated correctolly for our package,
# this process does not need.

```

```

# (0) From the above, we obtain "JafrocDatasetExample.xlsx"
# which is the multiple reader and multiple modality dataset
# for Jfroc analysis which is NOT implemented in our package,
# but Chakraborty's software called Jafroc or the R package Rjafroc.

#=====
#          step 1)      Convert a Jafroc data
#=====

# (1) Using "JafrocDatasetExample.xlsx" as an example excel file,
# we run the function to convert the excel file from Jafroc format
# to our format:

      dataList <- convertFromJafroc(
          No.of.Modalities =5,
          No.of.readers    =4,
          No.of.confidence.levels = 5
        )

# In the variable, there is no xlsx file, since it is selected by interactive manner.
# So, please select the xlsx file obtained in step 0) or your own Jafroc
# .xlsx file.

#=====
#          step 2)      Fitting a model to data converted from Jafroc
#=====

# (2) Now, we obtain a list of an FROC dataset as an R object named "dataList".
# Using this, we can fit a model to the dataset by the following code.

      fit <- fit_Bayesian_FROC(dataList )

]### Only run examples in interactive R sessions

## End(Not run)

      # Revised 2019. Jun 19
      # Revised 2019. Dec 13
      # Revised 2020 Feb

```

Revised 2020 April

CoronaVirus_Disease_2019

*Who should be inspected?***Description**

Even if a diagnosis test with respect to "all" said that it is positive, however the result cannot be correct in high probability. If we test no suspicious people, then it reduce our resource of diagnosis test and when some suspicious people needs the test, we cannot do the test.

So, the diagnosis test should be done for the suspicious people only. Not should be done for all people including no suspicious people. The medical resource is finite, we should use it for more optimal way.

Usage

CoronaVirus_Disease_2019(N, n, se, sp)

Arguments

N	The number of population, including diseased and non-diseased people
n	The number of diseased population
se	Sensitivity of a diagnostic test
sp	Specificity of a diagnostic test

Details

Diagnosis \ truth	Diseased	Non-diseased
Positive	$se*n$	$(N - n)(1 - sp)$
Negative	$(1-se)*n$	$(N - n)sp$
	n	$N - n$

For example,

if prevalence is 0.0001,

population is 10000,

specificity = 0.8,

sensitivity = 0.9,

then the table is the following.

We can calculate the probability of the event that a one whose diagnosis is positive is really diseased is

$$\frac{9}{1998 + 9} = 9/(1998 + 9) = 0.00448$$

Diagnosis \ truth	Diseased	Non-diseased
Positive	9	1998
Negative	1	7992
	$n = 10$	$N - n = 10000 - 10$

Value

Probability which is between 0 and 1. If you want to get percent, then it is 100 times the return value.

$$Prob(\text{Truth} = \text{diseased} | \text{Diagnosis} = \text{Positive}) = \frac{Se \times n}{Se \times n + (N - n) \times (1 - sp)}$$

where we denote the *conditional probability measure* of an event A given the assumed occurrence of G as an usual manner

$$P(A|G) := \frac{P(A \cap G)}{P(G)}.$$

Examples

CoronaVirus_Disease_2019(10000, 10, 0.9, 0.8)

9/(1998+9)

 CoronaVirus_Disease_2019_prevalence

Who should be inspected?

Description

Even if we test all people, the result is true with very low probabilities.

Usage

CoronaVirus_Disease_2019_prevalence(pre, se, sp)

Arguments

pre	Prevalence of population
se	Sensitivity of a diagnostic test
sp	Specificity of a diagnostic test

Details

Diagnosis \ truth	Diseased	Non-diseased
Positive	se*n	$(N - n)(1 - sp)$
Negative	$(1-se)*n$	$(N - n)sp$
	n	$N - n$

For example,
 if prevalence is 0.0001,
 population is 10000,
 specificity = 0.8,
 sensitivity = 0.9,
 then the table is the following.

We can calculate the probability of the event that a one whose diagnosis is positive is really diseased is

$$\frac{9}{1998 + 9} = 9/(1998 + 9) = 0.00448$$

Diagnosis \ truth	Diseased	Non-diseased
Positive	9	1998
Negative	1	7992
	$n = 10$	$N - n = 10000 - 10$

Value

same as `CoronaVirus_Disease_2019()`

$$Prob(Truth = diseased | Diagnosis = Positive) = \frac{Se \times pre}{Se \times pre + (1 - pre) \times (1 - sp)}$$

where we denotes the *conditional probability measure* of an event A given the assumed occurrence of G as an usual manner

$$P(A|G) := \frac{P(A \cap G)}{P(G)}.$$

See Also

`CoronaVirus_Disease_2019()`

Examples

```
CoronaVirus_Disease_2019_prevalence(0.0001, 0.9, 0.8)
CoronaVirus_Disease_2019_prevalence(0.03, 0.9, 0.8)
CoronaVirus_Disease_2019_prevalence(0.3, 0.9, 0.8)
```

```
#####
# If Sensitivity and Specificity is larger, then, the probability is also larger
#####
```

```
x <- stats::runif(1111, 0, 1)
y <- CoronaVirus_Disease_2019_prevalence(0.1, x, x)
```

```
dark_theme(4)
plot(x, y)
```



```
x <- stats::runif(1111,0,1)
y <- CoronaVirus_Disease_2019_prevalence(0.01,x,x)
```

```
dark_theme(4)
plot(x,y)
```

```
x <- stats::runif(1111,0,1)
y <- CoronaVirus_Disease_2019_prevalence(0.001,x,x)
```

```
dark_theme(4)
plot(x,y)
```

```
#####
# linear case:
#
# If prevalence is 0.5
# and sensitivity = specificity
# then, the probability is exactly same as sensitivity = specificity
#
#####
```

```
x <- stats::runif(1111,0,1)
y <- CoronaVirus_Disease_2019_prevalence(0.5,x,x)
```

```
dark_theme(4)
plot(x,y)
```

```
sum(x==y)==length(x)
```

```
# Because the last is true, the probablity is same as sensitivity
# when the prevalence is 0.5.
```

```

=====
# If the prevalence is larger, then, the probability is also larger
=====

x <- stats::runif(1111,0,1)
y <- CoronaVirus_Disease_2019_prevalence(x,0.9,0.9)

dark_theme(4)
plot(x,y)

```

create_dataList_MRMC *Creates a Single Dataset in Case of MRMC*

Description

From a given model parameter, creates a FROC dataset in case of multiple readers and multiple modality, briefly MRMC. The dataset consists of the number of hits and false alarms and ID vectors of readers, modalities, confidences, etc.

The created dataset is a list (which can be passed to [fit_Bayesian_FROC\(\)](#)). Model parameters are thresholds, mean and standard deviation of signal Gaussian.

Usage

```

create_dataList_MRMC(
  z.truth = BayesianFROC::z_truth,
  mu.truth = BayesianFROC::mu_truth,
  v.truth = BayesianFROC::v_truth,
  NI = 57,
  NL = 142,
  ModifiedPoisson = FALSE,
  seed = 123,
  summary = FALSE
)

```

Arguments

z.truth	Vector (of dimension C) represents the thresholds.
mu.truth	array of dimension (M,Q). Mean of the signal distribution of bi-normal assumption.
v.truth	array of dimension (M,Q). Standard Deviation of represents the signal distribution of bi-normal assumption.
NI	The number of images,
NL	The number of lesions,
ModifiedPoisson	

Logical, that is TRUE or FALSE.

If ModifiedPoisson = TRUE, then Poisson rate of false alarm is calculated *per lesion*, and model is fitted so that the FROC curve is an expected curve of points consisting of the pairs of TPF per lesion and FPF *per lesion*.

Similarly,

If ModifiedPoisson = TRUE, then Poisson rate of false alarm is calculated *per image*, and model is fitted so that the FROC curve is an expected curve of points consisting of the pair of TPF per lesion and FPF *per image*.

For more details, see the author's paper in which I explained *per image* and *per lesion*. (for details of models, see [vignettes](#), now, it is omitted from this package, because the size of vignettes are large.)

If ModifiedPoisson = TRUE, then the *False Positive Fraction (FPF)* is defined as follows (F_c denotes the number of false alarms with confidence level c)

$$\frac{F_1 + F_2 + F_3 + F_4 + F_5}{N_L},$$

$$\frac{F_2 + F_3 + F_4 + F_5}{N_L},$$

$$\frac{F_3 + F_4 + F_5}{N_L},$$

$$\frac{F_4 + F_5}{N_L},$$

$$\frac{F_5}{N_L},$$

where N_L is a number of lesions (signal). To emphasize its denominator N_L , we also call it the *False Positive Fraction (FPF) per lesion*.

On the other hand,

if ModifiedPoisson = FALSE (Default), then *False Positive Fraction (FPF)* is given by

$$\frac{F_1 + F_2 + F_3 + F_4 + F_5}{N_I},$$

$$\frac{F_2 + F_3 + F_4 + F_5}{N_I},$$

$$\frac{F_3 + F_4 + F_5}{N_I},$$

$$\frac{F_4 + F_5}{N_I},$$

$$\frac{F_5}{N_I},$$

where N_I is the number of images (trial). To emphasize its denominator N_I , we also call it the *False Positive Fraction (FPF) per image*.

The model is fitted so that the estimated FROC curve can be regarded as the expected pairs of FPF per image and TPF per lesion (ModifiedPoisson = FALSE)

or as the expected pairs of FPF per image and TPF per lesion (ModifiedPoisson = TRUE)

If ModifiedPoisson = TRUE, then FROC curve means the expected pair of **FPF per lesion** and TPF.

On the other hand, if ModifiedPoisson = FALSE, then FROC curve means the expected pair of **FPF per image** and TPF.

So, data of FPF and TPF are changed thus, a fitted model is also changed whether ModifiedPoisson = TRUE or FALSE. In traditional FROC analysis, it uses only per images (trial). Since we can divide one image into two images or more images, number of trial is not important. And more important is per signal. So, the author also developed FROC theory to consider FROC analysis under per signal. One can see that the FROC curve is rigid with respect to change of a number of images, so, it does not matter whether ModifiedPoisson = TRUE or FALSE. This rigidity of curves means that the number of images is redundant parameter for the FROC trial and thus the author try to exclude it.

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seed	The seed for creating hits which are synthesized by the binomial distributions with the specified seed.
summary	Logical: TRUE or FALSE. Whether to print the verbose summary. If TRUE then verbose summary is printed in the R console. If FALSE, the output is minimal. I regret, this variable name should be verbose.

Details

Specifying model parameters, we can replicate fake datasets. Different seed gives different fake data. Model parameters are the following.

z. truth

mu. truth

v. truth.

Probability law of hits Random variables of hits are distributed as follows.

$$H_{5,m,r} \sim \text{Binomial}(p_{5,m,r}(\theta), N_L),$$

then $H_{4,m,r}$ should be drawn from the binomial distribution with remaining targets

$$H_{4,m,r} \sim \text{Binomial}\left(\frac{p_{4,m,r}(\theta)}{1 - p_{5,m,r}(\theta)}, N_L - H_{5,m,r}\right).$$

Similarly, because we already found $H_{4,m,r} + H_{5,m,r}$ targets, the remained targets are $N_L - H_{5,m,r} - H_{4,m,r}$. Thus it natural to assume the following. Note that the hit rate is defined so that the resulting model satisfy certain equations which is not explained here.

$$H_{3,m,r} \sim \text{Binomial}\left(\frac{p_{3,m,r}(\theta)}{1 - p_{5,m,r}(\theta) - p_{4,m,r}(\theta)}, N_L - H_{5,m,r} - H_{4,m,r}\right).$$

$$H_{2,m,r} \sim \text{Binomial}\left(\frac{p_{2,m,r}(\theta)}{1 - p_{5,m,r}(\theta) - p_{4,m,r}(\theta) - p_{3,m,r}(\theta)}, N_L - H_{5,m,r} - H_{4,m,r} - H_{3,m,r}\right).$$

$$H_{1,m,r} \sim \text{Binomial}\left(\frac{p_{1,m,r}(\theta)}{1 - p_{5,m,r}(\theta) - p_{4,m,r}(\theta) - p_{3,m,r}(\theta) - p_{2,m,r}(\theta)}, N_L - H_{5,m,r} - H_{4,m,r} - H_{3,m,r} - H_{2,m,r}\right).$$

Probability law of false alarms

$$F_{5,m,r} \sim \text{Poisson}(q_{5,m,r}(\theta)N_X),$$

$$F_{4,m,r} \sim \text{Poisson}(q_{4,m,r}(\theta)N_X),$$

$$F_{3,m,r} \sim \text{Poisson}(q_{3,m,r}(\theta)N_X),$$

$$F_{2,m,r} \sim \text{Poisson}(q_{2,m,r}(\theta)N_X),$$

$$F_{1,m,r} \sim \text{Poisson}(q_{1,m,r}(\theta)N_X),$$

where subscripts m, r mean the m -th modality and the r -th reader, respectively. Note that N_X is the following two cases.

- 1) $N_X = N_L$ (The number of lesions), if `ModifiedPoisson = TRUE`.
- 2) $N_X = N_I$ (The number of images), if `ModifiedPoisson = FALSE`.

We fix the $N_X = N_L$ or $N_X = N_I$ through out this paper.

The rate $p_{c,m,r}(\theta)$ and $q_{c,m,r}(\theta)$ are calculated from the model parameter θ .

In the R code, the model parameter θ is denoted by

`z.truth`

`mu.truth`

`v.truth`.

By specifying these model parameters we can make a fake dataset consisting of hit data $H_{c,m,r}$ false alarm data $F_{c,m,r}$ for each c, m, r .

See Also

[chi_square_at_replicated_data_and_MCMC_samples_MRMC\(\)](#) [replicate_MRMC_dataList\(\)](#) (To make many MRMC datasets, see [replicate_MRMC_dataList\(\)](#))

Examples

```
## Not run:
  dataList <- create_dataList_MRMC()

  fit_Bayesian_FROC(dataList,
                    summary = FALSE,
                    ite = 1111)

# In the above example, we use a default values for true parameters for
# the distributions. The reason why the default values exists is difficulty
# for the user who is not familiar with FROC data nor konws the resions
# in which parameters of FROC model move.
# So, in the Bayesian model is merely model for FROC data.
# If user input the abnormal data, then the model does not fit nor converge
# in the Hamiltonian Monte Carlo simulations.

plot_FPF_and_TPF_from_a_dataset(create_dataList_MRMC() )

#=====
#   plot various MRMC datasets with fixed signal distribution but change thresholds
#=====
```



```

    0,
    1.2,
    2.3,
    3.3,
    4,
    5,
    6)
))

plot_FPF_and_TPF_from_a_dataset(create_dataList_MRMC( z.truth = c(-1,
    -0.5,
    0,
    1.2,
    2.3,
    3.3,
    4,
    5,
    6,
    7)
))

plot_FPF_and_TPF_from_a_dataset(create_dataList_MRMC( z.truth = c(-1,
    -0.5,
    0,
    1.2,
    2.3,
    3.3,
    4,
    5,
    6,
    7,
    8,
    9,
    10)
))

#####
#      Smoothing of Scatter Plot for FPF and TPF
#####

v <- v_truth_creator_for_many_readers_MRMC_data(M=1,Q=17)
m <- mu_truth_creator_for_many_readers_MRMC_data(M=1,Q=17)
d <- create_dataList_MRMC(mu.truth = m,v.truth = v)

d<-metadata_to_fit_MRMC(d)
df <- data.frame(FPF = d$ffN, TPF = d$hhN)
# require(graphics)

```



```
dark_theme()
graphics::plot(df, main = "lowess(cars)")
graphics::lines(stats::lowess(df), col = 2)
graphics::lines(stats::lowess(df, f = .2), col = 3)
graphics::legend(5, 120, c(paste("f = ", c("2/3", ".2"))), lty = 1, col = 2:3)

## End(Not run)
```

create_dataset	<i>Create a dataset</i>
----------------	-------------------------

Description

Create a dataset to apply the function [fit_Bayesian_FROC](#) .

Usage

```
create_dataset()
```

Details

This is an interactive creator of an FROC dataset. Using this return value, we can fit a FROC model to data by applying the function [fit_Bayesian_FROC](#) in this package.

To tell the truth, the author never use this function to create dataset. So,... this function is not so good.

Value

A list of FROC data to which we fit a FROC model.

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Examples

```
## Not run:
## Only run examples in interactive R sessions
if (interactive()) {

  create_dataset()

}### Only run examples in interactive R sessions

## End(Not run)
```

Credible_Interval_for_curve

Draw FROC curves which means credible interval.

Description

Plot FROC curves based on two parameters a and b.

Usage

```
Credible_Interval_for_curve(
  dataList,
  StanS4class.fit_MRMC_versionTWO,
  mesh.for.drawing.curve = 10000,
  upper_x = upper_x,
  upper_y = upper_y,
  lower_y = lower_y
)
```

Arguments

`dataList` A list, specifying an FROC data to be fitted a model. It consists of data of numbers of TPs, FPs, lesions, images. .In addition, if in case of mutiple readers or mutiple modalities, then modaity ID and reader ID are included also. The `dataList` will be passed to the function `rstan::sampling()` of **rstan**. This is a variable in the function `rstan::sampling()` in which it is named `data`. For the single reader and a single modality data, the `dataList` is made by the following manner:

```
dataList.Example <-list(
h = c(41,22,14,8,1),# number of hits for each confidence level
f = c(1,2,5,11,13),# number of false alarms for each confidence level

NL = 124,# number of lesions (signals)
NI = 63,# number of images (trials)
C = 5) # number of confidence,.. the author thinks it can be calculated
as the length of h or f ...? ha,why I included this. ha .. should be omitted.
```

Using this object `dataList.Example`, we can apply `fit_Bayesian_FROC()` such as `fit_Bayesian_FROC(dataList.Example)`.

To make this R object `dataList` representing FROC data, this package provides three functions:

- `convertFromJafroc()` If data is a **JAFROC** **xlsx** formulation.
- `dataset_creator_new_version()` Enter TP and FP data **by table** .
- `create_dataset()` Enter TP and FP data by **interactive** manner.

Before fitting a model, we can confirm our dataset is correctly formulated by using the function `viewdata()`.

A Single reader and a single modality (SRSC) case.

In a single reader and a single modality case (srsc), `dataList` is a list consisting of `f, h, NL, NI, C` where `f, h` are numeric vectors and `NL, NI, C` are positive integers.

- `f` Non-negative integer vector specifying number of false alarms associated with each confidence level. The first component corresponding to the highest confidence level.
- `h` Non-negative integer vector specifying number of Hits associated with each confidence level. The first component corresponding to the highest confidence level.

`NL` A positive integer, representing Number of Lesions.

`NI` A positive integer, representing Number of Images.

`C` A positive integer, representing Number of Confidence level.

The detail of these dataset, see the datasets endowed with this package. Note that the maximal number of confidence level, denoted by `C`, are included, however, Note that confidence level vector `c` should not be specified. If specified, will be ignored, since it is created by `c <- c(rep(C:1))` in the program and do not refer from user input data, where `C` is the highest number of confidence levels. So, you should write down your hits and false alarms vector so that it is compatible with this automatically created `c` vector.

data Format:

A single reader and a single modality case

NI=63, NL=124 In R console ->	confidence level c	No. of false alarms f	No. of hits h
definitely present	$c[1] = 5$	$f[1] = F_5 = 1$	$h[1] = H_5 = 41$
probably present	$c[2] = 4$	$f[2] = F_4 = 2$	$h[2] = H_4 = 22$
equivocal	$c[3] = 3$	$f[3] = F_3 = 5$	$h[3] = H_3 = 14$
subtle	$c[4] = 2$	$f[4] = F_2 = 11$	$h[4] = H_2 = 8$
very subtle	$c[5] = 1$	$f[5] = F_1 = 13$	$h[5] = H_1 = 1$

* *false alarms* = False Positives = FP

* *hits* = True Positives = TP

Note that in FROC data, all confidence level means *present (diseased, lesion)* case only, no confidence level indicating absent. Since each reader marks his suspicious location only if he thinks lesions are *present*, and marked positions

generates the hits or false alarms, *thus* each confidence level represents that lesion is *present*. In the absent case, reader dose not mark any locations and hence, the absent confidence level does not relate this dataset. So, if reader think it is no lesion, then in such case confidence level is not needed.

Note that the first column of confidence level vector c should not be specified. If specified, will be ignored, since it is created by $c \leftarrow c(\text{rep}(C:1))$ automatically in the program and do not refer from user input data even if it is specified explicitly, where C is the highest number of confidence levels. So you should check the compatibility of your data and the confidence level vector $c \leftarrow c(\text{rep}(C:1))$ via a table which can be displayed by the function `viewdata()`.

Multiple readers and multiple modalities case, i.e., MRMC case

In case of multiple readers and multiple modalities, i.e., MRMC case, in order to apply the function `fit_Bayesian_FROC()`, dataset represented by an R list object representing FROC data must contain components $m, q, c, h, f, NL, C, M, Q$.

- C A positive integer, representing the **highest** number of confidence level, this is a scalar.
- M A positive integer vector, representing the number of **modalities**.
- Q A positive integer, representing the number of **readers**.
- m A vector of positive integers, representing the **modality ID** vector.
- q A vector of positive integers, representing the **reader ID** vector.
- c A vector of positive integers, representing the **confidence level**. This vector must be made by `rep(rep(C:1), M*Q)`
- h A vector of non-negative integers, representing the number of **hits**.
- f A vector of non-negative integers, representing the number of **false alarms**.
- NL A positive integer, representing the Total number of **lesions** for all images, this is a scalar.

Note that the maximal number of confidence level (denoted by C) are included in the above R object. However, each confidence level vector is not included in the data, because it is created automatically from C . To confirm false positives and hits are correctly ordered with respect to the automatically generated confidence vector,

the function `viewdata()` shows the table. Revised 2019 Nov 27 Revised 2019 Dec 5

Example data.

Multiple readers and multiple modalities (i.e., MRMC)

Modality ID	Reader ID	Confidence levels	No. of false alarms	No. of hits.
m	q	c	f	h
1	1	3	20	111
1	1	2	29	55
1	1	1	21	22

1	2	3	6	100
1	2	2	15	44
1	2	1	22	11
2	1	3	6	66
2	1	2	24	55
2	1	1	23	1
2	2	3	5	66
2	2	2	30	55
2	2	1	40	44

—

* *false alarms* = False Positives = FP
 * *hits* = True Positives = TP

StanS4class.fit_MRMC_versionTWO
 A return value of fit_MRMC_versionTWO.

mesh.for.drawing.curve
 A positive large integer, indicating number of dots drawing the curves, Default =10000.

upper_x
 A positive real number, indicating the frame size of drawing picture.

upper_y
 A positive real number, indicating the frame size of drawing picture.

lower_y
 A positive real number, indicating the frame size of drawing picture.

d

*Data: A Single Reader and A Single Modality***Description**

A list, representing FROC data. This is used to build a hierarchical FROC model. This data is exactly same as `dataList.Chakra.1`.

Details

This data is same as [dataList.Chakra.1.with.explantation](#). The author name it d for the sake of simplicity, that is, it is easy to write, because only one character!!

Author(s)

Issei Tsunoda <tsunoda.issei1111@gmail.com >

References

Maximum likelihood analysis of free-response receiver operating characteristic (FROC) data, Dev P. Chakraborty.

See Also

[dataList.Chakra.1.with.explantation](#) which is exactly same in this data d.

dark_theme

Dark Theme

Description

Executing this function before plotting, the plot region becomes the dark theme.

Usage

```
dark_theme(type = 1)
```

Arguments

type An integer

Details

A function specifies the color in graphic devices.

Value

Nothing

Examples

```
## Not run:  
  
dark_theme(1)  
  
graphics::plot(c(1,2,3),c(1,2,3))  
  
dark_theme(2)  
  
graphics::plot(c(1,2,3),c(1,2,3))  
  
# 2019.05.21 Revised.  
  
dark_theme(3)  
  
graphics::plot(c(1,2,3),c(1,2,3))
```

```

dark_theme(4)

graphics::plot(c(1,2,3),c(1,2,3))

# 2019 Oct 19 Revised

## End(Not run)# dottest

```

data.bad.fit

Data: Single reader and Single modality

Description

A list, representing FROC data consisting of hits, false alarms, number of lesions, number of images, to which we fit a FROC model.

Format

A list consists of two integer vectors f , h and three integers NL , NI , C .

- f Non-negative integer vector specifying number of false alarms associated with each confidence level. The first component corresponding to the highest confidence level.
- h Non-negative integer vector specifying number of Hits associated with each confidence level. The first component corresponding to the highest confidence level.
- NL A positive integer, representing Number of Lesions.
- NI A positive integer, representing Number of Images.
- C A positive integer, representing Number of Confidence level.

Contents:

A single reader and single modality case

NI=57, NL=259 In R console ->	confidence level	No. of false alarms	No. of hits
	c	f	h
definitely present	4	11	11
probably present	3	1	97
subtle	2	14	32
very subtle	1	74	31

* *false alarms* = False Positives = FP

* *hits* = True Positives = TP

Note that in FROC data, the confidence level means present (deseased, positive) case only. Since each reader marks their suspicious location only and it generate the hits and false alarms for his confidenc level representing that lesion is present. In the absent case, reader dose not mark any locations and hence, the absent cofidence level does not relate this dataset.

Note that the first column of confidence level vector *c* should not be specified. If specified, will be ignored , since it is created by `c<-c(rep(C:1))` automatically in the program and it does not refer from user input data even if it is specified explicitly, where *C* is the highest number of confidence levels. So you should check the compatibility of your data and the program's generating new confidence level vector by a table which can be displayed by the function `viewdata()`.

Note that The format for the above example data must be made by the following forms:

```
dat <-list(
h = c(11,97,32,31),
f = c( 11,1,14,74),
NL = 259,
NI = 57,
C = 4)
```

This object *dat* can be passed to the function `fit_Bayesian_FROC()` as the following manner `fit_Bayesian_FROC(dat)`.

Details

This data-set is very bad fitting. Even if the MCMC sampling is very good, however, the FPF and TPF are not on the FROC curve.

Note that the maximal number of confidence level, denoted by *C*, are included, however, confidence level vector *c* should not be specified. If specified, will be ignored , since it is created by `c<-c(rep(C:1))` in the program and it does not refer from user input data, where *C* is the highest number of confidence levels. Should write down your hits and false alarms vector so that it is compatible with this automatically created vector *c*.

Author(s)

Issei Tsunoda <tsunoda.issei1111@gmail.com >

References

I love you.

See Also

`viewdata()`, which shows your data confortably by `knitr::kable()`.

`data.hier.fictitious` *Multiple reader and Multiple modality data*

Description

This is used to build a hierarchical FROC model.

Details

This data is fictitious.

Author(s)

Issei Tsunoda <tsunoda.issei1111@gmail.com >

References

The author' preprint

`data.MultiReaderMultiModality`
Multiple reader and Multiple modality data

Description

This is used to build a hierarchical FROC model. This data is same as `dataList.Chakra.Web`.

Details

This data appeared in Chakraborty's paper (1988)

Author(s)

Issei Tsunoda <tsunoda.issei1111@gmail.com >

References

Maximum likelihood analysis of free-response receiver operating characteristic (FROC) data, Dev P. Chakraborty.

data.nonconverge.srsc **Non-Convergent Data: Single reader and Single modality**

Description

A list, representing **non-convergent** FROC data (which does not converge in the sense of R hat) of hits and false alarms. This is used to build a non-hierarchical FROC model.

Format

A list consists of two integer vectors f , h and three integers NL , NI , C .

- f Non-negative integer vector specifying number of false alarms associated with each confidence level. The first component corresponding to the highest confidence level.
- h Non-negative integer vector specifying number of Hits associated with each confidence level. The first component corresponding to the highest confidence level.
- NL A positive integer, representing Number of Lesions.
- NI A positive integer, representing Number of Images.
- C A positive integer, representing Number of Confidence level.

Contents:

A single reader and single modality case

NI=57, NL=269 In R console ->	confidence level	No. of false alarms	No. of hits
	c	f	h
definitely present	3	99	88
probably present	2	0	0
questionable	1	0	0

* *false alarms* = False Positives = FP

* *hits* = True Positives = TP

Note that in FROC data, the confidence level means present (diseased, positive) case only. Since each reader marks their suspicious location only and it generate the hits and false alarms for his confidence level representing that lesion is present. In the absent case, reader dose not mark any locations and hence, the absent confidence level does not relate this dataset.

Note that the first column of confidence level vector c should not be specified. If specified, will be ignored, since it is created by `c<-c(rep(C:1))` automatically in the program and it does not refer from user input data even if it is specified explicitly, where C is the highest number of confidence levels. So you should check the compatibility of your data and the program's generating new confidence level vector by a table which can be displayed by the function `viewdata()`.

Note that The format for the above example data must be made by the following forms:

```
dat <-list(  
  h = c(99, 0, 0),  
  f = c( 88, 0, 0),  
  NL = 111,  
  NI = 111,  
  C = 3)
```

This object dat can be passed to the function `fit_Bayesian_FROC()` as the following manner `fit_Bayesian_FROC(dat)`.

Details

Note that the maximal number of confidence level, denoted by C, are included, however, confidence level vector `c` should not be specified. If specified, will be ignored, since it is created by `c <-c(rep(C:1))` in the program and it does not refer from user input data, where C is the highest number of confidence levels. Should write down your hits and false alarms vector so that it is compatible with this automatically created vector `c`.

Author(s)

Issei Tsunoda <tsunoda.issei1111@gmail.com >

See Also

[dataList.Chakra.1.with.explantation](#)

data.SingleReaderSingleModality

Data: A Single Reader and A Single Modality

Description

A list, representing FROC data. This is used to build a hierarchical FROC model. This data is same as `dataList.Chakra.1`.

Details

This data appeared in Chakraborty's paper (1988)

Author(s)

Issei Tsunoda <tsunoda.issei1111@gmail.com >

References

Maximum likelihood analysis of free-response receiver operating characteristic (FROC) data, Dev P. Chakraborty.

See Also

[dataList.Chakra.1.with.explantation](#)

dataList.Chakra.1 *Data: A Single Reader and A Single Modality*

Description

A list, representing FROC data consisting of hits, false alarms, number of lesions, number of images. We fit a FROC model to the data.

Format

A list consists of two integer vectors f , h and three integers NL , NI , C .

f Non-negative integer vector specifying number of false alarms associated with each confidence level. The first component corresponding to the highest confidence level.

h Non-negative integer vector specifying number of Hits associated with each confidence level. The first component corresponding to the highest confidence level.

NL A positive integer, representing Number of Lesions.

NI A positive integer, representing Number of Images.

C A positive integer, representing Number of Confidence level.

Contents:

A single reader and a single modality case

NI=57, NL=259 In R console ->	confidence level c	No. of false alarms f	No. of hits h
definitely present	3	1	97
probably present	2	14	32
questionable	1	74	31

* *false alarms* = False Positives = FP

* *hits* = True Positives = TP

Note that in FROC data, the confidence level means present (diseased, positive) case only. Since each reader marks their suspicious location only and it generate the hits and false alarms for his confidence level representing that lesion is present. In the absent case, reader dose not mark any locations and hence, the absent confidence level does not relate this dataset.

Note that the first column of confidence level vector c should not be specified. If specified, will

be ignored , since it is created by `c<-c(rep(C:1))` automatically in the program and it does not refer from user input data even if it is specified explicitly, where C is the highest number of confidence levels. So you should check the compatibility of your data and the program's generating new confidence level vector by a table which can be displayed by the function `viewdata()`.

Note that The format for the above example data must be made by the following forms:

```
dat <-list(  
h = c(97, 32, 31 ),  
f = c(1 , 14, 74 ),  
NL = 259,  
NI = 57,  
C = 3)
```

This object `dat` can be passed to the function `fit_Bayesian_FROC()` as the following manner `fit_Bayesian_FROC(dat)`.

Details

Note that the maximal number of confidence level, denoted by C, are included, however, confidence level vector `c` should not be specified. If specified, will be ignored , since it is created by `c<-c(rep(C:1))` in the program and it does not refer from user input data, where C is the highest number of confidence levels. Should write down your hits and false alarms vector so that it is compatible with this automatically created vector `c`.

This data appeared in Chakraborty's paper (1988).

Author(s)

Issei Tsunoda <tsunoda.issei1111@gmail.com >

References

Maximum likelihood analysis of free-response receiver operating characteristic (FROC) data, Dev P. Chakraborty.

See Also

[dataList.Chakra.1.with.explantation](#)

dataList.Chakra.1.with.explantation

Data: A Single Reader and A Single Modality

Description

A list, representing an FROC dataset consisting of hits, false alarms, number of lesions, number of images. We fit a FROC model to the data.

Format

A list consists of two integer vectors f , h and three integers NL , NI , C .

- f Non-negative integer vector specifying number of false alarms associated with each confidence level. The first component corresponding to the highest confidence level.
- h Non-negative integer vector specifying number of Hits associated with each confidence level. The first component corresponding to the highest confidence level.
- NL A positive integer, representing Number of Lesions.
- NI A positive integer, representing Number of Images.
- C A positive integer, representing Number of Confidence level.

Contents:

A single reader and a single modality case

NI=57, NL=259 In R console ->	confidence level c	No. of false alarms f	No. of hits h
definitely present	3	1	97
probably present	2	14	32
questionable	1	74	31

* *false alarms* = False Positives = FP

* *hits* = True Positives = TP

Note that in FROC data, the confidence level means present (deseased, positive) case only. Since each reader marks their suspicious location only and it generate the hits and false alarms for his confidenc level representing that lesion is present. In the absent case, reader dose not mark any locations and hence, the absent cofidence level does not relate this dataset.

Note that the first column of confidence level vector c should not be specified. If specified, will be ignored , since it is created by $c \leftarrow c(\text{rep}(C:1))$ automatically in the program and it does not refer from user input data even if it is specified explicitly, where C is the highest number of confidence levels. So you should check the compatibility of your data and the program's generating new confidence level vector by a table which can be displayed by the function `viewdata()`.

Note that The format for the above example data must be made by the following forms:

```
dat <-list(
h = c(97, 32, 31 ),
f = c(1 , 14, 74 ),
NL = 259,
NI = 57,
C = 3)
```

This object `dat` can be passed to the function `fit_Bayesian_FROC()` as the following manner `fit_Bayesian_FROC(dat)`.

Details

Note that the maximal number of confidence level, denoted by `C`, are included, however, confidence level vector `c` should not be specified. If specified, will be ignored, since it is created by `c <-c(rep(C:1))` in the program and it does not refer from user input data, where `C` is the highest number of confidence levels. Should write down your hits and false alarms vector so that it is compatible with this automatically created vector `c`.

This data appeared in Chakraborty's paper (1988). This dataset is same as `dataList.Chakra.1`. The difference between two dataset is only explanations for vectors. That is I attached the name for each vector by `names()`. I hope it help user for understanding what it is.

Author(s)

Issei Tsunoda <tsunoda.issei1111@gmail.com >

Source

Maximum likelihood analysis of free-response receiver operating characteristic (FROC) data, Dev P. Chakraborty.

References

Maximum likelihood analysis of free-response receiver operating characteristic (FROC) data, Dev P. Chakraborty.

`dataList.Chakra.2` *Data: A Single Reader and A Single Modality*

Description

A list, representing FROC data consisting of hits, false alarms, number of lesions, number of images. We fit a FROC model to the data.

Format

A list consists of two integer vectors `f`, `h` and three integers `NL`, `NI`, `C`.

- `f` Non-negative integer vector specifying number of false alarms associated with each confidence level. The first component corresponding to the highest confidence level.
- `h` Non-negative integer vector specifying number of Hits associated with each confidence level. The first component corresponding to the highest confidence level.
- `NL` A positive integer, representing Number of Lesions.
- `NI` A positive integer, representing Number of Images.

C A positive integer, representing Number of Confidence level.

Contents:

A single reader and a single modality case

NI=57 ,NL=269 In R console ->	confidence level c	No. of false alarms f	No. of hits h
definitely present	3	4	122
probably present	2	13	31
questionable	1	44	20

* *false alarms* = False Positives = FP

* *hits* = True Positives = TP

Note that in FROC data, the confidence level means present (deseased, positive) case only. Since each reader marks their suspicious location only and it generate the hits and false alarms for his confidenc level representing that lesion is present. In the absent case, reader dose not mark any locations and hence, the absent confidenc level does not relate this dataset.

Note that the first column of confidence level vector *c* should not be specified. If specified, will be ignored , since it is created by `c<-c(rep(C:1))` automatically in the program and it does not refer from user input data even if it is specified explicitly, where *C* is the highest number of confidence levels. So you should check the compatibility of your data and the program's generating new confidence level vector by a table which can be displayed by the function `viewdata()`.

Note that The format for the above example data must be made by the following forms:

```
dat <-list(
h = c(122,31,20 ),
f = c( 4,13,44 ),
NL = 269,
NI = 57,
C = 3)
```

This object *dat* can be passed to the function `fit_Bayesian_FROC()` as the following manner `fit_Bayesian_FROC(dat)`.

Details

Note that the maximal number of confidence level, denoted by *C*, are included, however, confidence level vector *c* should not be specified. If specified, will be ignored , since it is created by `c<-c(rep(C:1))` in the program and it does not refer from user input data, where *C* is the highest number of confidence levels. Should write down your hits and false alarms vector so that it is compatible with this automatically created vector *c*.

This data appeared in Chakraborty's paper (1988).

Author(s)

Issei Tsunoda <tsunoda.issei1111@gmail.com >

References

Maximum likelihood analysis of free-response receiver operating characteristic (FROC) data, Dev P. Chakraborty.

See Also

[dataList.Chakra.1.with.explantation](#)

dataList.Chakra.3 *Data: A Single Reader and A Single Modality*

Description

A list, representing FROC data consisting of hits, false alarms, number of lesions, number of images. We fit a FROC model to the data.

Format

A list consists of two integer vectors f , h and three integers NL , NI , C .

- f Non-negative integer vector specifying number of false alarms associated with each confidence level. The first component corresponding to the highest confidence level.
- h Non-negative integer vector specifying number of Hits associated with each confidence level. The first component corresponding to the highest confidence level.
- NL A positive integer, representing Number of Lesions.
- NI A positive integer, representing Number of Images.
- C A positive integer, representing Number of Confidence level.

Contents:

A single reader and a single modality case

NI=57, NL=269 In R console ->	confidence level	No. of false alarms	No. of hits
	c	f	h
definitely present	3	2	96
probably present	2	16	39
questionable	1	48	13

* *false alarms* = False Positives = FP

* *hits* = True Positives = TP

Note that in FROC data, the confidence level means present (deseased, positive) case only. Since each reader marks their suspicious location only and it generate the hits and false alarms for his confidenc level representing that lesion is present. In the absent case, reader dose not mark any locations and hence, the absent cofidence level does not relate this dataset.

Note that the first column of confidence level vector *c* should not be specified. If specified, will be ignored , since it is created by `c<-c(rep(C:1))` automatically in the program and it does not refer from user input data even if it is specified explicitly, where C is the highest number of confidence levels. So you should check the compatibility of your data and the program's generating new confidence level vector by a table which can be displayed by the function `viewdata()`.

Note that The format for the above example data must be made by the following forms:

```
dat <-list(
h = c(96, 39, 13 ),
f = c( 2, 16, 48),
NL = 269,
NI = 57,
C = 3)
```

This object *dat* can be passed to the function `fit_Bayesian_FROC()` as the following manner `fit_Bayesian_FROC(dat)`.

Details

Note that the maximal number of confidence level, denoted by C, are included, however, confidence level vector *c* should not be specified. If specified, will be ignored , since it is created by `c<-c(rep(C:1))` in the program and it does not refer from user input data, where C is the highest number of confidence levels. Should write down your hits and false alarms vector so that it is compatible with this automatically created vector *c*.

This data appeared in Chakraborty's paper (1988).

Author(s)

Issei Tsunoda <tsunoda.issei1111@gmail.com >

References

Maximum likelihood analysis of free-response receiver operating characteristic (FROC) data, Dev P. Chakraborty.

See Also

[dataList.Chakra.1.with.explantation](#)

dataList.Chakra.4 *Data: A Single Reader and A Single Modality*

Description

A list, representing FROC data consisting of hits, false alarms, number of lesions, number of images. We fit a FROC model to the data.

Format

A list consists of two integer vectors f , h and three integers NL , NI , C .

- f Non-negative integer vector specifying number of false alarms associated with each confidence level. The first component corresponding to the highest confidence level.
- h Non-negative integer vector specifying number of Hits associated with each confidence level. The first component corresponding to the highest confidence level.
- NL A positive integer, representing Number of Lesions.
- NI A positive integer, representing Number of Images.
- C A positive integer, representing Number of Confidence level.

Contents:

A single reader and a single modality case

NI=50, NL=397 In R console ->	confidence level	No. of false alarms	No. of hits
	c	f	h
definitely present	4	8	160
probably present	3	16	25
subtle	2	18	15
very subtle	1	13	7

* *false alarms* = False Positives = FP

* *hits* = True Positives = TP

Note that in FROC data, the confidence level means present (diseased, positive) case only. Since each reader marks their suspicious location only and it generate the hits and false alarms for his confidence level representing that lesion is present. In the absent case, reader dose not mark any locations and hence, the absent confidence level does not relate this dataset.

Note that the first column of confidence level vector c should not be specified. If specified, will be ignored, since it is created by `c<-c(rep(C:1))` automatically in the program and it does not refer from user input data even if it is specified explicitly, where C is the highest number of

confidence levels. So you should check the compatibility of your data and the program's generating new confidence level vector by a table which can be displayed by the function `viewdata()`.

Note that The format for the above example data must be made by the following forms:

```
dat <-list(  
  h = c(160,25,15,7),  
  f = c( 8,16,18,13),  
  NL = 397,  
  NI = 50,  
  C = 4)
```

This object `dat` can be passed to the function `fit_Bayesian_FROC()` as the following manner `fit_Bayesian_FROC(dat)`.

Details

Note that the maximal number of confidence level, denoted by `C`, are included, however, confidence level vector `c` should not be specified. If specified, will be ignored, since it is created by `c <-c(rep(C:1))` in the program and it does not refer from user input data, where `C` is the highest number of confidence levels. Should write down your hits and false alarms vector so that it is compatible with this automatically created vector `c`.

This data appeared in Chakraborty's paper (1988).

Author(s)

Issei Tsunoda <tsunoda.issei1111@gmail.com >

References

Maximum likelihood analysis of free-response receiver operating characteristic (FROC) data, Dev P. Chakraborty.

See Also

[dataList.Chakra.1.with.explantation](#)

dataList.Chakra.Web *An FROC Data of Multiple-Reader and Multiple-Modality*

Description

A list, representing FROC data in case of MRMC.

Details

This data is based on an example data of Chakraborty's JAFROC software. The author have calculated hits and false alarms from this example data formulated for Jafroc.

Contents:

Multiple readers and Multiple modalities case, i.e., MRMC case

ModalityID	ReaderID	Confidence levels	No. of false alarms	No. of hits.
q	m	c	f	h
1	1	5	0	50
1	1	4	4	30
1	1	3	20	11
1	1	2	29	5
1	1	1	21	1
1	2	5	0	15
1	2	4	0	29
1	2	3	6	29
1	2	2	15	1
1	2	1	22	0
1	3	5	1	39
1	3	4	15	31
1	3	3	18	8
1	3	2	31	10
1	3	1	19	3
1	4	5	1	10
1	4	4	2	8
1	4	3	4	25
1	4	2	16	45
1	4	1	17	14
2	1	5	1	52
2	1	4	1	25
2	1	3	21	13
2	1	2	24	4
2	1	1	23	1
2	2	5	1	27
2	2	4	1	28
2	2	3	5	29
2	2	2	30	1
2	2	1	40	0
2	3	5	2	53
2	3	4	19	29
2	3	3	31	13
2	3	2	56	2
2	3	1	42	4
2	4	5	2	9
2	4	4	0	16

2	4	3	2	22
2	4	2	30	43
2	4	1	32	14
3	1	5	1	43
3	1	4	7	29
3	1	3	13	11
3	1	2	28	6
3	1	1	19	0
3	2	5	0	18
3	2	4	1	29
3	2	3	7	21
3	2	2	7	0
3	2	1	31	0
3	3	5	7	43
3	3	4	15	29
3	3	3	28	6
3	3	2	41	7
3	3	1	9	1
3	4	5	0	10
3	4	4	2	14
3	4	3	5	19
3	4	2	24	32
3	4	1	31	23
4	1	5	1	61
4	1	4	4	19
4	1	3	18	12
4	1	2	21	9
4	1	1	23	3
4	2	5	1	16
4	2	4	1	29
4	2	3	0	34
4	2	2	11	1
4	2	1	35	0
4	3	5	6	52
4	3	4	14	29
4	3	3	37	10
4	3	2	36	4
4	3	1	18	3
4	4	5	0	10
4	4	4	2	16
4	4	3	4	23
4	4	2	18	43
4	4	1	25	15
5	1	5	0	35
5	1	4	2	29
5	1	3	19	18
5	1	2	23	9
5	1	1	18	0

5	2	5	0	17
5	2	4	2	27
5	2	3	6	24
5	2	2	10	0
5	2	1	30	0
5	3	5	2	34
5	3	4	25	33
5	3	3	40	7
5	3	2	29	13
5	3	1	24	2
5	4	5	1	12
5	4	4	1	16
5	4	3	4	21
5	4	2	24	35
5	4	1	32	15

Author(s)

Issei Tsunoda <tsunoda.issei1111@gmail.com >

References

Example data of Jafroc software

See Also

[dataList.Chakra.Web.orderd](#) d

Examples

```
viewdata(BayesianFROC::dataList.Chakra.Web)
```

`dataList.Chakra.Web.orderd`

An FROC Data of Multiple-Reader and Multiple-Modality

Description

To be fitted an FROC model.

Details

This data was calculated from an example dataset which appears in Chakraborty's JAFROC. The author has ordered the dataset `dataList.Chakra.Web` (or `dd`) so that the modality ID means the order of AUC. For example modality ID = 1 means its AUC is the highest. modalityID = 2 means that its AUC is the secondly high AUC.

So, let A_1, A_2, A_3, A_4, A_5 be the AUCs for the modality ID 1, 2, 3, 4, 5, respectively.

Then it follows that

$$A_1 > A_2 > A_3 > A_4 > A_5.$$

So, modality ID in this dataset corresponds the modality ID of `dataList.Chakra.Web` (or `dd`) as (4 2 1 5 3).

That is, let us denote the modality ID of this dataset (1',2',3',4',5') and let modality ID of the dataset named `dataList.Chakra.Web` (or `dd`) be (1,2,3,4,5).

Then we can write the correspondence as follows;

$$(1', 2', 3', 4', 5') = (4, 2, 1, 5, 3).$$

Contents:

Multiple readers and Multiple modalities case, i.e., MRMC case

ModalityID	ReaderID	Confidence levels	No. of false alarms	No. of hits.
q	m	c	f	h
1	1	5	1	61
1	1	4	4	19
1	1	3	18	12
1	1	2	21	9
1	1	1	23	3
1	2	5	1	16
1	2	4	1	29
1	2	3	0	34
1	2	2	11	1
1	2	1	35	0
1	3	5	6	52
1	3	4	14	29
1	3	3	37	10
1	3	2	36	4
1	3	1	18	3
1	4	5	0	10
1	4	4	2	16
1	4	3	4	23
1	4	2	18	43
1	4	1	25	15
2	1	5	1	52

2	1	4	1	25
2	1	3	21	13
2	1	2	24	4
2	1	1	23	1
2	2	5	1	27
2	2	4	1	28
2	2	3	5	29
2	2	2	30	1
2	2	1	40	0
2	3	5	2	53
2	3	4	19	29
2	3	3	31	13
2	3	2	56	2
2	3	1	42	4
2	4	5	2	9
2	4	4	0	16
2	4	3	2	22
2	4	2	30	43
2	4	1	32	14
3	1	5	0	50
3	1	4	4	30
3	1	3	20	11
3	1	2	29	5
3	1	1	21	1
3	2	5	0	15
3	2	4	0	29
3	2	3	6	29
3	2	2	15	1
3	2	1	22	0
3	3	5	1	39
3	3	4	15	31
3	3	3	18	8
3	3	2	31	10
3	3	1	19	3
3	4	5	1	10
3	4	4	2	8
3	4	3	4	25
3	4	2	16	45
3	4	1	17	14
4	1	5	0	35
4	1	4	2	29
4	1	3	19	18
4	1	2	23	9
4	1	1	18	0
4	2	5	0	17
4	2	4	2	27
4	2	3	6	24
4	2	2	10	0

4	2	1	30	0
4	3	5	2	34
4	3	4	25	33
4	3	3	40	7
4	3	2	29	13
4	3	1	24	2
4	4	5	1	12
4	4	4	1	16
4	4	3	4	21
4	4	2	24	35
4	4	1	32	15
5	1	5	1	43
5	1	4	7	29
5	1	3	13	11
5	1	2	28	6
5	1	1	19	0
5	2	5	0	18
5	2	4	1	29
5	2	3	7	21
5	2	2	7	0
5	2	1	31	0
5	3	5	7	43
5	3	4	15	29
5	3	3	28	6
5	3	2	41	7
5	3	1	9	1
5	4	5	0	10
5	4	4	2	14
5	4	3	5	19
5	4	2	24	32
5	4	1	31	23

Author(s)

Issei Tsunoda <tsunoda.issei1111@gmail.com >

References

Maximum likelihood analysis of free-response receiver operating characteristic (FROC) data, Dev P. Chakraborty.

See Also

[dataList.Chakra.Web d](#)

dataList.divergent.transition.in.case.of.srsc

*An FROC Dataset with **Divergent Transitions** in case of A Single reader and A Single modality*

Description

A list, representing an FROC dataset with **divergent transitions** .

Note that the maximal number of confidence level, denoted by C, are included, however, confidence level vector c should not be specified. If specified, will be ignored , since it is created by `c <-c(rep(C:1))` in the program and it does not refer from user input data, where C is the highest number of confidence levels. Should write down your hits and false alarms vector so that it is compatible with this automatically created vector c.

Format

A list consists of the following integer vectors f ,h and integers NL ,NI , C.

- f Non-negative integer vector specifying number of false alarms associated with each confidence level. The first component corresponding to the highest confidence level.
- h Non-negative integer vector specifying number of Hits associated with each confidence level. The first component corresponding to the highest confidence level.
- NL A positive integer, representing Number of Lesions.
- NI A positive integer, representing Number of Images.
- C A positive integer, representing Number of Confidence level.

Contents:

A single reader and single modality case

NI=57 ,NL=269 In R console ->	confidence level c	No. of false alarms f	No. of hits h
definitely present	3	0	21
probably present	2	7	4
questionable	1	36	3

* *false alarms* = False Positives = FP

* *hits* = True Positives = TP

Note that in FROC data, the confidence level means present (deseased, positive) case only. Since each reader marks their suspicious location only and it generate the hits and false alarms for his

confidence level representing that lesion is present. In the absent case, reader dose not mark any locations and hence, the absent confidence level does not relate this dataset.

Note that the first column of confidence level vector `c` should not be specified. If specified, will be ignored, since it is created by `c<-c(rep(C:1))` automatically in the program and it does not refer from user input data even if it is specified explicitly, where `C` is the highest number of confidence levels. So you should check the compatibility of your data and the program's generating new confidence level vector by a table which can be displayed by the function `viewdata()`.

Note that The format for the above example data must be made by the following forms:

```
dat <-list(
  c=c(3,2,1),#Confidence level
  h=c(21,4,3),#Number of hits for each confidence level
  f=c(0,7,36),#Number of false alarms for each confidence level
  NL=60,#Number of lesions
  NI=30,#Number of images
  C=3) #Number of confidence level
```

This R object `dat` can be passed to the function `fit_Bayesian_FROC()` as the following manner `fit_Bayesian_FROC(dat)`.

Examples

```
## Not run:
#=====
# Change the zero cell to 1,
# then The number of divergent transitions are significantly decrease
# Thus, the divergent transtions is not rigid.
#=====

data <- dataList.divergent.transition.in.case.of.srsc
data$f <- c(1,7,36)
f <- fit_Bayesian_FROC( ite = 1111, cha = 1, summary = TRUE, dataList = data )

## End(Not run)#dontrun
```

dataList.High

Data: Single reader and Single modality

Description

A list, representing FROC data. This is used to build a hierarchical FROC model. This data is same as `dataList.Chakra.1`.

Details

This data-set is fictitious.

Author(s)

Issei Tsunoda <tsunoda.issei1111@gmail.com >

References

Maximum likelihood analysis of free-response receiver operating characteristic (FROC) data, Dev P. Chakraborty.

See Also

[dataList.Chakra.1.with.explantation](#)

dataList.high.ability *Data: A Single Reader and A Single Modality*

Description

A list, representing FROC data. This is used to build a hierarchical FROC model. This data is same as `dataList.Chakra.1`.

Details

This data-set is fictitious.

Author(s)

Issei Tsunoda <tsunoda.issei1111@gmail.com >

References

Maximum likelihood analysis of free-response receiver operating characteristic (FROC) data, Dev P. Chakraborty.

See Also

[dataList.Chakra.1.with.explantation](#)

`dataList.Low`*Data: Single reader and Single modality*

Description

A list, representing FROC data to which we fit a FROC model. This data is same as `dataList.Chakra.1`.

Details

This data-set is fictitious.

Author(s)

Issei Tsunoda <tsunoda.issei1111@gmail.com >

References

Maximum likelihood analysis of free-response receiver operating characteristic (FROC) data, Dev P. Chakraborty.

See Also

[dataList.Chakra.1.with.explantation](#)

`dataList.low.ability`*Data: A Single Reader and A Single Modality*

Description

A list, representing FROC data. This is used to build a hierarchical FROC model. This data is same as `dataList.Chakra.1`.

Details

This data-set is fictitious.

Author(s)

Issei Tsunoda <tsunoda.issei1111@gmail.com >

References

Maximum likelihood analysis of free-response receiver operating characteristic (FROC) data, Dev P. Chakraborty.

See Also

[dataList.Chakra.1.with.explantation](#)

dataList.one.modality dataset of Multiple reader and one modality

Description

This is used to build a hierarchical FROC model.

Details

This data contains only one modality. If see = 12, then the model has converged.

Author(s)

Issei Tsunoda <tsunoda.issei1111@gmail.com >

References

Nothing in 2018

dataset_creator_by_specifying_only_M_Q
Creates dataset

Description

creates dataset

Usage

`dataset_creator_by_specifying_only_M_Q(M = 2, Q = 15)`

Arguments

M A positive integer, indicating number of modalities.
Q A positive integer, indicating number of readers.

Value

An MRMC dataset.

Examples

```

#####1##### #####2##### #####3##### #####4##### #####5##### #####6##### #####7##### #####8##### #####9#####
#=====
#                               make a data of a single modality and 36 readers
#=====

d<- dataset_creator_by_specifying_only_M_Q(M=1,Q=36)

check_hit_is_less_than_NL(d)

#   plot_FPF_and_TPF_from_a_dataset(d)
#   plot_FPF_TPF_via_dataframe_with_split_factor(d)

#####1##### #####2##### #####3##### #####4##### #####5##### #####6##### #####7##### #####8##### #####9#####
#=====
#                               make a data of 2 modalities and 36 readers
#=====

d<- dataset_creator_by_specifying_only_M_Q(M=2,Q=36)

check_hit_is_less_than_NL(d)

#   plot_FPF_and_TPF_from_a_dataset(d)
#   plot_FPF_TPF_via_dataframe_with_split_factor(d)

#=====
#                               make a data of 2 modalities and 6 readers
#=====

d<- dataset_creator_by_specifying_only_M_Q(M=2,Q=6)

check_hit_is_less_than_NL(d)

#   plot_FPF_and_TPF_from_a_dataset(d)
#   plot_FPF_TPF_via_dataframe_with_split_factor(d)

## Not run:

```



```
# Stan runs
  fit_a_model_to(dataList = d,
                seed_for_MCMC = 1234)

## End(Not run)
```

```
dataset_creator_for_many_Readers
  create data for MRMC
```

Description

create data for MRMC

Usage

```
dataset_creator_for_many_Readers(M, Q)
```

Arguments

M a positive integer, specifies the number of modalities
Q a positive integer, specifies the number of readers

Value

data, to which fit a model

Examples

```
d <- dataset_creator_for_many_Readers(1,11)
```

```
dataset_creator_new_version
  Create a Dataset (version 2) Interactively
```

Description

Create the Passing data to the function [fit_Bayesian_FROC](#).
This is an interactive creator of dataset for FROC data.

Usage

```
dataset_creator_new_version()
```

Details

This provide the interactive making of FROC dataset by using table to summarize hits and false alarm data.

Using this return value, you can build the FROC model for your data by applying the function `fit_Bayesian_FROC()` in this package.

Should carefully for the order of confidence levels.

Value

A list representing FROC data, to build FROC fitted model object by `fit_Bayesian_FROC()`.

Examples

```
## Not run:
## Only run examples in interactive R sessions
if (interactive()) {

  dataset_creator_new_version()

}### Only run examples in interactive R sessions

## End(Not run)
#'
```

data_2modalities_2readers_3confidence

data: 2 readers, 2 modalities and 3 confideneces

Description

Example data-set which has small samples.

Details

the number of modalities, denoted by M. M = 2 modalities

the number of Confidences, denoted by C. C = 3 Confidence levels

the number of readers, denoted by Q. Q = 2 readers

Contents

NL = 142 (Number of Lesions)

NI = 57 (Number of Images)#'

Contents:

Multiple readers and multiple modalities case, i.e., MRMC case

ModalityID	ReaderID	Confidence levels	No. of false alarms	No. of hits.
m	q	c	f	h
1	1	3	20	111
1	1	2	29	55
1	1	1	21	22
1	2	3	6	100
1	2	2	15	44
1	2	1	22	11
2	1	3	6	66
2	1	2	24	55
2	1	1	23	1
2	2	3	5	66
2	2	2	30	55
2	2	1	40	44

Author(s)

Issei Tsunoda <tsunoda.issei1111@gmail.com >

References

Example data of Jafroc software

See Also

Not [dataList.Chakra.Web](#) But [dataList.Chakra.Web.orderd](#) Not [dd](#)

Examples

```

#=====
#                               Show data by table
#=====

viewdata(data_of_36_readers_and_a_single_modality)

plot_FPF_and_TPF_from_a_dataset(data_of_36_readers_and_a_single_modality)

#####1#### #####2#### #####3#### #####4#### #####5#### #####6#### #####7#### #####8#### #####9####
#=====
#                               make this data from functions in this package
#=====

```

```
v <- v_truth_creator_for_many_readers_MRMC_data(M=1,Q=36)
m <- mu_truth_creator_for_many_readers_MRMC_data(M=1,Q=36)
d <- create_dataList_MRMC(mu.truth = m,v.truth = v)
```

```
# The last object named d is the desired dataset.
```

```
data_of_36_readers_and_a_single_modality
      36 readers and a sinle modality data
```

Description

An example data-set whose sample size is large.

Details

Frequentist methods fails when a sample size is large. Namely, p value monotonically decreases when the sample size tends to large.

On the other hands, in Bayesian methods, the large samples such as large readers in FROC context fails the MCMC algorithm. Thus Bayesian methods is also not free from such large sample problem in this sense.

This dataset is made for validation that wheter Bayes factor well work which is a subset of `data dataList.Chakra.Web.orderd`

the number of modalities, denoted by M which is now 1 modality

the number of Confidences, denoted by C which is now 5 Confidence levels

the number of readers, denoted by Q which is now 36 readers

Contents of data_of_36_readers_and_a_single_modality

NL = 142 (Number of Lesions)

NI = 57 (Number of Images)#'

Contents:

Multiple readers and multiple modalities case, i.e., MRMC case

ModalityID	ReaderID	Confidence levels	No. of false alarms	No. of hits.
m	q	c	f	h
1	1	5	0	12
1	1	4	3	22
1	1	3	7	18
1	1	2	12	18
1	1	1	8	15
1	2	5	0	14
1	2	4	4	24
1	2	3	9	17

1	2	2	14	15
1	2	1	10	6
1	3	5	0	26
1	3	4	3	39
1	3	3	6	23
1	3	2	11	16
1	3	1	7	6
1	4	5	0	9
1	4	4	1	17
1	4	3	4	15
1	4	2	8	18
1	4	1	5	25
1	5	5	0	9
1	5	4	2	17
1	5	3	5	16
1	5	2	9	19
1	5	1	6	27
1	6	5	0	39
1	6	4	0	46
1	6	3	2	22
1	6	2	15	13
1	6	1	2	3
1	7	5	0	9
1	7	4	1	17
1	7	3	4	14
1	7	2	8	16
1	7	1	5	17
1	8	5	1	11
1	8	4	5	19
1	8	3	10	16
1	8	2	16	17
1	8	1	12	15
1	9	5	0	15
1	9	4	1	26
1	9	3	3	20
1	9	2	6	18
1	9	1	4	12
1	10	5	0	31
1	10	4	4	40
1	10	3	8	22
1	10	2	13	16
1	10	1	9	5
1	11	5	0	13
1	11	4	2	23
1	11	3	5	19
1	11	2	9	19
1	11	1	6	17
1	12	5	0	8

1	12	4	3	16
1	12	3	7	15
1	12	2	11	17
1	12	1	8	22
1	13	5	0	13
1	13	4	1	23
1	13	3	4	19
1	13	2	7	21
1	13	1	4	20
1	14	5	0	36
1	14	4	4	45
1	14	3	9	22
1	14	2	14	13
1	14	1	10	3
1	15	5	0	17
1	15	4	2	27
1	15	3	5	20
1	15	2	9	18
1	15	1	6	10
1	16	5	0	8
1	16	4	4	15
1	16	3	8	13
1	16	2	13	16
1	16	1	9	22
1	17	5	0	9
1	17	4	1	16
1	17	3	4	15
1	17	2	8	17
1	17	1	5	20
1	18	5	0	12
1	18	4	2	21
1	18	3	6	17
1	18	2	10	17
1	18	1	7	12
1	19	5	0	19
1	19	4	3	33
1	19	3	8	21
1	19	2	12	19
1	19	1	9	13
1	20	5	0	8
1	20	4	1	15
1	20	3	3	14
1	20	2	6	16
1	20	1	4	21
1	21	5	0	33
1	21	4	2	41
1	21	3	5	21
1	21	2	9	13

1	21	1	6	3
1	22	5	0	15
1	22	4	3	26
1	22	3	7	20
1	22	2	12	20
1	22	1	8	15
1	23	5	0	9
1	23	4	4	17
1	23	3	8	15
1	23	2	12	18
1	23	1	9	23
1	24	5	0	10
1	24	4	0	19
1	24	3	3	17
1	24	2	6	20
1	24	1	4	23
1	25	5	0	8
1	25	4	1	15
1	25	3	3	14
1	25	2	6	17
1	25	1	4	22
1	26	5	0	12
1	26	4	1	21
1	26	3	4	18
1	26	2	8	19
1	26	1	5	18
1	27	5	0	19
1	27	4	1	32
1	27	3	4	18
1	27	2	7	13
1	27	1	5	4
1	28	5	1	10
1	28	4	5	18
1	28	3	9	16
1	28	2	15	19
1	28	1	11	26
1	29	5	0	16
1	29	4	2	27
1	29	3	6	21
1	29	2	10	20
1	29	1	7	16
1	30	5	1	9
1	30	4	4	18
1	30	3	9	16
1	30	2	14	19
1	30	1	10	25
1	31	5	0	10
1	31	4	3	19


```

viewdata(data_of_36_readers_and_a_single_modality)

plot_FPF_and_TPF_from_a_dataset(data_of_36_readers_and_a_single_modality)

#####1#####2#####3#####4#####5#####6#####7#####8#####9#####
#=====
#
#           make this data from functions in this package
#=====

v <- v_truth_creator_for_many_readers_MRMC_data(M=1,Q=36)
m <- mu_truth_creator_for_many_readers_MRMC_data(M=1,Q=36)
d <- create_dataList_MRMC(mu.truth = m,v.truth = v)

# The last object named d is the desired dataset.

```

dd

*Multiple Reader and Multiple Modality Data***Description**

A list, representing FROC data of MRMC. This is same as [dataList.Chakra.Web](#).

Details

This data is based on in Chakraborty's JAFROC software in which example data exists. The author have calculated hits and false alarms from this Jafroc example data.

Contents:

Multiple readers and multiple modalities case, i.e., MRMC case

ModalityID	ReaderID	Confidence levels	No. of false alarms	No. of hits.
q	m	c	f	h
1	1	5	0	50
1	1	4	4	30
1	1	3	20	11
1	1	2	29	5
1	1	1	21	1
1	2	5	0	15
1	2	4	0	29
1	2	3	6	29

1	2	2	15	1
1	2	1	22	0
1	3	5	1	39
1	3	4	15	31
1	3	3	18	8
1	3	2	31	10
1	3	1	19	3
1	4	5	1	10
1	4	4	2	8
1	4	3	4	25
1	4	2	16	45
1	4	1	17	14
2	1	5	1	52
2	1	4	1	25
2	1	3	21	13
2	1	2	24	4
2	1	1	23	1
2	2	5	1	27
2	2	4	1	28
2	2	3	5	29
2	2	2	30	1
2	2	1	40	0
2	3	5	2	53
2	3	4	19	29
2	3	3	31	13
2	3	2	56	2
2	3	1	42	4
2	4	5	2	9
2	4	4	0	16
2	4	3	2	22
2	4	2	30	43
2	4	1	32	14
3	1	5	1	43
3	1	4	7	29
3	1	3	13	11
3	1	2	28	6
3	1	1	19	0
3	2	5	0	18
3	2	4	1	29
3	2	3	7	21
3	2	2	7	0
3	2	1	31	0
3	3	5	7	43
3	3	4	15	29
3	3	3	28	6
3	3	2	41	7
3	3	1	9	1
3	4	5	0	10

3	4	4	2	14
3	4	3	5	19
3	4	2	24	32
3	4	1	31	23
4	1	5	1	61
4	1	4	4	19
4	1	3	18	12
4	1	2	21	9
4	1	1	23	3
4	2	5	1	16
4	2	4	1	29
4	2	3	0	34
4	2	2	11	1
4	2	1	35	0
4	3	5	6	52
4	3	4	14	29
4	3	3	37	10
4	3	2	36	4
4	3	1	18	3
4	4	5	0	10
4	4	4	2	16
4	4	3	4	23
4	4	2	18	43
4	4	1	25	15
5	1	5	0	35
5	1	4	2	29
5	1	3	19	18
5	1	2	23	9
5	1	1	18	0
5	2	5	0	17
5	2	4	2	27
5	2	3	6	24
5	2	2	10	0
5	2	1	30	0
5	3	5	2	34
5	3	4	25	33
5	3	3	40	7
5	3	2	29	13
5	3	1	24	2
5	4	5	1	12
5	4	4	1	16
5	4	3	4	21
5	4	2	24	35
5	4	1	32	15

Author(s)

Issei Tsunoda <tsunoda.issei1111@gmail.com >

References

Example data of Jafroc software

See Also

[dataList.Chakra.Web](#) [dataList.Chakra.Web.orderd](#) [d](#)

Examples

```
viewdata(BayesianFROC::dd)
```

```
#####
# dd is same as dataList.Chakra.Web, since the following code is all TRUE
#####
```

```
dd$f==dataList.Chakra.Web$f
```

```
#####
# Code to make the dataset dd
#####
```

```
h<-c(
  50,30,11,5,1,15,29,29,1,0,39,31,8 ,10,3,10,8 ,25,45,14, # modality 1
  52,25,13,4,1,27,28,29,1,0,53,29,13,2 ,4,9 ,16,22,43,14, # modality 2
  43,29,11,6,0,18,29,21,0,0,43,29,6 ,7 ,1,10,14,19,32,23, # modality 3
  61,19,12,9,3,16,29,34,1,0,52,29,10,4 ,3,10,16,23,43,15, # modality 4
  35,29,18,9,0,17,27,24,0,0,34,33,7 ,13,2,12,16,21,35,15 # modality 5
)
```

```
f <-c(
  0 ,4,20,29,21,0,0,6,15,22,1 ,15,18,31,19,1,2,4,16,17,# modality 1
  1 ,1,21,24,23,1,1,5,30,40,2 ,19,31,56,42,2,0,2,30,32,# modality 2
  1, 7,13,28,19,0,1,7, 7,31, 7,15,28,41,9 ,0,2,5,24,31,# modality 3
  1, 4,18,21,23,1,1,0,11,35, 6,14,37,36,18,0,2,4,18,25,# modality 4
```

```

0, 2,19,23,18,0,2,6,10,30, 2,25,40,29,24,1,1,4,24,32)# modality 5

a <- m_q_c_vector_from_M_Q_C(5,4,5)

m <- a$m
c <- a$c
q <- a$q

NI<-199
NL <-142
C<-5
M<-5
Q<-4

dd <- list(
  h=h,
  f=f,
  m=m,
  c=c,
  q=q,
  NI=NI,
  NL=NL,
  M=M,
  Q=Q,
  C=C
)

```

dd.orderd

Multiple Reader and Multiple Modality Data

Description

A list, representing FROC data of MRMC. This is same as [dataList.Chakra.Web](#) .

Details

This data is based on in Chakraborty's JAFROC software in which example data exists. The author have calculated hits and false alarms from this Jafroc example data. Moreover the author ordered it such that the modality ID also means its observer performance, namely Modality ID = 1 means it has the most high AUC.

contents

ModalityID	ReaderID	Confidence levels	No. of hits	No. of false alarms
------------	----------	-------------------	-------------	---------------------

<u>m</u>	<u>q</u>	<u>c</u>	<u>h</u>	<u>f</u>
1	1	5	61	1
1	1	4	19	4
1	1	3	12	18
1	1	2	9	21
1	1	1	3	23
1	2	5	16	1
1	2	4	29	1
1	2	3	34	0
1	2	2	1	11
1	2	1	0	35
1	3	5	52	6
1	3	4	29	14
1	3	3	10	37
1	3	2	4	36
1	3	1	3	18
1	4	5	10	0
1	4	4	16	2
1	4	3	23	4
1	4	2	43	18
1	4	1	15	25
2	1	5	52	1
2	1	4	25	1
2	1	3	13	21
2	1	2	4	24
2	1	1	1	23
2	2	5	27	1
2	2	4	28	1
2	2	3	29	5
2	2	2	1	30
2	2	1	0	40
2	3	5	53	2
2	3	4	29	19
2	3	3	13	31
2	3	2	2	56
2	3	1	4	42
2	4	5	9	2
2	4	4	16	0
2	4	3	22	2
2	4	2	43	30
2	4	1	14	32
3	1	5	50	0
3	1	4	30	4
3	1	3	11	20
3	1	2	5	29
3	1	1	1	21
3	2	5	15	0

3	2	4	29	0
3	2	3	29	6
3	2	2	1	15
3	2	1	0	22
3	3	5	39	1
3	3	4	31	15
3	3	3	8	18
3	3	2	10	31
3	3	1	3	19
3	4	5	10	1
3	4	4	8	2
3	4	3	25	4
3	4	2	45	16
3	4	1	14	17
4	1	5	35	0
4	1	4	29	2
4	1	3	18	19
4	1	2	9	23
4	1	1	0	18
4	2	5	17	0
4	2	4	27	2
4	2	3	24	6
4	2	2	0	10
4	2	1	0	30
4	3	5	34	2
4	3	4	33	25
4	3	3	7	40
4	3	2	13	29
4	3	1	2	24
4	4	5	12	1
4	4	4	16	1
4	4	3	21	4
4	4	2	35	24
4	4	1	15	32
5	1	5	43	1
5	1	4	29	7
5	1	3	11	13
5	1	2	6	28
5	1	1	0	19
5	2	5	18	0
5	2	4	29	1
5	2	3	21	7
5	2	2	0	7
5	2	1	0	31
5	3	5	43	7
5	3	4	29	15
5	3	3	6	28
5	3	2	7	41

5	3	1	1	9
5	4	5	10	0
5	4	4	14	2
5	4	3	19	5
5	4	2	32	24
5	4	1	23	31

Author(s)

Issei Tsunoda <tsunoda.issei1111@gmail.com >

References

Example data of Jafroc software

Examples

```
viewdata(BayesianFROC::dd.orderd)
```

```
#####
#
#                               Code to make the dataset dd
#
#####

h<-c(
  61,19,12,9,3,16,29,34,1,0,52,29,10,4 ,3,10,16,23,43,15, # modality 4 of dataset dd
  52,25,13,4,1,27,28,29,1,0,53,29,13,2 ,4,9 ,16,22,43,14, # modality 2 of dataset dd
  50,30,11,5,1,15,29,29,1,0,39,31,8 ,10,3,10,8 ,25,45,14, # modality 1 of dataset dd
  35,29,18,9,0,17,27,24,0,0,34,33,7 ,13,2,12,16,21,35,15, # modality 5 of dataset dd
  43,29,11,6,0,18,29,21,0,0,43,29,6 ,7 ,1,10,14,19,32,23 # modality 3  of dataset dd
)

f <-c(
  1, 4,18,21,23,1,1,0,11,35, 6,14,37,36,18,0,2,4,18,25,# modality 4  of dataset dd
  1 ,1,21,24,23,1,1,5,30,40,2 ,19,31,56,42,2,0,2,30,32,# modality 2 of dataset dd
  0 ,4,20,29,21,0,0,6,15,22,1 ,15,18,31,19,1,2,4,16,17,# modality 1 of dataset dd
  0, 2,19,23,18,0,2,6,10,30, 2,25,40,29,24,1,1,4,24,32,# modality 5 of dataset dd
  1, 7,13,28,19,0,1,7, 7,31, 7,15,28,41,9 ,0,2,5,24,31# modality 3 of dataset dd
```



```

)
a <- m_q_c_vector_from_M_Q_C(5,4,5)

m <- a$m
c <- a$c
q <- a$q

NI<-199
NL <-142
C<-5
M<-5
Q<-4

dd.orderd <- list(
  h=h,
  f=f,
  m=m,
  c=c,
  q=q,
  NI=NI,
  NL=NL,
  M=M,
  Q=Q,
  C=C
)

```

ddd

Multiple reader and Multiple modality data

Description

This is a subset of [dd](#)

This dataset has different dimension for each modality and reader and confidence levels. To confirm my program is correct, the author made this.

In the following I emphasize that this data set has distinct C, M, Q:

ddd\$C 5 Confidence levels

ddd\$M 3 modalities

ddd\$Q 4 readers

So, all number, i.e. M, C, Q is *different* each other and this is the reason why the author made this dataset.

Details

The WAIC is finite which surprizes me, because a dataset dd has no finite WAIC. Why??

I forgot when I wrote this and what model was fitted to this data, so I am not sure the current model has finite WAIC.

Revised 2019 Nov. 21

Contents of dd

NL = 142 (Number of Lesions)

NI = 199 (Number of Images)

ModalityID	ReaderID	Confidence levels	No. of false alarms	No. of hits.
m	q	c	f	h
1	1	5	0	50
1	1	4	4	30
1	1	3	20	11
1	1	2	29	5
1	1	1	21	1
1	2	5	0	15
1	2	4	0	29
1	2	3	6	29
1	2	2	15	1
1	2	1	22	0
1	3	5	1	39
1	3	4	15	31
1	3	3	18	8
1	3	2	31	10
1	3	1	19	3
1	4	5	1	10
1	4	4	2	8
1	4	3	4	25
1	4	2	16	45
1	4	1	17	14
2	1	5	1	52
2	1	4	1	25
2	1	3	21	13
2	1	2	24	4
2	1	1	23	1
2	2	5	1	27
2	2	4	1	28
2	2	3	5	29
2	2	2	30	1
2	2	1	40	0
2	3	5	2	53
2	3	4	19	29
2	3	3	31	13

2	3	2	56	2
2	3	1	42	4
2	4	5	2	9
2	4	4	0	16
2	4	3	2	22
2	4	2	30	43
2	4	1	32	14
3	1	5	1	43
3	1	4	7	29
3	1	3	13	11
3	1	2	28	6
3	1	1	19	0
3	2	5	0	18
3	2	4	1	29
3	2	3	7	21
3	2	2	7	0
3	2	1	31	0
3	3	5	7	43
3	3	4	15	29
3	3	3	28	6
3	3	2	41	7
3	3	1	9	1
3	4	5	0	10
3	4	4	2	14
3	4	3	5	19
3	4	2	24	32
3	4	1	31	23

Author(s)

Issei Tsunoda <tsunoda.issei1111@gmail.com >

References

Nothing in 2018

Examples

```
#####1##### #####2##### #####3##### #####4##### #####5##### #####6##### #####7##### #####8##### #####9#####
#=====
#           make an object ddd from an object dd
#=====
```

```
ddd <- data.frame(m=dd$m,q=dd$q,c=dd$c,h=dd$h,f=dd$f)
```

```

        dddd <- ddd[ddd$m <4,] # Reduce the dataset ddd, i.e., dd

ddd <- list(
  m=ddd$m,
  q=ddd$q,
  c=ddd$c,
  h=ddd$h,
  f=ddd$f,
  NL=142,
  NI=199, # 2020 April 6
  C=max(ddd$c),
  M=max(ddd$m),
  Q=max(ddd$q)
)

```

 dddd

One reader and Multiple modality data

Description

This is a subset of `dd`. For this dataset, the function `fit_Bayesian_FROC()` will work. So, even if the number of reader is one, my program is available. Even if not available, I think it does not cause my model but my programming.

ddd\$m 5 modalities

ddd\$c 5 Confidence levels

ddd\$Q 1 readers

Details

Model converged in 2019 Jun 21.

Contents of dddd

NL = 142 (Number of Lesions)

NI = 199 (Number of Images)

Contents:

Multiple readers and multiple modalities case, i.e., MRMC case

ModalityID	ReaderID	Confidence levels	No. of false alarms	No. of hits.
q	m	c	f	h
1	1	5	0	50
1	1	4	4	30


```

viewdata(BayesianFROC::dddd)

#=====
#           make an object dddd from an object dd
#=====

ddd <- data.frame(m=dd$m,q=dd$q,c=dd$c,h=dd$h,f=dd$f)

dddd <- ddd[ddd$q < 2,] # Reduce the dataset ddd, i.e., dd

ddd <- list(
  m=dddd$m,
  q=dddd$q,
  c=dddd$c,
  h=dddd$h,
  f=dddd$f,
  NL=142,
  NI=199, # 2020 April 6
  C=max(dddd$c),
  M=max(dddd$m),
  Q=max(dddd$q)
)

dddd <- ddd

#=====
#           Fit model to the object dddd
#=====
# Unfortunately, R CMD check require running time to be less than 5 which is difficult
# for rstan::sampling(), thus, we cannot run the following from roxygen2 example.
#
#
# For Fitting, execute the following R code;
#
#
#

```

Description

This is a subset of [dd](#). In the past, this model did not converge in the **Model_MRMC.stan**, thus I made a new stan file to get convergence estimates. The stan file named *Model_Hiera_OneModalityMultipleReader_TargetFor*. Thus, even if the number of modalityt is 1, we can pool the AUCs over all readers by using this new model. The author believes this pooling is the most natural, primitive, simple way.

dddd\$M 1 modality <— ATTENTION!!
dddd\$C 5 Confidence levels
dddd\$Q 4 readers

Details

The model *did not* converge both null model and alternative model in 2019 Jun 21.

Contents of dddd

NL = 142 (Number of Lesions)

NI = 199 (Number of Images)#'

Contents:

Multiple readers and multiple modalities case, i.e., MRMC case

ModalityID	ReaderID	Confidence levels	No. of false alarms	No. of hits.
q	m	c	f	h
1	1	5	0	50
1	1	4	4	30
1	1	3	20	11
1	1	2	29	5
1	1	1	21	1
1	2	5	0	15
1	2	4	0	29
1	2	3	6	29
1	2	2	15	1
1	2	1	22	0
1	3	5	1	39
1	3	4	15	31
1	3	3	18	8
1	3	2	31	10
1	3	1	19	3
1	4	5	1	10
1	4	4	2	8
1	4	3	4	25
1	4	2	16	45
1	4	1	17	14

Author(s)

Issei Tsunoda <tsunoda.issei1111@gmail.com >

References

Example data of Jafroc software

See Also

[dataList.Chakra.Web](#) [dataList.Chakra.Web.orderd](#) [dd](#)

Examples

```

#=====
#                               Show data by table
#=====

viewdata(BayesianFROC::dddd)

#####1##### 2##### 3##### 4##### 5##### 6##### 7##### 8##### 9#####
#=====
#                               make an object dddd from an object dd
#=====

ddd <- data.frame(m=dd$m,q=dd$q,c=dd$c,h=dd$h,f=dd$f)

dddd <- ddd[ddd$m < 2,] # Reduce the dataset ddd, i.e., dd

ddd <- list(
  m=dddd$m,
  q=dddd$q,
  c=dddd$c,
  h=dddd$h,
  f=dddd$f,
  NL=142,
  NI=199, # 2020 April 6
  C=max(dddd$c),
  M=max(dddd$m),
  Q=max(dddd$q)
)

dddd <- ddd

```

dddddd

Multiple reader and one modality data

Description

This is a subset of [dd](#)

This dataset is made, as a toy data, *which is a subset of data dd*

dddddd\$M 2 modalities

dddddd\$C 3 Confidence levels

dddddd\$Q 2 readers

Details

The model did not converge both null model and alternative model in 2019 Jun 21.

Contents of ddddd

NL = 142 (Number of Lesions)

NI = 199 (Number of Images)#'

Contents:

Multiple readers and multiple modalities case, i.e., MRMC case

ModalityID	ReaderID	Confidence levels	No. of false alarms	No. of hits.
q	m	c	f	h
1	1	3	20	11
1	1	2	29	5
1	1	1	21	1
1	2	3	6	29
1	2	2	15	1
1	2	1	22	0
2	1	3	21	13
2	1	2	24	4
2	1	1	23	1
2	2	3	5	29
2	2	2	30	1
2	2	1	40	0

Author(s)

Issei Tsunoda <tsunoda.issei1111@gmail.com >

References

Example data of Jafroc software

See Also

[dataList.Chakra.Web](#) [dataList.Chakra.Web.orderd](#) [dd](#)

Examples

```

#=====
#                               Show data by table
#=====

                               viewdata(dddddd)

#####1##### #####2##### #####3##### #####4##### #####5##### #####6##### #####7##### #####8##### #####9#####
#=====
#                               make an object dddd from an object dd
#=====

ddd <- data.frame(m=dd$m,q=dd$q,c=dd$c,h=dd$h,f=dd$f)
dddd <- ddd[ddd$q < 3,]

# The following code extract the first and the second modality from dd
dddd <- dddd[dddd$m < 3,] # Reduce the dataset ddd, i.e., dd
dddd <- dddd[dddd$c <4,]
ddd <- list(
  m=dddd$m,
  q=dddd$q,
  c=dddd$c,
  h=dddd$h,
  f=dddd$f,
  NL=142,
  NI=199, # 2020 April 6
  C=max(dddd$c),
  M=max(dddd$m),

```

```

    Q=max(dddd$q)
  )

  ddddd <-ddd

# This dataset is made in 2019 July 6, for the aim of easy exhibition
# This dataset is very minimum, and it is easy to view

```

ddddddd	<i>Multiple reader and 2 modalities data such that all modalities have same AUC.</i>
---------	--

Description

This is a subset of [dataList.Chakra.Web.orderd](#)

Details

The author made this dataset to validate the scheme of Bayes factor well works in our Bayesian FROC models

This dataset is made for validation that wheter Bayes factor well work *which is a subset of data dataList.Chakra.Web.orderd*

dddddd\$M 2 modalities of almost *same* AUC

dddddd\$C 3 Confidence levels

dddddd\$Q 2 readers

If Bayes factor admit the null hypothesis that all modality are same, that is, 1-st and 2-nd modality of [dataList.Chakra.Web.orderd](#) are same, then, the Bayes factor well works.

Contents of ddddd

NL = 142 (Number of Lesions)

NI = 199 (Number of Images)#'

Contents:

Multiple readers and multiple modalities case, i.e., MRMC case

Author(s)

Issei Tsunoda <tsunoda.issei1111@gmail.com >

References

Example data of Jafroc software

See Also

Not `dataList.Chakra.Web` But `dataList.Chakra.Web.orderd` Not `dd`

Examples

```

#=====
#                               Show data by table
#=====

                               viewdata(dddddd)

#####1##### #####2##### #####3##### #####4##### #####5##### #####6##### #####7##### #####8##### #####9#####
#=====
#                               make an object dddd from an object dataList.Chakra.Web.orderd
#=====

ddd <- data.frame(m=dataList.Chakra.Web.orderd$m,
                  q=dataList.Chakra.Web.orderd$q,
                  c=dataList.Chakra.Web.orderd$c,
                  h=dataList.Chakra.Web.orderd$h,
                  f=dataList.Chakra.Web.orderd$f
)

dddd <- ddd[ddd$q < 3,]

# The following code extract the first and the second modality from dd
dddd <- dddd[ddd$m < 3,] # Reduce the dataset ddd, i.e., dd
dddd <- dddd[ddd$c < 4,]
ddd <- list(
  m=ddd$m,
  q=ddd$q,
  c=ddd$c,
  h=ddd$h,
  f=ddd$f,
  NL=142,
  NI=199, # 2020 April 6
  C=max(ddd$c),
  M=max(ddd$m),
  Q=max(ddd$q)
)

ddddddd <-ddd

```

```
# This dataset is made in 2019 July 6, for the aim of easy exhibition  
# This dataset is very minimum, and it is easy to view
```

```
demo_Bayesian_FROC      demonstration
```

Description

demonstration

Usage

```
demo_Bayesian_FROC()
```

Details

The author often forget the R script for execute the demos or bother to write the code to execute demo, thus I made this.

Value

none

Examples

```
## Not run:  
  
demo_Bayesian_FROC()  
  
# 2019.05.21 Revised.  
  
## End(Not run)# doctest
```

```
demo_Bayesian_FROC_without_pause  
      demonstration without pause
```

Description

demonstration without pause

Usage

```
demo_Bayesian_FROC_without_pause()
```

Value

none

draw.CFP.CTP.from.dataList

Plot the pairs of CFPs and CTPs

Description

It plot the empirical FROC curves (not depicted the line).

Usage

```
draw.CFP.CTP.from.dataList(
  dataList,
  ModifiedPoisson = FALSE,
  new.imaging.device = TRUE
)
```

Arguments

dataList A list, specifying an FROC data to be fitted a model. It consists of data of numbers of TPs, FPs, lesions, images. .In addition, if in case of mutiple readers or mutiple modalities, then modaity ID and reader ID are included also. The **dataList** will be passed to the function `rstan::sampling()` of **rstan**. This is a variable in the function `rstan::sampling()` in which it is named **data**. For the single reader and a single modality data, the **dataList** is made by the following manner:

```
dataList.Example <-list(
  h = c(41,22,14,8,1),# number of hits for each confidence level
  f = c(1,2,5,11,13),# number of false alarms for each confidence level

  NL = 124,# number of lesions (signals)
  NI = 63,# number of images (trials)
  C = 5) # number of confidence,.. the author thinks it can be calculated
as the length of h or f ...? ha,why I included this. ha .. should be omitted.
```

Using this object **dataList.Example**, we can apply `fit_Bayesian_FROC()` such as `fit_Bayesian_FROC(dataList.Example)`. To make this R object **dataList** representing FROC data, this package provides three functions:

- `convertFromJafroc()` If data is a **JAFROC xlsx** formulation.
- `dataset_creator_new_version()` Enter TP and FP data **by table** .
- `create_dataset()` Enter TP and FP data by **interactive** manner.

Before fitting a model, we can confirm our dataset is correctly formulated by using the function `viewdata()`.

A Single reader and a single modality (SRSC) case.

In a single reader and a single modality case (srsc), `dataList` is a list consisting of `f, h, NL, NI, C` where `f, h` are numeric vectors and `NL, NI, C` are positive integers.

- `f` Non-negative integer vector specifying number of false alarms associated with each confidence level. The first component corresponding to the highest confidence level.
- `h` Non-negative integer vector specifying number of Hits associated with each confidence level. The first component corresponding to the highest confidence level.

`NL` A positive integer, representing Number of Lesions.

`NI` A positive integer, representing Number of Images.

`C` A positive integer, representing Number of Confidence level.

The detail of these dataset, see the datasets endowed with this package. 'Note that the maximal number of confidence level, denoted by `C`, are included, however, Note that confidence level vector `c` should not be specified. If specified, will be ignored, since it is created by `c <- c(rep(C:1))` in the program and do not refer from user input data, where `C` is the highest number of confidence levels. So, you should write down your hits and false alarms vector so that it is compatible with this automatically created `c` vector.

data Format:

A single reader and a single modality case

NI=63, NL=124 In R console ->	confidence level c	No. of false alarms f	No. of hits h
definitely present	$c[1] = 5$	$f[1] = F_5 = 1$	$h[1] = H_5 = 41$
probably present	$c[2] = 4$	$f[2] = F_4 = 2$	$h[2] = H_4 = 22$
equivocal	$c[3] = 3$	$f[3] = F_3 = 5$	$h[3] = H_3 = 14$
subtle	$c[4] = 2$	$f[4] = F_2 = 11$	$h[4] = H_2 = 8$
very subtle	$c[5] = 1$	$f[5] = F_1 = 13$	$h[5] = H_1 = 1$

* *false alarms* = False Positives = FP

* *hits* = True Positives = TP

Note that in FROC data, all confidence level means *present (diseased, lesion)* case only, no confidence level indicating absent. Since each reader marks his suspicious location only if he thinks lesions are *present*, and marked positions

generates the hits or false alarms, *thus* each confidence level represents that lesion is *present*. In the absent case, reader dose not mark any locations and hence, the absent confidence level does not relate this dataset. So, if reader think it is no lesion, then in such case confidence level is not needed.

Note that the first column of confidence level vector c should not be specified. If specified, will be ignored, since it is created by $c \leftarrow c(\text{rep}(C:1))$ automatically in the program and do not refer from user input data even if it is specified explicitly, where C is the highest number of confidence levels. So you should check the compatibility of your data and the confidence level vector $c \leftarrow c(\text{rep}(C:1))$ via a table which can be displayed by the function `viewdata()`.

Multiple readers and multiple modalities case, i.e., MRMC case

In case of multiple readers and multiple modalities, i.e., MRMC case, in order to apply the function `fit_Bayesian_FROC()`, dataset represented by an R list object representing FROC data must contain components $m, q, c, h, f, NL, C, M, Q$.

- C A positive integer, representing the **highest** number of confidence level, this is a scalar.
- M A positive integer vector, representing the number of **modalities**.
- Q A positive integer, representing the number of **readers**.
- m A vector of positive integers, representing the **modality ID** vector.
- q A vector of positive integers, representing the **reader ID** vector.
- c A vector of positive integers, representing the **confidence level**. This vector must be made by `rep(rep(C:1), M*Q)`
- h A vector of non-negative integers, representing the number of **hits**.
- f A vector of non-negative integers, representing the number of **false alarms**.
- NL A positive integer, representing the Total number of **lesions** for all images, this is a scalar.

Note that the maximal number of confidence level (denoted by C) are included in the above R object. However, each confidence level vector is not included in the data, because it is created automatically from C . To confirm false positives and hits are correctly ordered with respect to the automatically generated confidence vector,

the function `viewdata()` shows the table. Revised 2019 Nov 27 Revised 2019 Dec 5

Example data.

Multiple readers and multiple modalities (i.e., MRMC)

Modality ID	Reader ID	Confidence levels	No. of false alarms	No. of hits.
m	q	c	f	h
1	1	3	20	111
1	1	2	29	55
1	1	1	21	22

1	2	3	6	100
1	2	2	15	44
1	2	1	22	11
2	1	3	6	66
2	1	2	24	55
2	1	1	23	1
2	2	3	5	66
2	2	2	30	55
2	2	1	40	44

* *false alarms* = False Positives = FP

* *hits* = True Positives = TP

ModifiedPoisson

Logical, that is TRUE or FALSE.

If ModifiedPoisson = TRUE, then Poisson rate of false alarm is calculated *per lesion*, and model is fitted so that the FROC curve is an expected curve of points consisting of the pairs of TPF per lesion and FPF *per lesion*.

Similarly,

If ModifiedPoisson = TRUE, then Poisson rate of false alarm is calculated *per image*, and model is fitted so that the FROC curve is an expected curve of points consisting of the pair of TPF per lesion and FPF *per image*.

For more details, see the author's paper in which I explained *per image* and *per lesion*. (for details of models, see *vignettes*, now, it is omitted from this package, because the size of vignettes are large.)

If ModifiedPoisson = TRUE, then the *False Positive Fraction (FPF)* is defined as follows (F_c denotes the number of false alarms with confidence level c)

$$\frac{F_1 + F_2 + F_3 + F_4 + F_5}{N_L},$$

$$\frac{F_2 + F_3 + F_4 + F_5}{N_L},$$

$$\frac{F_3 + F_4 + F_5}{N_L},$$

$$\frac{F_4 + F_5}{N_L},$$

$$\frac{F_5}{N_L},$$

where N_L is a number of lesions (signal). To emphasize its denominator N_L , we also call it the *False Positive Fraction (FPF) per lesion*.

On the other hand,

if ModifiedPoisson = FALSE (Default), then *False Positive Fraction (FPF)* is given by

$$\frac{F_1 + F_2 + F_3 + F_4 + F_5}{N_I},$$

$$\frac{F_2 + F_3 + F_4 + F_5}{N_I},$$

$$\frac{F_3 + F_4 + F_5}{N_I},$$

$$\frac{F_4 + F_5}{N_I},$$

$$\frac{F_5}{N_I},$$

where N_I is the number of images (trial). To emphasize its denominator N_I , we also call it the *False Positive Fraction (FPF) per image*.

The model is fitted so that the estimated FROC curve can be regarded as the expected pairs of FPF per image and TPF per lesion (ModifiedPoisson = FALSE)

or as the expected pairs of FPF per image and TPF per lesion (ModifiedPoisson = TRUE)

If ModifiedPoisson = TRUE, then FROC curve means the expected pair of **FPF per lesion** and TPF.

On the other hand, if ModifiedPoisson = FALSE, then FROC curve means the expected pair of **FPF per image** and TPF.

So, data of FPF and TPF are changed thus, a fitted model is also changed whether ModifiedPoisson = TRUE or FALSE. In traditional FROC analysis, it uses only per images (trial). Since we can divide one image into two images or more images, number of trial is not important. And more important is per signal. So, the author also developed FROC theory to consider FROC analysis under per signal. One can see that the FROC curve is rigid with respect to change of a number of images, so, it does not matter whether ModifiedPoisson = TRUE or FALSE. This rigidity of curves means that the number of images is redundant parameter for the FROC trial and thus the author try to exclude it.

Revised 2019 Dec 8 Revised 2019 Nov 25 Revised 2019 August 28

new.imaging.device

Logical: TRUE or FALSE. If TRUE (default), then open a new device to draw curve. Using this we can draw curves in same plain by new.imaging.device=FALSE.

Value

CFPs and CTPs

See Also

[plot_FPF_and_TPF_from_a_dataset\(\)](#)

[plot_FPF_TPF_via_dataframe_with_split_factor\(\)](#)

Examples

```
draw.CFP.CTP.from.dataList(dataList.Chakra.1)
```

DrawCurves

Draw the FROC curves

Description

The function makes a plot of the FROC curve, the AFROC curve and *FPF* and *TPF*.

Usage

```
DrawCurves(  
  StanS4class,  
  modalityID,  
  readerID,  
  title = TRUE,  
  indexCFPCTP = FALSE,  
  upper_x,  
  upper_y,  
  new.imaging.device = TRUE,  
  Colour = TRUE,  
  DrawFROCcurve = TRUE,  
  DrawAFROCcurve = FALSE,  
  DrawAUC = TRUE,  
  DrawCFPCTP = TRUE,  
  Draw.Flexible.upper_y = TRUE,  
  Draw.Flexible.lower_y = TRUE,  
  summary = TRUE,  
  type = 4,  
  color_is_changed_by_each_reader = FALSE,  
  Draw.inner.circle.for.CFPCTPs = TRUE  
)
```

Arguments

StanS4class	An S4 object of class <code>stanfitExtended</code> which is an inherited class from the S4 class <code>stanfit</code> . This R object is a fitted model object as a return value of the function <code>fit_Bayesian_FROC()</code> . It can be passed to <code>DrawCurves()</code> , <code>ppp()</code> and ... etc
modalityID	A positive integer vector indicating modalityID. If it is not given, then the first modality is chosen.
readerID	A positive integer vector indicating readerID. If it is not given, then the first reader is chosen.
title	Logical: TRUE of FALSE. If TRUE (default), then title of curves are drawn.
indexCFPCTP	TRUE of FALSE. If TRUE, then the cumulative false and hits are specified with its confidence level.
upper_x	This is a upper bound for the axis of the horisontal coordinate of FROC curve.
upper_y	This is a upper bound for the axis of the vertical coordinate of FROC curve.
new.imaging.device	Logical: TRUE of FALSE. If TRUE (default), then open a new device to draw curve. Using this we can draw curves in same plain by <code>new.imaging.device=FALSE</code> .
Colour	Logical: TRUE of FALSE. whether Colour of curves is dark theme or not.
DrawFROCcurve	Logical: TRUE of FALSE. Whether or not FROC curves are shown.
DrawAFROCcurve	Logical: TRUE of FALSE. Whether or not AFROC curves are shown.
DrawAUC	TRUE of FALSE. If TRUE then area under the AFROC curves are painted.
DrawCFPCTP	Logical: TRUE of FALSE. Whether or not the pairs of <i>FPF</i> and <i>TPF</i> are shown.
Draw.Flexible.upper_y	Logical: TRUE of FALSE. Whether or not the upper bounds of vertical axis are determined automatically.
Draw.Flexible.lower_y	Logical: TRUE of FALSE. Whether or not the lower bounds of vertical axis are determined automatically.
summary	Logical: TRUE of FALSE. Whether to print the verbose summary. If TRUE then verbose summary is printed in the R console. If FALSE, the output is minimal. I regret, this variable name should be verbose.
type	An integer, for the color of background and etc.
color_is_changed_by_each_reader	A logical, if TRUE, then the FROC curves, AFROC curves, and FPF, TPF are colored accordingly by each reader. The aim of FROC analysis is to compare the modality and not reader, so the default value is false, and curves and FPF and TPF are colored by each modalities.
Draw.inner.circle.for.CFPCTPs	TRUE or FALSE. If true, then to plot the cumulative false positives and true positives the plot points is depicted by two way, one is a large circle and one is a small circle. By see the small circle, user can see the more precise position of these points.

Details

The function makes a plot of the FROC curves and AFROC curves for user's specified modality and user's specified reader. Using this function **repeatedly**, we can draw the different reader and modality in a **same** plane simultaneously. So, we can visualize the difference of modality (reader).

Examples

```
#####The first example#####
## Not run:
#1) Fit a model to data by the following:

fit <- fit_Bayesian_FROC(
  BayesianFROC::dataList.Chakra.Web, # data to which fit the model
  ite=1111 # iteration of MCMC is too small
)

#Note that the return value "fit" is an object of an inherited S4 class from stanfit

#2) Using the above S4 class object, we draw the curves.

DrawCurves(
  fit,
  modality = 1,
  reader = 4)

#From this code, an FROC curve for the first modality and the fourth reader is drawn.

#3) By changing, e.g., the modality,
#we can draw the curves for different modalities.
#This shows the comparison of modalities.
# In the following,
# the first script plots a curve for the 2 nd modality and the fourth reader,
# and the second script plots a curve for the 3rd modality and the 4 th reader,
# respectively.

DrawCurves(fit,modality = 2,reader = 4)
DrawCurves(fit,modality = 3,reader = 4)
```

```

# Curves are overwritten in a single imaging device for the comparison.

#4) By applying the function with respect to different modalities
#   in this manner, we can draw AFROC (FROC) curves in the same plain.

#5) If you want to draw the FROC curves
#for reader ID =1,2,3,4 and modality ID =1,2, then the code is as follows;

        DrawCurves(
            fit,
            modalityID = c(1,2,3,4),
            readerID   = c(1,2)
        )
# Each color of curves corresponds to the modality ID.
# So, the curves of "different" readers will have the "same" color,
# if their modalities are "same".

# 6) To show only data points, i.e. FPF and TPF,
#     use DrawFROCcurve = F as follows;

DrawCurves(fit,
            DrawCFPCTP   = TRUE, # This implies data points are plotted.
            DrawFROCcurve = FALSE, # From this, the curves are not drawn.
            modalityID   = c(1,2,3,4),
            readerID     = c(1)
            )

#7) If you use the plot in submission and it is not allowed to use color, then
#   by Colour = FALSE, you can get black and white plots, e.g.,

DrawCurves(fit,
            DrawCFPCTP   = TRUE,
            DrawFROCcurve = TRUE,

```

```
modalityID = c(1,2,3,4),
readerID   = c(1),
Colour = FALSE # From this, you can get plots without colors.
)
```

#8) For AFROC, use DrawAFROCcurve = T

```
DrawCurves(fit,
  DrawFROCcurve = FALSE,
  DrawAFROCcurve = TRUE,
  modalityID = c(1,2,3,4),
  readerID = c(1)
)
```

#9)

```
# In order to compare modality, we draw curves by each modality
# The 1-st modality with all readers 1,2,3,4:
```

```
DrawCurves(fit,modalityID = 1,readerID = 1:4, new.imaging.device = TRUE)
```

```
#The 2-nd modality with all readers 1,2,3,4:
```

```
DrawCurves(fit,modalityID = 2,readerID = 1:4, new.imaging.device = FALSE)
```

```
#The 3-rd modality with all readers 1,2,3,4:
```

```
DrawCurves(fit,modalityID = 3,readerID = 1:4, new.imaging.device = FALSE)
```

```
#The 4-th modality with all readers 1,2,3,4:
```

```
DrawCurves(fit,modalityID = 4,readerID = 1:4, new.imaging.device = FALSE)
```

```
#The 5-th modality with all readers 1,2,3,4:
```

```
DrawCurves(fit,modalityID = 5,readerID = 1:4, new.imaging.device = FALSE)
```

```
# Draw for all pairs of modalities and readers:
```

```
DrawCurves(
```

```

    modalityID = 1:fit@dataList$M,
      readerID = 1:fit@dataList$Q,
    StanS4class = fit
  )

```

```

# Changes the color by

```

```

    DrawCurves(fit, type = 2)
    DrawCurves(fit, type = 3)
    DrawCurves(fit, type = 4)
    DrawCurves(fit, type = 5)
    DrawCurves(fit, type = 6)
    DrawCurves(fit, type = 7)

```

```

#=====The Second Example=====

```

```

# This function is available in the case of a single reader and a single modality.
# The reason why the maintainer separate the function for two processes, one is
# the fitting and the second is to plot curves is, in MRMC case,
# it takes a time to drawing, but in the a single reader and a single modality case, drawing
# the curve is very fast, so in fitting process the curves are also depicted, however
# by this function user can draw the FROC curves.

```

```

#First, we prepare the data endowed with this package.

```

```

dat <- get(data("dataList.Chakra.1"))

```

```

#Second, we fit a model to data named "dat"

```



```
fit <- fit_srsc(dat)

# Drawing the curves by

DrawCurves(fit)

# Changes the color by

DrawCurves(fit, type = 2)
DrawCurves(fit, type = 3)
DrawCurves(fit, type = 4)
DrawCurves(fit, type = 5)
DrawCurves(fit, type = 6)
DrawCurves(fit, type = 7)

# Close the graphic device to avoid errors in R CMD check.
Close_all_graphic_devices()

## End(Not run)# dottest
```

DrawCurves_MRMC *Draw the FROC curves for all modalities and readers*

Description

Draw the FROC curves and AFROC curves for all specified modalities and readers.

Usage

```
DrawCurves_MRMC(StanS4class, type = 1)
```

Arguments

StanS4class	An S4 object of class <code>stanfitExtended</code> which is an inherited class from the S4 class <code>stanfit</code> . This R object is a fitted model object as a return value of the function <code>fit_Bayesian_FROC()</code> . It can be passed to <code>DrawCurves()</code> , <code>ppp()</code> and ... etc
type	An integer, for the color of background and etc.

Examples

```
## Not run:
fit <- fit_Bayesian_FROC(
  dataList.Chakra.Web.orderd,
  ite = 1111,
  summary =FALSE
)

DrawCurves_MRMC(fit)

# 2019.05.21 Revised.

## End(Not run)# dottest
```

DrawCurves_MRMC_pairwise

Draw the FROC curves with Colour

Description

Draw *FROC curves* and *AFROC curves* for user's specified modalities and user's specified readers. Using this function **repeatedly**, we can draw the different reader and modality in a **same** plane simultaneously.

Usage

```
DrawCurves_MRMC_pairwise(
  StanS4class,
  modalityID,
  readerID,
  Colour = TRUE,
  DrawFROCcurve = TRUE,
  DrawAFROCcurve = FALSE,
  DrawCFPCTP = TRUE,
  Draw.Flexible.upper_y = TRUE,
```

```

Draw.Flexible.lower_y = TRUE,
new.imaging.device = TRUE,
summary = TRUE,
color_is_changed_by_each_reader = FALSE,
type = 1
)

```

Arguments

StanS4class	An S4 object of class <code>stanfitExtended</code> which is an inherited class from the S4 class <code>stanfit</code> . This R object is a fitted model object as a return value of the function <code>fit_Bayesian_FROC()</code> . It can be passed to <code>DrawCurves()</code> , <code>ppp()</code> and ... etc
modalityID	This is a vector indicating modalityID whose component is natural number.
readerID	This is a vector indicating readerID whose component is natural number.
Colour	Logical, that is TRUE or FALSE. Whether plot of curves are with dark theme. Default is TRUE indicating dark theme.
DrawFROCcurve	Logical: TRUE of FALSE. Whether the FROC curve is to be drawn.
DrawAFROCcurve	Logical: TRUE of FALSE. Whether the AFROC curve is to be drawn.
DrawCFPCTP	Logical: TRUE of FALSE. Whether the CFP and CTP points are to be drawn. CFP: Cumulative false positive per lesion (or image) which is also called False Positive Fraction (FPF). CTP Cumulative True Positive per lesion which is also called True Positive Fraction (TPF)..
Draw.Flexible.upper_y	Logical, that is TRUE or FALSE. Whether or not the upper bounds of vertical axis are determined automatically.
Draw.Flexible.lower_y	Logical, that is TRUE or FALSE. Whether or not the lower bounds of vertical axis are determined automatically.
new.imaging.device	Logical: TRUE of FALSE. If TRUE (default), then open a new device to draw curve. Using this we can draw curves in same plain by <code>new.imaging.device=FALSE</code> .
summary	Logical: TRUE of FALSE. Whether to print the verbose summary. If TRUE then verbose summary is printed in the R console. If FALSE, the output is minimal. I regret, this variable name should be verbose.
color_is_changed_by_each_reader	A logical, if TRUE, then the FROC curves, AFROC curves, and FPF, TPF are colored accordingly by each reader. The aim of FROC analysis is to compare the modality and not reader, so the default value is false, and curves and FPF and TPF are colored by each modalities.
type	An integer, for the color of background and etc.

Details

By drawing different modality FROC curves in the same plane, we can compare the modality. E.g., if some modality FROC curve is upper then other modality curves, then we may say that the upper modality is better observer performance, i.e., higher AUC.

Author(s)

Issei Tsunoda

Examples

Not run:

#1) Fit a model to data by the following:

```
fit <- fit_Bayesian_FROC(dataList.Chakra.Web, ite = 1111)
```

#Note that the return value "fit" is an object of an inherited S4 class from stanfit

#2) Using the above S4 class object, we draw the curves.

```
DrawCurves_MRMC_pairwise(fit,  
                          modality = 1,  
                          reader = 4  
                          )
```

#3) By changing the modality (or reader),

#we can draw the curves with respect to different modalities.

#This shows the comparison of modalities.

```
DrawCurves_MRMC_pairwise(fit,  
                          modality = 2,  
                          reader = 4  
                          )
```

```
DrawCurves_MRMC_pairwise(fit,  
                          modality = 3,  
                          reader = 4  
                          )
```

#4) By repeating in this manner for different modalities or readers,

we can draw AFROC (FROC) curves in a single imaging device.

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#5) If you want to draw the FROC curves

#for reader ID =1,2,3,4 and modality ID =1,2, then the code is as follows;

```

DrawCurves_MRMC_pairwise(
  fit,
  modalityID = c(1,2,3,4),
  readerID = c(1,2)
)
# Each color of curves corresponds to the modality ID.
# So, even if curves are different readers and same modality, then color is same.

# Close the graphic device
Close_all_graphic_devices()

## End(Not run) # dottest

```

```

DrawCurves_MRMC_pairwise_BlackWhite
  Draw the FROC curves without colour

```

Description

Plot curves without colors (dark theme), that is, black and white (white background with black curves). Draw FROC curves and AFROC curves for user's specified modality and user's specified reader. Using this function **repeatedly**, we can draw curves simultaneously, and we compare observer performance of the different reader and modality **intuitively**. So, we can visualize the difference of modality (reader).

Usage

```

DrawCurves_MRMC_pairwise_BlackWhite(
  StanS4class,
  modalityID,
  readerID,
  new.imaging.device = TRUE,
  DrawFROCcurve = TRUE,
  DrawAFROCcurve = FALSE,
  DrawCFPCTP = TRUE,

```

```

Draw.Flexible.upper_y = TRUE,
Draw.Flexible.lower_y = TRUE,
summary = TRUE,
type = 1
)

```

Arguments

StanS4class	An S4 object of class <code>stanfitExtended</code> which is an inherited class from the S4 class <code>stanfit</code> . This R object is a fitted model object as a return value of the function <code>fit_Bayesian_FROC()</code> . It can be passed to <code>DrawCurves()</code> , <code>ppp()</code> and ... etc
modalityID	This is a vector indicating modalityID whose component is natural number.
readerID	This is a vector indicating readerID whose component is natural number.
new.imaging.device	Logical: TRUE of FALSE. If TRUE (default), then open a new device to draw curve. Using this we can draw curves in same plain by <code>new.imaging.device=FALSE</code> .
DrawFROCcurve	Logical: TRUE of FALSE. Whether the FROC curve is to be drawn.
DrawAFROCcurve	Logical: TRUE of FALSE. Whether the AFROC curve is to be drawn.
DrawCFPCTP	Logical: TRUE of FALSE. Whether the CFP and CTP points are to be drawn. CFP: Cumulative false positive per lesion (or image) which is also called False Positive Fraction (FPF). CTP Cumulative True Positive per lesion which is also called True Positive Fraction (TPF)..
Draw.Flexible.upper_y	Logical, that is TRUE or FALSE. Whether or not the upper bounds of vertical axis are determined automatically.
Draw.Flexible.lower_y	Logical, that is TRUE or FALSE. Whether or not the lower bounds of vertical axis are determined automatically.
summary	Logical: TRUE of FALSE. Whether to print the verbose summary. If TRUE then verbose summary is printed in the R console. If FALSE, the output is minimal. I regret, this variable name should be verbose.
type	An integer, for the color of background and etc.

DrawCurves_MRMC_pairwise_col

Draw the FROC curves with Colour

Description

Draw an FROC curves and an AFROC curves for user's specified modality and user's specified reader. Using this function **repeatedly**, we can draw the different reader and modality in a **same** plane simultaneously. So, we can visualize the difference of modality (reader).

Usage

```

DrawCurves_MRMC_pairwise_col(
  StanS4class,
  modalityID,
  readerID,
  type = 1,
  color_is_changed_by_each_reader = FALSE,
  new.imaging.device = TRUE,
  DrawFROCcurve = TRUE,
  DrawAFROCcurve = FALSE,
  DrawCFPCTP = TRUE,
  Draw.Flexible.upper_y = TRUE,
  Draw.Flexible.lower_y = TRUE,
  summary = TRUE
)

```

Arguments

- | | |
|---------------------------------|---|
| StanS4class | An S4 object of class <code>stanfitExtended</code> which is an inherited class from the S4 class <code>stanfit</code> . This R object is a fitted model object as a return value of the function <code>fit_Bayesian_FROC()</code> .
It can be passed to <code>DrawCurves()</code> , <code>ppp()</code> and ... etc |
| modalityID | This is a vector indicating modalityID whose component is natural number. |
| readerID | This is a vector indicating readerID whose component is natural number. |
| type | An integer, for the color of background and etc. |
| color_is_changed_by_each_reader | A logical, if TRUE, then the FROC curves, AFROC curves, and FPF, TPF are colored accordingly by each reader. The aim of FROC analysis is to compare the modality and not reader, so the default value is false, and curves and FPF and TPF are colored by each modalities. |
| new.imaging.device | Logical: TRUE of FALSE. If TRUE (default), then open a new device to draw curve. Using this we can draw curves in same plain by new.imaging.device=FALSE. |
| DrawFROCcurve | Logical: TRUE of FALSE. Whether the FROC curve is to be drawn. |
| DrawAFROCcurve | Logical: TRUE of FALSE. Whether the AFROC curve is to be drawn. |
| DrawCFPCTP | Logical: TRUE of FALSE. Whether the CFP and CTP points are to be drawn. CFP: Cumulative false positive per lesion (or image) which is also called False Positive Fraction (FPF). CTP Cumulative True Positive per lesion which is also called True Positive Fraction (TPF).. |
| Draw.Flexible.upper_y | Logical, that is TRUE or FALSE. Whether or not the upper bounds of vertical axis are determined automatically. |
| Draw.Flexible.lower_y | Logical, that is TRUE or FALSE. Whether or not the lower bounds of vertical axis are determined automatically. |

summary Logical: TRUE of FALSE. Whether to print the verbose summary. If TRUE then verbose summary is printed in the R console. If FALSE, the output is minimal. I regret, this variable name should be verbose.

DrawCurves_srsr *Draw the FROC curves*

Description

Draw an FROC curves and an AFROC curves.

Usage

```
DrawCurves_srsr(
  StanS4class,
  type = 4,
  title = TRUE,
  indexCFPCTP = FALSE,
  upper_x,
  upper_y,
  new.imaging.device = TRUE,
  Drawcol = TRUE,
  DrawFROCcurve = TRUE,
  DrawAFROCcurve = FALSE,
  DrawCFPCTP = TRUE,
  Draw.inner.circle.for.CFPCTPs = TRUE,
  DrawAUC = TRUE
)
```

Arguments

StanS4class An S4 object of class `stanfitExtended` which is an inherited class from the S4 class `stanfit`. This R object is a fitted model object as a return value of the function `fit_Bayesian_FROC()`.
It can be passed to `DrawCurves()`, `ppp()` and ... etc

type An integer, for the color of background and etc.

title Logical: TRUE of FALSE. If TRUE (default), then title of curves are drawn.

indexCFPCTP TRUE of FALSE. If TRUE, then the cumulative false and hits are specified with its confidence level.

upper_x This is a upper bound for the axis of the horisontal coordinate of FROC curve.

upper_y This is a upper bound for the axis of the vertical coordinate of FROC curve.

new.imaging.device Logical: TRUE of FALSE. If TRUE (default), then open a new device to draw curve. Using this we can draw curves in same plain by `new.imaging.device=FALSE`.

Drawcol	Logical: TRUE of FALSE. Whether the (A)FROC curve is to be drawn by using color of dark theme. The Default value is a TRUE.
DrawFROCcurve	Logical: TRUE of FALSE. Whether or not FROC curves are shown.
DrawAFROCcurve	Logical: TRUE of FALSE. Whether or not AFROC curves are shown.
DrawCFPCTP	Logical: TRUE of FALSE. Whether or not the pairs of <i>FPF</i> and <i>TPF</i> are shown.
Draw.inner.circle.for.CFPCTPs	TRUE or FALSE. If true, then to plot the cumulative false positives and true positives the plot points is depicted by two way, one is a large circle and one is a small circle. By see the small circle, user can see the more precise position of these points.
DrawAUC	TRUE of FALSE. If TRUE then area under the AFROC curves are painted.

Draw_an_area_of_AUC_for_srsc

Draw a Region of the area under the AFROC curve

Description

Draw a Region of the area under the AFROC curve

Usage

```
Draw_an_area_of_AUC_for_srsc(StanS4class)
```

Arguments

StanS4class An S4 object of class [stanfitExtended](#) which is an inherited class from the S4 class [stanfit](#). This R object is a fitted model object as a return value of the function [fit_Bayesian_FROC\(\)](#).
It can be passed to [DrawCurves\(\)](#), [ppp\(\)](#) and ... etc

Value

None

Examples

```
## Not run:

fit <- fit_Bayesian_FROC(dataList.Chakra.1)

Draw_an_area_of_AUC_for_srsc(fit)

## End(Not run)# dottest
```

Draw_AUC

*Draw the Region of AUC of AFROC***Description**

An AFROC curve has two parameter denoted by a, b . By specifying a, b , we can draw an AFROC curve.

Def of AFROC

$$(\xi(t), \eta(t)) = (1 - e^{-t}, \Phi(b\Phi^{-1}(\exp(-t)) - a)).$$

Def of AUC of AFROC

$$AUC = \int \eta d\xi = \frac{a}{\sqrt{1+b^2}}.$$

Usage

Draw_AUC(a = 0.13, b = 0.19, mesh.for.drawing.curve = 2222)

Arguments

a One of the parameter of model which characterize AFROC curve
b One of the parameter of model which characterize AFROC curve
mesh.for.drawing.curve A positive large integer, indicating number of dots drawing the curves, Default =10000.

Details

We define the so-called FROC curve as a map from 1-dimensional Euclidean space to 2-dimensional Euclidean space, mapping each $t > 0$ to

$$(x(t), y(t)) = (t, \Phi(\frac{\Phi^{-1}(\exp(-t)) - \mu}{\sigma}))$$

Since $x(t) = t, t > 0$ is not bounded, the area under the FROC curve is infinity.

To calculates aleternative notion of AUC in the ordinal ROC theory, we define the so-called AFROC curve:

$$(\xi(t), \eta(t)) = (1 - e^{-t}, \Phi(\frac{\Phi^{-1}(\exp(-t)) - \mu}{\sigma}))$$

which contained in the rectangular space $[0, 1]^2$. Introducing new parameter $a := \mu/\sigma$ and $b := 1/\sigma$, we also write

$$(\xi(t), \eta(t)) = (1 - e^{-t}, \Phi(b\Phi^{-1}(\exp(-t)) - a))$$

The area Under the (AFROC) curve (briefly, we call it AUC) represents the observer performance. For example, if radiologist detects more lesions with small False Positives (FPs), then AUC would be high.

Using the parameter of the signal distribution, we express AUC as follows,

$$AUC = \frac{\mu/\sigma}{\sqrt{1 + 1/\sigma^2}}.$$

Using new parameter $a := \mu/\sigma$ and $b := 1/\sigma$, we also write

$$AUC = \frac{a}{\sqrt{1 + b^2}}.$$

Value

none.

Examples

```
Draw_AUC()
```

Draw_a_prior_sample *Draw One Sample from Prior*

Description

Draw One Sample from Prior

Usage

```
Draw_a_prior_sample(sd = 5, C = 5, seed.for.drawing.a.prior.sample = 1111)
```

Arguments

sd	Standard deviation of priors. Very large number.
C	No. of Confidence level
seed.for.drawing.a.prior.sample	
seed	

Value

w, v, m, dz, z

Examples

```
## Not run:

Draw.a.prior.sample <- Draw_a_prior_sample()

## End(Not run)# dottest
```

Draw_a_simulated_data_set

Draw a simulated dataset from model distributions with specified parameters from priors

Description

Draw a simulated dataset from model distributions with specified parameters from priors

Usage

```
Draw_a_simulated_data_set(
  sd = 5,
  C = 5,
  seed.for.drawing.a.prior.sample = 1111,
  fun = stats::var,
  NI = 259,
  NL = 259,
  initial.seed.for.drawing.a.data = 1234,
  ModifiedPoisson = FALSE,
  ite = 1111
)
```

Arguments

sd	Standard Deviation of priors
C	No. of Confidence levels
seed.for.drawing.a.prior.sample	seed
fun	An one dimensional real valued function defined on the parameter space. This is used in the definition of the rank statistics. Generally speaking, the element of the parameter space is a vector, so the function should be defined on vectors. In my model parameter is mean, standard deviation, C thresholds of the latent Gaussian, so this function should be defined on the C+2 dimensional Euclidean space.
NI	No. of images

NL No. of Lesions
 initial.seed.for.drawing.a.data
 seed
 ModifiedPoisson

Logical, that is TRUE or FALSE.

If ModifiedPoisson = TRUE, then Poisson rate of false alarm is calculated **per lesion**, and model is fitted so that the FROC curve is an expected curve of points consisting of the pairs of TPF per lesion and FPF **per lesion**.

Similarly,

If ModifiedPoisson = TRUE, then Poisson rate of false alarm is calculated **per image**, and model is fitted so that the FROC curve is an expected curve of points consisting of the pair of TPF per lesion and FPF **per image**.

For more details, see the author's paper in which I explained *per image* and *per lesion*. (for details of models, see **vignettes** , now, it is omitted from this package, because the size of vignettes are large.)

If ModifiedPoisson = TRUE, then the *False Positive Fraction (FPF)* is defined as follows (F_c denotes the number of false alarms with confidence level c)

$$\frac{F_1 + F_2 + F_3 + F_4 + F_5}{N_L},$$

$$\frac{F_2 + F_3 + F_4 + F_5}{N_L},$$

$$\frac{F_3 + F_4 + F_5}{N_L},$$

$$\frac{F_4 + F_5}{N_L},$$

$$\frac{F_5}{N_L},$$

where N_L is a number of lesions (signal). To emphasize its denominator N_L , we also call it the *False Positive Fraction (FPF) per lesion*.

On the other hand,

if ModifiedPoisson = FALSE (Default), then *False Positive Fraction (FPF)* is given by

$$\frac{F_1 + F_2 + F_3 + F_4 + F_5}{N_I},$$

$$\frac{F_2 + F_3 + F_4 + F_5}{N_I},$$

$$\frac{F_3 + F_4 + F_5}{N_I},$$

$$\frac{F_4 + F_5}{N_I},$$

$$\frac{F_5}{N_I},$$

where N_I is the number of images (trial). To emphasize its denominator N_I , we also call it the *False Positive Fraction (FPF) per image*.

The model is fitted so that the estimated FROC curve can be regarded as the expected pairs of FPF per image and TPF per lesion (ModifiedPoisson = FALSE)

or as the expected pairs of FPF per image and TPF per lesion (ModifiedPoisson = TRUE)

If ModifiedPoisson = TRUE, then FROC curve means the expected pair of **FPF per lesion** and TPF.

On the other hand, if ModifiedPoisson = FALSE, then FROC curve means the expected pair of **FPF per image** and TPF.

So, data of FPF and TPF are changed thus, a fitted model is also changed whether ModifiedPoisson = TRUE or FALSE. In traditional FROC analysis, it uses only per images (trial). Since we can divide one image into two images or more images, number of trial is not important. And more important is per signal. So, the author also developed FROC theory to consider FROC analysis under per signal. One can see that the FROC curve is rigid with respect to change of a number of images, so, it does not matter whether ModifiedPoisson = TRUE or FALSE. This rigidity of curves means that the number of images is redundant parameter for the FROC trial and thus the author try to exclude it.

Revised 2019 Dec 8 Revised 2019 Nov 25 Revised 2019 August 28

`iter` A variable to be passed to the function `rstan::sampling()` of **rstan** in which it is named `iter`. A positive integer representing the number of samples synthesized by Hamiltonian Monte Carlo method, and, Default = 10000.

Value

A single synthesized data-set

Examples

```
## Not run:
  one.dataList <- Draw_a_simulated_data_set()
```

```
## End(Not run)# dottest
```

Draw_a_simulated_data_set_and_Draw_posterior_samples
Draw a dataset and MCMC samples

Description

Draw a dataset and MCMC samples.

1. draw a model parameter from prior distribution,
2. draw a dataset from the model with the parameter drawn in step 1,
3. draw a collection of posterior samples for the dataset drawn in step 2.

Usage

```
Draw_a_simulated_data_set_and_Draw_posterior_samples(
  sd = 5,
  C = 5,
  seed.for.drawing.a.prior.sample = 1111,
  fun = stats::var,
  NI = 259,
  NL = 259,
  initial.seed.for.drawing.a.data = 1234,
  ModifiedPoisson = FALSE,
  PreciseLogLikelihood = TRUE,
  ite = 1111,
  DrawCurve = FALSE
)
```

Arguments

sd	Standard Deviation of priors
C	No. of Confidence levels
seed.for.drawing.a.prior.sample	seed
fun	An one dimensional real valued function defined on the parameter space. This is used in the definition of the rank statistics. Generally speaking, the element of the parameter space is a vector, so the function should be defined on vectors. In my model parameter is mean, standard deviation, C thresholds of the latent Gaussian, so this function should be defined on the C+2 dimensional Euclidean space.
NI	No. of images
NL	No. of Lesions
initial.seed.for.drawing.a.data	seed

ModifiedPoisson

Logical, that is TRUE or FALSE.

If ModifiedPoisson = TRUE, then Poisson rate of false alarm is calculated *per lesion*, and model is fitted so that the FROC curve is an expected curve of points consisting of the pairs of TPF per lesion and FPF *per lesion*.

Similarly,

If ModifiedPoisson = TRUE, then Poisson rate of false alarm is calculated *per image*, and model is fitted so that the FROC curve is an expected curve of points consisting of the pair of TPF per lesion and FPF *per image*.

For more details, see the author's paper in which I explained *per image* and *per lesion*. (for details of models, see [vignettes](#), now, it is omitted from this package, because the size of vignettes are large.)

If ModifiedPoisson = TRUE, then the *False Positive Fraction (FPF)* is defined as follows (F_c denotes the number of false alarms with confidence level c)

$$\frac{F_1 + F_2 + F_3 + F_4 + F_5}{N_L},$$

$$\frac{F_2 + F_3 + F_4 + F_5}{N_L},$$

$$\frac{F_3 + F_4 + F_5}{N_L},$$

$$\frac{F_4 + F_5}{N_L},$$

$$\frac{F_5}{N_L},$$

where N_L is a number of lesions (signal). To emphasize its denominator N_L , we also call it the *False Positive Fraction (FPF) per lesion*.

On the other hand,

if ModifiedPoisson = FALSE (Default), then *False Positive Fraction (FPF)* is given by

$$\frac{F_1 + F_2 + F_3 + F_4 + F_5}{N_I},$$

$$\frac{F_2 + F_3 + F_4 + F_5}{N_I},$$

$$\frac{F_3 + F_4 + F_5}{N_I},$$

$$\frac{F_4 + F_5}{N_I},$$

$$\frac{F_5}{N_I},$$

where N_I is the number of images (trial). To emphasize its denominator N_I , we also call it the *False Positive Fraction (FPF) per image*.

The model is fitted so that the estimated FROC curve can be regarded as the expected pairs of FPF per image and TPF per lesion (ModifiedPoisson = FALSE)

or as the expected pairs of FPF per image and TPF per lesion (ModifiedPoisson = TRUE)

If ModifiedPoisson = TRUE, then FROC curve means the expected pair of **FPF per lesion** and TPF.

On the other hand, if ModifiedPoisson = FALSE, then FROC curve means the expected pair of **FPF per image** and TPF.

So, data of FPF and TPF are changed thus, a fitted model is also changed whether ModifiedPoisson = TRUE or FALSE. In traditional FROC analysis, it uses only per images (trial). Since we can divide one image into two images or more images, number of trial is not important. And more important is per signal. So, the author also developed FROC theory to consider FROC analysis under per signal. One can see that the FROC curve is rigid with respect to change of a number of images, so, it does not matter whether ModifiedPoisson = TRUE or FALSE. This rigidity of curves means that the number of images is redundant parameter for the FROC trial and thus the author try to exclude it.

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PreciseLogLikelihood

Logical, that is TRUE or FALSE. If PreciseLogLikelihood = TRUE (default), then Stan calculates the precise log likelihood with target formulation. If PreciseLogLikelihood = FALSE, then Stan calculates the log likelihood by dropping the constant terms in the likelihood function. In past, I distinct the stan file, one is target formulation and the another is not. But non-target formulation cause some Jacobian warning, thus I made all stanfile with target formulation when I uploaded to CRAN. Thus this variable is now meaningless.

ite

A variable to be passed to the function `rstan::sampling()` of **rstan** in which it is named `iter`. A positive integer representing the number of samples synthesized by Hamiltonian Monte Carlo method, and, Default = 10000.

DrawCurve

Logical: TRUE or FALSE. Whether the curve is to be drawn. TRUE or FALSE. If you want to draw the FROC and AFROC curves, then you set DrawCurve = TRUE, if not then DrawCurve = FALSE. The reason why the author make this variable DrawCurve is that it takes long time in MRMC case to draw curves, and thus Default value is FALSE in the case of MRMC data.

Value

Draw.a.prior.sample The Return value of Draw_a_prior_sample
 A dataList and an object of the stanfit S4 class with respect to the dataList

See Also

hits_false_alarms_creator_from_thresholds

Examples

```
## Not run:

# Draw a curve for various seeds and various number of confidence levels.
# Changing the seed, we can draw a parameter from priors and using this sample,
# we can draw the datasets from our model whose parameters are
# the priors samples.

# 1. draw a model parameter from prior distribution,
# 2. draw a dataset from the model with the parameter drawn in step 1,
# 3. draw a collection of posterior samples for the dataset drawn in step 2.

Draw_a_simulated_data_set_and_Draw_posterior_samples(
  seed.for.drawing.a.prior.sample = 1234,
  C=8)

  Draw_a_simulated_data_set_and_Draw_posterior_samples(
  seed.for.drawing.a.prior.sample = 12345,
  C=7)

  Draw_a_simulated_data_set_and_Draw_posterior_samples(
  seed.for.drawing.a.prior.sample = 123456,
  C=6)

  Draw_a_simulated_data_set_and_Draw_posterior_samples(
  seed.for.drawing.a.prior.sample = 1234567,
  C=5)

## End(Not run)# dottest
```

draw_latent_noise_distribution

Visualization of the Latent Gaussian for false rates

Description

Plot the posterior mean of model parameter θ and the latent function, i.e. the differential logarithmic Gaussian $d \log \Phi(z)$.

Usage

```
draw_latent_noise_distribution(
  StanS4class,
  dark_theme = TRUE,
  dig = 3,
  mesh = 1000,
  new.imaging.device = TRUE,
  hit.rate = FALSE,
  false.alarm.rate = TRUE,
  both.hit.and.false.rate = FALSE,
  density = 22,
  color = TRUE,
  mathematical.symbols = TRUE,
  type = 3
)
```

Arguments

StanS4class	An S4 object of class <code>stanfitExtended</code> which is an inherited class from the S4 class <code>stanfit</code> . This R object is a fitted model object as a return value of the function <code>fit_Bayesian_FROC()</code> . It can be passed to <code>DrawCurves()</code> , <code>ppp()</code> and ... etc
dark_theme	TRUE or FALSE
dig	A variable to be passed to the function <code>rstan::sampling()</code> of rstan in which it is named <code>...</code> ?. A positive integer representing the Significant digits, used in stan Cancellation. Default = 5,
mesh	Mesh for painting the area
new.imaging.device	Logical: TRUE or FALSE. If TRUE (default), then open a new device to draw curve. Using this we can draw curves in same plain by <code>new.imaging.device=FALSE</code> .
hit.rate	whether draws it. Default is TRUE.
false.alarm.rate	whether draws it. Default is TRUE.
both.hit.and.false.rate	whether draws it. Default is TRUE.
density	A natural number, indicating the density of shading lines, in lines per inch.
color	A color region is selected from black and white only. For more colors, put FALSE. For publication, the mono color is allowed in many case, so the author made this for such publication.
mathmatical.symbols	A logical, whether legend is in plot.
type	An integer, for the color of background and etc.

Details

Our FROC model use a latent Gaussian random variable to determine false rates which are defined as follows;

$$q_5(z_1, \dots, z_C) = \int_{z_5}^{\infty} d \log \Phi(z) dz$$

$$q_4(z_1, \dots, z_C) = \int_{z_4}^{z_5} d \log \Phi(z) dz$$

$$q_3(z_1, \dots, z_C) = \int_{z_3}^{z_4} d \log \Phi(z) dz$$

$$q_2(z_1, \dots, z_C) = \int_{z_2}^{z_3} d \log \Phi(z) dz$$

$$q_1(z_1, \dots, z_C) = \int_{z_1}^{z_2} d \log \Phi(z) dz$$

For example, in the following data, the number of false alarm data with confidence level 5 **41** which is considered as an sample from the Poisson distribution of its rate

$$q_5(z_1, \dots, z_C) = \int_{z_5}^{\infty} d \log \Phi(z) dz$$

So, this Gaussian distribution determines false rate, and this function `draw_latent_noise_distribution()` plot this Gaussian distribution $d \log \Phi$ and the density $Gaussian(z|\mu, \sigma)$ is also plotted to compare hit rates and false rates. thus, the author implement it in the `draw_latent_signal_distribution()`,

Example data:

A single reader and single modality case

NI=63, NL=124 In R console ->	confidence level c	No. of false alarms f	No. of hits h
<i>definitely</i> present	5	1	41
<i>probably</i> present	4	2	22
equivocal	3	5	14
subtle	2	11	8
<i>very</i> subtle	1	13	1

* *false alarms* = False Positives = FP

* *hits* = True Positives = TP

Value

Information of Latent Gaussians, such as mean and S.D. of the signal distributions and thresholds.

See Also

[draw_latent_signal_distribution\(\)](#)

Examples

```
## Not run:
#=====
# Shape of signal distribution strongly influences the value of AUC, so in the following
# the author shows how it affects the estimates of AUCs.
# We consider two data examples, one is a low AUC and the other is a high AUC.
# In the high AUC case, the Signal Gaussain will be low variance and
# in the low AUC case, the variance will desperse. 2019 August 4, 2019 Dec 17
#=====

#          ----- High AUC case -----

viewdata(dataList.High)

fit.High <- fit_Bayesian_FROC(dataList.High,ite=111)

draw_latent_signal_distribution(fit.High)

#          ----- Low AUC case -----

viewdata(dataList.Low)

fit.Low <- fit_Bayesian_FROC(dataList.Low)

draw_latent_signal_distribution(fit.Low)

## End(Not run)# dottest
```

draw_latent_signal_distribution

Visualization of Latent Gaussians (Signal Distribution)

Description

Plot the posterior mean of model parameter θ and the parameter of the latent function, i.e. the normal distribution denoted by $Gaussian(z|\mu, \sigma)$ with posterior mean estimates of its mean μ and standard deviation σ .

Usage

```
draw_latent_signal_distribution(
  StanS4class,
  dark_theme = TRUE,
  dig = 3,
  mesh = 1000,
  new.imaging.device = TRUE,
  hit.rate = TRUE,
  false.alarm.rate = FALSE,
  both.hit.and.false.rate = FALSE,
  density = 22,
  color = TRUE,
  mathematical.symbols = TRUE,
  type = 3
)
```

Arguments

StanS4class	An S4 object of class <code>stanfitExtended</code> which is an inherited class from the S4 class <code>stanfit</code> . This R object is a fitted model object as a return value of the function <code>fit_Bayesian_FROC()</code> . It can be passed to <code>DrawCurves()</code> , <code>ppp()</code> and ... etc
dark_theme	TRUE or FALSE
dig	An positive integer, indicating the digit for numbers in the R console.
mesh	Mesh for painting the area
new.imaging.device	Logical: TRUE or FALSE. If TRUE (default), then open a new device to draw curve. Using this we can draw curves in same plain by <code>new.imaging.device=FALSE</code> .
hit.rate	whether draws it. Default is TRUE.
false.alarm.rate	whether draws it. Default is TRUE.
both.hit.and.false.rate	whether draws it. Default is TRUE.
density	A natural number, indicating the density of shading lines, in lines per inch.
color	A color region is selected from black and white only. For more colors, put FALSE. For publication, the mono color is allowed in many case, so the author made this for such publication.
mathmatical.symbols	A logical, whether legend is in plot.
type	An integer, for the color of background and etc.

Details

Our FROC model use a latent Gaussian random variable to determine hit rates. That is, each hit rate is defined as follows;

$$p_5(z_1, \dots, z_C; \mu, \sigma) = \int_{z_5}^{\infty} \text{Gaussian}(z|\mu, \sigma) dz$$

$$p_4(z_1, \dots, z_C; \mu, \sigma) = \int_{z_4}^{z_5} \text{Gaussian}(z|\mu, \sigma) dz$$

$$p_3(z_1, \dots, z_C; \mu, \sigma) = \int_{z_3}^{z_4} \text{Gaussian}(z|\mu, \sigma) dz$$

$$p_2(z_1, \dots, z_C; \mu, \sigma) = \int_{z_2}^{z_3} \text{Gaussian}(z|\mu, \sigma) dz$$

$$p_1(z_1, \dots, z_C; \mu, \sigma) = \int_{z_1}^{z_2} \text{Gaussian}(z|\mu, \sigma) dz$$

For example, in the following data, the number of hit data with the most highest confidence level 5 is regarded as an sample from the Binomial distribution of hit rate $p_5(z_1, \dots, z_C; \mu, \sigma) = \int_{z_5}^{\infty} \text{Gaussian}(z|\mu, \sigma) dz$ with Bernoulli trial number is NL=142.

So, this Gaussian distribution determines hit rate, and this function `draw_latent_signal_distribution()` plot this Gaussian distribution $\text{Gaussian}(z|\mu, \sigma)$. And a reference distribution is the standard Gaussian and do not confuse that it is not the noise distribution, but only reference.

The noise distribution (denoted by $d \log \Phi$) determines the False alarm rates in the similar manner and plotted by using a line of dots. The author thinks the standard Gaussian is more comfortable to compare or confirm the shape of $\text{Gaussian}(z|\mu, \sigma)$ and thus, the author implement it in the `draw_latent_signal_distribution()`.

One would want to see the signal distribution and noise distribution simultaneously, then use the function `draw_latent_noise_distribution()`.

Value

Information of Latent Gaussians, such as mean and S.D. of the signal distributions and thresholds.

See Also

`draw_latent_noise_distribution()` Note that the difference of `draw_latent_noise_distribution()` and `draw_latent_signal_distribution()` is that the later use the standard Gaussian for the reference distribution and former uses the $d \log \Phi()$ for the reference distribution.

So, the old version `draw_latent_signal_distribution()` is also important and I like this old version also. Anyway who read this, I think my package size is very large,....ha,,,I have to reduce it,....but how?

Examples

```
## Not run:
#=====
# Shape of signal distribution strongly influences the value of AUC, so in the following
# the author shows how it affects the estimates of AUCs.
# We consider two data examples, one is a low AUC and the other is a high AUC.
```

```

# In the high AUC case, the Signal Gaussain will be low variance and
# in the low AUC case, the variance will desperse. 2019 August 4, 2019 Dec 17
#=====

#          ----- High AUC case -----

viewdata(dataList.High)

fit.High <- fit_Bayesian_FROC(dataList.High,ite=111)

draw_latent_signal_distribution(fit.High)

#          ----- Low AUC case -----

viewdata(dataList.Low)

fit.Low <- fit_Bayesian_FROC(dataList.Low)

draw_latent_signal_distribution(fit.Low)

#-----
#          2)          For submission (without color)
#-----

fit <- fit_Bayesian_FROC(
                        dataList = dataList.Chakra.1.with.explantation
                        )

# With legends

draw_latent_signal_distribution(fit,
                              dark_theme = FALSE,
                              color = TRUE,
                              density = 11
                              )

```



```
#' Without legends
draw_latent_signal_distribution(fit,
                               dark_theme      = FALSE,
                               color           = TRUE,
                               mathematical.symbols = FALSE
)
# 2019 Sept. 5
# 2020 March 12

## End(Not run)# dottest
```

dz *Threshold: parameter of an MRMC model*

Description

A posterior mean of the model parameter for data [ddd](#) as an example of truth parameter.

Author(s)

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See Also

[make_true_parameter_MRMC](#)

[Empirical_FROC_via_ggplot](#)
Empirical FROC curve via ggplot2

Description

Empirical FROC curve via ggplot2

Usage

```
Empirical_FROC_via_ggplot(dataList)
```

Arguments

`dataList`

A list, specifying an FROC data to be fitted a model. It consists of data of numbers of TPs, FPs, lesions, images. .In addition, if in case of mutple readers or mutple modalities, then modaity ID and reader ID are included also.

The `dataList` will be passed to the function `rstan::sampling()` of **rstan**. This is a variable in the function `rstan::sampling()` in which it is named `data`.

For the single reader and a single modality data, the `dataList` is made by the following manner:

```
dataList.Example <-list(
h = c(41,22,14,8,1),# number of hits for each confidence level
f = c(1,2,5,11,13),# number of false alarms for each confidence level

NL = 124,# number of lesions (signals)
NI = 63,# number of images (trials)
C = 5) # number of confidence,.. the author thinks it can be calculated
as the length of h or f ...? ha,why I included this. ha .. should be omitted.
```

Using this object `dataList.Example`, we can apply `fit_Bayesian_FROC()` such as `fit_Bayesian_FROC(dataList.Example)`.

To make this R object `dataList` representing FROC data, this package provides three functions:

- `convertFromJafroc()` If data is a **JAFROC** **xlsx** formulation.
- `dataset_creator_new_version()` Enter TP and FP data **by table** .
- `create_dataset()` Enter TP and FP data by **interactive** manner.

Before fitting a model, we can confirm our dataset is correctly formulated by using the function `viewdata()`.

A Single reader and a single modality (SRSC) case.

In a single reader and a single modality case (`srsc`), `dataList` is a list consisting of `f,h,NL,NI,C` where `f,h` are numeric vectors and `NL,NI,C` are positive integers.

- `f` Non-negative integer vector specifying number of false alarms associated with each confidence level. The first component corresponding to the highest confidence level.
- `h` Non-negative integer vector specifying number of Hits associated with each confidence level. The first component corresponding to the highest confidence level.
- `NL` A positive integer, representing Number of Lesions.
- `NI` A positive integer, representing Number of Images.
- `C` A positive integer, representing Number of Confidence level.

The detail of these dataset, see the datasets endowed with this package. 'Note that the maximal number of confidence level, denoted by `C`, are included, however, Note that confidence level vector `c` should not be specified. If specified,

will be ignored , since it is created by `c <-c(rep(C:1))` in the program and do not refer from user input data, where C is the highest number of confidence levels. So, you should write down your hits and false alarms vector so that it is compatible with this automatically created c vector.

data Format:

A single reader and a single modality case

NI=63, NL=124 In R console ->	confidence level c	No. of false alarms f	No. of hits h
definitely present	$c[1] = 5$	$f[1] = F_5 = 1$	$h[1] = H_5 = 41$
probably present	$c[2] = 4$	$f[2] = F_4 = 2$	$h[2] = H_4 = 22$
equivocal	$c[3] = 3$	$f[3] = F_3 = 5$	$h[3] = H_3 = 14$
subtle	$c[4] = 2$	$f[4] = F_2 = 11$	$h[4] = H_2 = 8$
very subtle	$c[5] = 1$	$f[5] = F_1 = 13$	$h[5] = H_1 = 1$

* *false alarms* = False Positives = FP

* *hits* = True Positives = TP

Note that in FROC data, all confidence level means *present (diseased, lesion)* case only, no confidence level indicating absent. Since each reader marks his suspicious location only if he thinks lesions are *present*, and marked positions generates the hits or false alarms, *thus* each confidence level represents that lesion is *present*. In the absent case, reader dose not mark any locations and hence, the absent confidence level does not relate this dataset. So, if reader think it is no lesion, then in such case confidence level is not needed.

Note that the first column of confidence level vector c should not be specified. If specified, will be ignored , since it is created by `c <-c(rep(C:1))` automatically in the program and do not refer from user input data even if it is specified explicitly, where C is the highest number of confidence levels. So you should check the compatibility of your data and the confidence level vector `c <-c(rep(C:1))` via a table which can be displayed by the function `viewdata()`.

Multiple readers and multiple modalities case, i.e., MRMC case

In case of multiple readers and multiple modalities, i.e., MRMC case, in order to apply the function `fit_Bayesian_FROC()`, dataset represented by an R list object representing FROC data must contain components m, q, c, h, f, NL, C, M, Q.

- C A positive integer, representing the **highest** number of confidence level, this is a scalar.
- M A positive integer vector, representing the number of **modalities**.
- Q A positive integer, representing the number of **readers**.

- m A vector of positive integers, representing the **modality ID** vector.
- q A vector of positive integers, representing the **reader ID** vector.
- c A vector of positive integers, representing the **confidence level**. This vector must be made by `rep(rep(C:1), M*Q)`
- h A vector of non-negative integers, representing the number of **hits**.
- f A vector of non-negative integers, representing the number of **false alarms**.
- NL A positive integer, representing the Total number of **lesions** for all images, this is a scalar.

Note that the maximal number of confidence level (denoted by C) are included in the above R object. However, each confidence level vector is not included in the data, because it is created automatically from C. To confirm false positives and hits are correctly ordered with respect to the automatically generated confidence vector,

the function `viewdata()` shows the table. Revised 2019 Nov 27 Revised 2019 Dec 5

Example data.

Multiple readers and multiple modalities (i.e., MRMC)

Modality ID	Reader ID	Confidence levels	No. of false alarms	No. of hits.
m	q	c	f	h
1	1	3	20	111
1	1	2	29	55
1	1	1	21	22
1	2	3	6	100
1	2	2	15	44
1	2	1	22	11
2	1	3	6	66
2	1	2	24	55
2	1	1	23	1
2	2	3	5	66
2	2	2	30	55
2	2	1	40	44

* *false alarms* = False Positives = FP

* *hits* = True Positives = TP

Value

none

Examples

```
Empirical_FROC_via_ggplot(  
  dataList = d  
)
```

```
Close_all_graphic_devices()
```

error_message

Error Message for Data Format

Description

Plot error messages to let user know his or her data format is wrong.

Usage

```
error_message(h, NL)
```

Arguments

h	A non-negative integer vector
NL	A positive integer, indicating Number of lesions

Details

If $\text{sum}(h) > \text{NL}$, then an error message will appear. The reason why the author uses the generic function `plot` for error messages instead of such as `message()` or `cat()` is to preserve GUIs in **Shiny**. So, this error message is shown in some plot plane in the Graphical User Interface of **Shiny** in which `message()` or `cat()` cannot use.

Value

Plot of an error message by the generic function `plot()` for Shiny GUI.

See Also

[fit_GUI\(\)](#)

Examples

```

=====
#           If  number of hits > number of lesion,  then an error message appears.
=====

# Make an example such that sum(h) > NL, that is, the sum of the number of hits is
# greater than the number of lesion, then, it launches an error message.

      h <- c(50,30,20)
      NL <- 3

      error_message(h,NL)

# Then, in an imaging device, an error message appears, because sum(h) = 100 > 3 = NL.
# In Shiny, even if plot cannot be done causing some error, Graphical User Interface
# can not change (now,... I can but.), so I have to use the graphical user interface.
# Thus. in such case, I use this function rather than the message() or cat().

# Who read this? My heart will be more empty when I wrote this manual.

# This function is made in 2019 July, 6.
# Doc is revised in 2020 Feb

```

```
error_message_on_imaging_device_rhat_values
```

Error message on a plot plane (imaging device)

Description

Since, shiny board fix user interface, and it let me make this; in graphical device, the error message should be shown on its device. So, usual functions such as `message()` or `cat()` cannot use in Shiny board. Since, the UI is already made and it is graphical device!

If a fitted model converges, then the error message is none and thus only in R console, the message is printed such as "A model converged." and does not print error message on a plot plane.

Usage

```

error_message_on_imaging_device_rhat_values(
  StanS4class,
  verbose = TRUE,
  xxx = 0.5,
  digits = 3
)

```

Arguments

StanS4class	An S4 object of class <code>stanfitExtended</code> which is an inherited class from the S4 class <code>stanfit</code> . This R object is a fitted model object as a return value of the function <code>fit_Bayesian_FROC()</code> . It can be passed to <code>DrawCurves()</code> , <code>ppp()</code> and ... etc
verbose	A logical. if TRUE, then the maximal R hat is printed in the R cosole.
xxx	A real number, indicating x-coordinate of error message in the imaging device
digits	digits to round r hat

Details

This is for non-convergent fitted model object, where convergence criteiron is R hat statistics for each model parameters.

Examples

```

=====
# Non convergent fitting and error on it via a graphic device
=====
## Not run:

# Creat a fitted model object which does not converge with R hat criterion:

fit <- fit_Bayesian_FROC( ite = 111,
                        cha = 1,
                        summary = TRUE,
                        Null.Hypothesis = FALSE,
                        dataList = dd # Here, non convergent data
                        )

# Nothing is plotted:

plot(0,0,
     type ="n",
     axes =FALSE,
     ann=FALSE
     )

# Error message on the above graphic device:

error_message_on_imaging_device_rhat_values(fit)

=====
# Plot
=====

DrawCurves(fit)

```

```
# It does not work , and it is ,, Ok since when non converges I will want to see
# plot, so this function is no need.

# 2019 August 18

## End(Not run)#dontrun
```

error_MRMC

Comparison of Estimates and Truth in case of MRMC

Description

In order to describe what this function calculates explicitly, let us denote a specified true model parameter by θ_0 , from which fake datasets are replicated and denoted by:

$$D_1, D_2, \dots, D_k, \dots, D_K.$$

We obtains estimates

$$\theta(D_1), \dots, \theta(D_K)$$

for each replicated dataset. Using these estimates, we calculates **the mean of the *absolute errors*** (= **an absolute difference between estimates and a true parameter θ_0**), namely,

$$\frac{1}{K} \sum_{k=1}^K |\theta(D_k) - \theta_0|,$$

or **the variance of estimates:**

$$\frac{1}{K} \sum_{k=1}^K (\theta(D_k) - \frac{1}{K} \sum_{k=1}^K \theta(D_k))^2.$$

Revised 2019 Nov 1

Revised 2020 Jan

Revised 2020 March

Usage

```

error_MRMC(
  replication.number = 2,
  initial.seed = 123,
  mu.truth = BayesianFROC::mu_truth,
  v.truth = BayesianFROC::v_truth,
  z.truth = BayesianFROC::z_truth,
  NI = 200,
  NL = 1142,
  ModifiedPoisson = FALSE,
  summary = FALSE,
  ite = 1111
)

```

Arguments

replication.number	For fixed number of lesions, images, the dataset of hits and false alarms are replicated, and the number of replicated datasets are specified by this variable.
initial.seed	The variable <code>initial.seed</code> is used to replicate datasets. That is, if you take <code>initial.seed = 1234</code> , then the seed 1234, 1235, 1236, 1237, 1238, etc are for the first replication, the second replication, the third replication, etc. If the n -th model does not converge for some n , then such model has no mean and thus the non-convergent models are omitted to calculate the errors.
mu.truth	array of dimension (M,Q). Mean of the signal distribution of bi-normal assumption.
v.truth	array of dimension (M,Q). Standard Deviation of represents the signal distribution of bi-normal assumption.
z.truth	This is a parameter of the latent Gaussian assumption for the noise distribution.
NI	Number of Images.
NL	Number of Lesions.
ModifiedPoisson	Logical, that is TRUE or FALSE. If <code>ModifiedPoisson = TRUE</code> , then Poisson rate of false alarm is calculated <i>per lesion</i> , and model is fitted so that the FROC curve is an expected curve of points consisting of the pairs of TPF per lesion and FPF <i>per lesion</i> . Similarly, If <code>ModifiedPoisson = TRUE</code> , then Poisson rate of false alarm is calculated <i>per image</i> , and model is fitted so that the FROC curve is an expected curve of points consisting of the pair of TPF per lesion and FPF <i>per image</i> . For more details, see the author's paper in which I explained <i>per image</i> and <i>per lesion</i> . (for details of models, see vignettes , now, it is omitted from this package, because the size of vignettes are large.) If <code>ModifiedPoisson = TRUE</code> , then the <i>False Positive Fraction (FPF)</i> is defined as follows (F_c denotes the number of false alarms with confidence level c)

$$\frac{F_1 + F_2 + F_3 + F_4 + F_5}{N_L},$$

$$\frac{F_2 + F_3 + F_4 + F_5}{N_L},$$

$$\frac{F_3 + F_4 + F_5}{N_L},$$

$$\frac{F_4 + F_5}{N_L},$$

$$\frac{F_5}{N_L},$$

where N_L is a number of lesions (signal). To emphasize its denominator N_L , we also call it the *False Positive Fraction (FPF) per lesion*.

On the other hand,

if ModifiedPoisson = FALSE (Default), then *False Positive Fraction (FPF)* is given by

$$\frac{F_1 + F_2 + F_3 + F_4 + F_5}{N_I},$$

$$\frac{F_2 + F_3 + F_4 + F_5}{N_I},$$

$$\frac{F_3 + F_4 + F_5}{N_I},$$

$$\frac{F_4 + F_5}{N_I},$$

$$\frac{F_5}{N_I},$$

where N_I is the number of images (trial). To emphasize its denominator N_I , we also call it the *False Positive Fraction (FPF) per image*.

The model is fitted so that the estimated FROC curve can be regarded as the expected pairs of FPF per image and TPF per lesion (ModifiedPoisson = FALSE)

or as the expected pairs of FPF per image and TPF per lesion (ModifiedPoisson = TRUE)

If ModifiedPoisson = TRUE, then FROC curve means the expected pair of **FPF per lesion** and TPF.

On the other hand, if ModifiedPoisson = FALSE, then FROC curve means the expected pair of **FPF per image** and TPF.

So, data of FPF and TPF are changed thus, a fitted model is also changed whether ModifiedPoisson = TRUE or FALSE. In traditional FROC analysis, it uses only per images (trial). Since we can divide one image into two images or more images, number of trial is not important. And more important is per signal. So, the author also developed FROC theory to consider FROC analysis under per signal. One can see that the FROC curve is rigid with respect to change of a number of images, so, it does not matter whether ModifiedPoisson = TRUE or FALSE. This rigidity of curves means that the number of images is redundant parameter for the FROC trial and thus the author try to exclude it.

Revised 2019 Dec 8 Revised 2019 Nov 25 Revised 2019 August 28

summary	Logical: TRUE of FALSE. Whether to print the verbose summary. If TRUE then verbose summary is printed in the R console. If FALSE, the output is minimal. I regret, this variable name should be verbose.
ite	A variable to be passed to the function <code>rstan::sampling()</code> of rstan in which it is named <code>iter</code> . A positive integer representing the number of samples synthesized by Hamiltonian Monte Carlo method, and, Default = 10000.

Details

2019 Sept 6 I found this program, I made this in several month ago? I forgot when this function is made. It well works, so it helps me now.

Value

list of errors, or vaiance of estimates over all replicated datasets.

error_srsc	<i>Validation via replicated datasets from a model at a given model parameter</i>
------------	---

Description

Print for a given true parameter, a errors of estimates from replicated dataset.

Also print a standard error which is the variance of estimates.

Suppose that θ_0 is a given true model parameter with a given number of images N_I and a given number of lesions N_L , specified by user.

(I)

(I.1) Synthesize a collection of dataset D_k ($k = 1, 2, \dots, K$) from a likelihood (model) at a given parameter θ_0 , namely

$$D_k \sim \text{likelihood}(\theta_0).$$

(I.2) Replicates K models fitted to each dataset D_k ($k = 1, 2, \dots, K$), namely, draw MCMC samples $\{\theta_i(D_k); i = 1, \dots, N_I\}$.
 $\theta_i(D_k) \sim \pi(|D_k).$

(I.3) Calculate posterior means for the set of data D_k ($k = 1, 2, \dots, K$), namely $\bar{\theta}(D_k) := \frac{1}{N_I} \sum_i \theta_i(D_k).$

(I.4) Calculates error for each dataset D_k $\epsilon_k := \text{Truth} - \text{estimates} = \theta_0 - \bar{\theta}(D_k).$

(II) Calculates mean of errors over all datasets D_k ($k = 1, 2, \dots, K$) mean of errors $\bar{\epsilon}(\theta_0, N_I, N_L) = \frac{1}{K} \sum \epsilon_k.$

NOTE We note that if a fitted model does not converge, (namely \hat{R} is far from one), then it is omitted from this calculation.

(III) Calculates mean of errors for various number of lesions and images mean of errors $\bar{\epsilon}(\theta_0, N_I, N_L)$

For example, if $(N_I^1, N_L^1), (N_I^2, N_L^2), (N_I^3, N_L^3), \dots, (N_I^m, N_L^m)$, then $\bar{\epsilon}(\theta_0, N_I^1, N_L^1), \bar{\epsilon}(\theta_0, N_I^2, N_L^2), \bar{\epsilon}(\theta_0, N_I^3, N_L^3), \dots, \bar{\epsilon}(\theta_0, N_I^m, N_L^m)$ are calculated.

To obtain precise error, The number of replicated fitted models (denoted by K) should be large enough. If K is small, then it causes a bias. $K = \text{replicate.datset}$: a variable of the function `error_srsc`.

Running this function, we can see that the error $\bar{\epsilon}(\theta_0, N_I, N_L)$ decreases monotonically as a given number of images N_I or a given number of lesions N_L increases.

Also, the scale of error also will be found. Thus this function can show how our estimates are correct. Scale of error differs for each component of model parameters.

Revised 2019 August 28

Usage

```
error_srsc(
  NLvector = c(100L, 10000L, 1000000L),
  ratio = 2,
  replicate.datset = 3,
  ModifiedPoisson = FALSE,
  mean.truth = 0.6,
  sd.truth = 5.3,
  z.truth = c(-0.8, 0.7, 2.38),
  ite = 2222,
  cha = 1
)
```

Arguments

NLvector A vector of positive integers, indicating a collection of numbers of Lesions.

ratio A positive *rational* number, with which Number of Images is determined by the formula: (number of images) = ratio times (number of lesions). Note that in calculation, it rounds $\text{ratio} * \text{NLvector}$ to an integer.

replicate.datset A Number indicate that how many you replicate dataset from user's specified dataset.

ModifiedPoisson

Logical, that is TRUE or FALSE.

If ModifiedPoisson = TRUE, then Poisson rate of false alarm is calculated *per lesion*, and model is fitted so that the FROC curve is an expected curve of points consisting of the pairs of TPF per lesion and FPF *per lesion*.

Similarly,

If ModifiedPoisson = TRUE, then Poisson rate of false alarm is calculated *per image*, and model is fitted so that the FROC curve is an expected curve of points consisting of the pair of TPF per lesion and FPF *per image*.

For more details, see the author's paper in which I explained *per image* and *per lesion*. (for details of models, see [vignettes](#), now, it is omitted from this package, because the size of vignettes are large.)

If ModifiedPoisson = TRUE, then the *False Positive Fraction (FPF)* is defined as follows (F_c denotes the number of false alarms with confidence level c)

$$\frac{F_1 + F_2 + F_3 + F_4 + F_5}{N_L},$$

$$\frac{F_2 + F_3 + F_4 + F_5}{N_L},$$

$$\frac{F_3 + F_4 + F_5}{N_L},$$

$$\frac{F_4 + F_5}{N_L},$$

$$\frac{F_5}{N_L},$$

where N_L is a number of lesions (signal). To emphasize its denominator N_L , we also call it the *False Positive Fraction (FPF) per lesion*.

On the other hand,

if ModifiedPoisson = FALSE (Default), then *False Positive Fraction (FPF)* is given by

$$\frac{F_1 + F_2 + F_3 + F_4 + F_5}{N_I},$$

$$\frac{F_2 + F_3 + F_4 + F_5}{N_I},$$

$$\frac{F_3 + F_4 + F_5}{N_I},$$

$$\frac{F_4 + F_5}{N_I},$$

$$\frac{F_5}{N_I},$$

where N_I is the number of images (trial). To emphasize its denominator N_I , we also call it the *False Positive Fraction (FPF) per image*.

The model is fitted so that the estimated FROC curve can be regarded as the expected pairs of FPF per image and TPF per lesion (ModifiedPoisson = FALSE)

or as the expected pairs of FPF per image and TPF per lesion (ModifiedPoisson = TRUE)

If ModifiedPoisson = TRUE, then FROC curve means the expected pair of **FPF per lesion** and TPF.

On the other hand, if ModifiedPoisson = FALSE, then FROC curve means the expected pair of **FPF per image** and TPF.

So, data of FPF and TPF are changed thus, a fitted model is also changed whether ModifiedPoisson = TRUE or FALSE. In traditional FROC analysis, it uses only per images (trial). Since we can divide one image into two images or more images, number of trial is not important. And more important is per signal. So, the author also developed FROC theory to consider FROC analysis under per signal. One can see that the FROC curve is rigid with respect to change of a number of images, so, it does not matter whether ModifiedPoisson = TRUE or FALSE. This rigidity of curves means that the number of images is redundant parameter for the FROC trial and thus the author try to exclude it.

Revised 2019 Dec 8 Revised 2019 Nov 25 Revised 2019 August 28

mean.truth	This is a parameter of the latent Gaussian assumption for the noise distribution.
sd.truth	This is a parameter of the latent Gaussian assumption for the noise distribution.
z.truth	This is a parameter of the latent Gaussian assumption for the noise distribution.
ite	A variable to be passed to the function <code>rstan::sampling()</code> of rstan in which it is named <code>iter</code> . A positive integer representing the number of samples synthesized by Hamiltonian Monte Carlo method, and, Default = 10000.
cha	A variable to be passed to the function <code>rstan::sampling()</code> of rstan in which it is named <code>chains</code> . A positive integer representing the number of chains generated by Hamiltonian Monte Carlo method, and, Default = 1.

Details

In Bayesian inference, if sample size is large, then posterior tends to the Dirac measure. So, the error and variance of estimates should be tends to zero as sample size tends to infinity.

This function check this phenomenon.

If model has problem, then it contains some non-decreasing bias with respect to sample size.

Revised 2019 Nov 1

Provides a reliability of our posterior mean estimates. Using this function, we can find what digit makes sense.

In the real world, the data for modality comparison or observer performance evaluation is 100 images or 200 images. In such scale data, any estimate of AUC will contain error at most 0.0113.... So, the value of AUC should round in 0.XXX and not 0.XXXX or 0.XXXXX or more. Since error is 0.00113... and hence 4 digit or more digit is meaningless. In such manner, we can analyze the errors.

We note that if we increase the number of images or lesions, the errors decrease.

For example, if we use 20000 images in FROC trial, then the error of AUC will be 0.0005... and thus, and so on. Thus large number of images gives us more reliable AUC. However the radiologist cannot read such large (20000) images.

Thus, the error will be 0.00113...

If the number of images are given before hand and moreover if we obtain the estimates, then we can run this function using these two, we can find the estimated errors by simulation. Of course, the estimates is not the truth, but roughly speaking, if we assume that the estimates is not so far from truth, and the error analysis is rigid with respect to changing the truth, then we can say using estimates as truth, the result of this error analysis can be regarded as an actual error.

I want to go home. Unfortunately, my house is ...

Value

Replicated datasets, estimates, errors,...etc I made this program 1 years ago? and now I forget ... the precise return values. When I see today, 2019 August. It retains too many return values to explain all of them.

Examples

```
## Not run:
#=====
#          0)          0-th example
#=====

datasets <-error_srsc(
  NLvector = c(100,10000,1000000),
  ite = 2222
)

# By the following, we can extract only datasets whose
# model has converged.
datasets$convergent.dataList.as.dataframe

#=====
#          1)          1-st example
#=====
```

```
# Long width is required in R console.
```

```
datasets <-error_srsc(NLvector = c(
  50L,
  111L,
  11111L
),
# NIVector,
ratio=2,
replicate.datset =3,
ModifiedPoisson = FALSE,
mean.truth=0.6,
sd.truth=5.3,
z.truth =c(-0.8,0.7,2.38),
ite =2222
)
```

```
#####
#          2)          Plot the error of AUC with respect to NI
#####
```

```
a <-error_srsc(NLvector = c(
  33L,
  50L,
  111L,
  11111L
),
# NIVector,
ratio=2,
replicate.datset =3,
ModifiedPoisson = FALSE,
mean.truth=0.6,
sd.truth=5.3,
z.truth =c(-0.8,0.7,2.38),
ite =2222
)
```

```
aa <- a$Bias.for.various.NL
```

```
error.of.AUC <- aa[8,]
y <- subset(aa[8,], select = 2:length(aa[8,]))
y <- as.numeric(y)
```



```

y <- abs(y)
upper_y <- max(y)
lower_y <- min(y)

x <- 1:length(y)

plot(x,y, ylim=c(lower_y, upper_y))

# From this plot, we cannot see whether the error has decreased or not.
# Thus, we replot with the log y-axis, the we will see that the error
# has decreased with respect to number of images and lesions.

ggplot(data.frame(x=x,y=y), aes(x = x, y = y)) +
  geom_line() +
  geom_point() +
  scale_y_log10()

# Revised 2019 Sept 25

# General print of log scale
df<-data.frame(x=c(10,100,1000,10,100,1000),
               y=c(1100,220000,33000000,1300,240000,36000000),
               group=c("1","1","1","2","2","2"))

ggplot2::ggplot(df, aes(x = x, y = y, shape = group)) +
  ggplot2::geom_line(position = position_dodge(0.2)) + # Dodge lines by 0.2
  ggplot2::geom_point(position = position_dodge(0.2), size = 4)+ # Dodge points by 0.2
  ggplot2::scale_y_log10()+
  ggplot2::scale_x_log10()

#=====
# 2) Add other param into plot plain of the error of AUC with respect to NI
#=====

a <-error_srsc(NLvector = c(
  111L,
  11111L
),

```

```

# NIVector,
ratio=2,
replicate.datset =3,
ModifiedPoisson = FALSE,
mean.truth=0.6,
sd.truth=5.3,
z.truth =c(-0.8,0.7,2.38),
ite =2222
)
  aa <- a$Bias.for.various.NL

  error.of.AUC <- aa[8,]
  y1 <- subset(aa[8,], select = 2:length(aa[8,]))
  y1 <- as.numeric(y1)
  y1 <- abs(y1)

  LLL <-length(y1)

  y2 <- subset(aa[7,], select = 2:length(aa[7,]))
  y2 <- as.numeric(y2)
  y2 <- abs(y2)

  y <- c(y1,y2)

  upper_y <- max(y)
  lower_y <- min(y)

  group <- rep(seq(1,2,1),1 , each=LLL)
  x <- rep(seq(1,LLL,1),2 , each=1)
  group <- as.character(group)
  df <- data.frame(x=x,y=y,group=group)

  ggplot2::ggplot(df, aes(x = x, y = y, shape = group)) +
ggplot2::geom_line(position = position_dodge(0.2)) + # Dodge lines by 0.2
ggplot2::geom_point(position = position_dodge(0.2), size = 4)+ # Dodge points by 0.2
  ggplot2::scale_y_log10()
  # ggplot2::scale_x_log10()

#=====
#           Confidence level = 4
#=====

```

```
datasets <-error_srsc(NLvector = c(
  111L,
  11111L
),
# NIVector,
ratio=2,
replicate.datset =3,
ModifiedPoisson = FALSE,
mean.truth=-0.22,
sd.truth=5.72,
z.truth =c(-0.46,-0.20,0.30,1.16),
ite =2222
)

error_srsc_variance_visualization(datasets)

# The parameter of model is 7 in which the ggplot2 fails with the following warning:

# The shape palette can deal with a maximum of 6 discrete values because more than 6
# becomes difficult to
# discriminate; you have 7. Consider specifying shapes manually if you must have them.

## End(Not run)# dontrun
```

```
error_srsc_error_visualization
      Visualization for Error of Estimator
```

Description

The function plot the graph of errors with respect to sample sizes.

Error plot

x-axis Sample sizes

y-axis Error for each parameter

Usage

```
error_srsc_error_visualization(  
  return.value.of_error_srsc,  
  log_scale_x.axis = TRUE  
)
```

Arguments

```
return.value.of_error_srsc  
  A return value of the function error\_srsc\(\).  
log_scale_x.axis  
  A logical, whether x axis is log scale or not.
```

Value

A long format dataframe of error and its parameter name

See Also

[error_srsc_variance_visualization](#)

Examples

```
# General plot  
  
df <- data.frame(x=runif(100),y=runif(100),g= as.factor(rep(1:5,10)))  
  
ggplot(df, aes(x = x, y = y, shape = g)) +  
  geom_point(size = 3) +  
  scale_shape_manual(values = c(1,2,3,4,5,6,7,8,9))  
  
  
df <- data.frame(x=runif(100),y=runif(100),g= as.factor(rep(1:25,4)))  
  
# Use slightly larger points and use custom values for the shape scale  
  
ggplot(df, aes(x = x, y = y, shape = g)) +  
  geom_point(size = 3) +  
  scale_shape_manual(values = c(1,2,3,4,5,6,7,8,9,10,  
                                11,12,13,14,15,16,17,18,19,20,21,22,23,24,25))  
  
## Not run:
```

```
a <- error_srsc()

error_srsc_error_visualization(a)

#=====
#           In case of C = 4, arbitrary C is available.
#=====

a <-error_srsc(NLvector = c(
100,
10000,
1000000
),
ratio=2,
replicate.datset =2,
ModifiedPoisson = FALSE,
mean.truth=0.6,
sd.truth=5.3,
z.truth =c(-0.8,0.7,2.38,3), # Here we use the C=4
ite =500
)

error_srsc_error_visualization(a)
error_srsc_variance_visualization(a)

#=====
#           In case of C = 7, arbitrary C is available.
#=====

#
a <-error_srsc(NLvector = c(
  100,
  10000,
  100000
),
ratio=2,
```

```
replicate.datset =2,  
ModifiedPoisson = FALSE,  
mean.truth=0.6,  
sd.truth=5.3,  
z.truth =c(-0.8,0.7,2.38,3,3.4,3.6,3.8), # Here we use the C=7  
ite =500  
)  
  
error_srsc_error_visualization(a)  
error_srsc_variance_visualization(a)
```

```
## End(Not run)
```

error_srsc_variance_visualization

Visualization Of variance Analysis

Description

Visualization Of variance Analysis

Usage

```
error_srsc_variance_visualization(  
  return.value.of_error_srsc,  
  log_scale_x.axis = TRUE  
)
```

Arguments

return.value.of_error_srsc
A return value of the function `error_srsc()`.

log_scale_x.axis
A logical, whether x axis is log scale.

Value

A long format dataframe of error and its parameter name

Examples

```
## Not run:  
a <- error_srsc()  
  
error_srsc_variance_visualization(a)  
  
a <- error_srsc(replicate.datset = 10)  
error_srsc_variance_visualization(a)  
  
## End(Not run)
```

```
explanation_about_package_BayesianFROC  
      Explanation of this package
```

Description

In R console, explanation are shown.

Usage

```
explanation_about_package_BayesianFROC()
```

Examples

```
explanation_about_package_BayesianFROC()
```

```
explanation_for_what_curves_are_drawn  
      Print out about what curves are drawn
```

Description

For package developer.

Usage

```
explanation_for_what_curves_are_drawn(modalityID, readerID)
```

Arguments

```
modalityID    A vector.
readerID      A vector..
```

Value

Nothing

Examples

```
## Not run:

#=====The first example=====

modalityID <-c(1,2)
readerID <-c(1,2,3)

explanation_for_what_curves_are_drawn( modalityID, readerID )

#=====The second example=====

modalityID <- 1
readerID <-c(1,2,3)

explanation_for_what_curves_are_drawn( modalityID, readerID )

## End(Not run)# dottest
```

extractAUC

Extract AUC

Description

Extract AUC for both srsc and MRMC data.

Usage

```
extractAUC(
  StanS4class,
  dig = 3,
  summary = TRUE,
  new.imaging.device = TRUE,
  print_CI_of_AUC = TRUE
)
```

Arguments

StanS4class	An S4 object of class <code>stanfitExtended</code> which is an inherited class from the S4 class <code>stanfit</code> . This R object is a fitted model object as a return value of the function <code>fit_Bayesian_FROC()</code> . It can be passed to <code>DrawCurves()</code> , <code>ppp()</code> and ... etc
dig	digits of estimates.
summary	Logical: TRUE of FALSE. Whether to print the verbose summary. If TRUE then verbose summary is printed in the R console. If FALSE, the output is minimal. I regret, this variable name should be verbose.
new.imaging.device	Logical: TRUE of FALSE. If TRUE (default), then open a new device to draw curve. Using this we can draw curves in same plain by <code>new.imaging.device=FALSE</code> .
print_CI_of_AUC	Logical, if TRUE then Credible intervals of AUCs for each modality are plotted.

Value

The estimates of AUC with respect to modalities. It also retains the name vector, `nname=c(A[1],A[2],...,A[M])`

```
extract_data_frame_from_dataList_MRMC
```

Extract sub data frame from list of FROC data

Description

Makes a dataframe from a list consisting of vectors `m, q, c, h, f` and positive integers `NL, C, M, Q, NI`. The resulting data-frame is constructed by vectors `m, q, c, h, f`.

Usage

```
extract_data_frame_from_dataList_MRMC(dataList)
```

Arguments

dataList	A list of MRMC data.
----------	----------------------

Value

A data frame consisting of vectors m, q, c, h, f .

- m A vector of positive integers, representing the **modality** ID vector.
- q A vector of positive integers, representing the **reader** ID vector.
- c A vector of positive integers, representing the **confidence level**. This vector must be made by `rep(rep(C:1), M*Q)`
- h A vector of non-negative integers, representing the number of **hits**.
- f A vector of non-negative integers, representing the number of **false alarms**.

Examples

```
## Not run:

#=====
#                               From example dataset named dddddd
#=====

## Only run examples in interactive R sessions
if (interactive()) {

  fit_GUI_Shiny_MRMC(DF=extract_data_frame_from_dataList_MRMC(ddd))

}## Only run examples in interactive R sessions

## End(Not run)
```

`extract_EAP_by_array` *Extract Estimates Preserving Array Format.*

Description

Extract posterior mean estimates (**EAP**) by array format.

Usage

```
extract_EAP_by_array(StanS4class, name.of.parameter)
```

Arguments

`StanS4class` An S4 object of class `stanfitExtended` which is an inherited class from the S4 class `stanfit`. This R object is a fitted model object as a return value of the function `fit_Bayesian_FROC()`.
It can be passed to `DrawCurves()`, `ppp()` and ... etc

`name.of.parameter` An parameter name (given as a character string, should not surround by ""). The name of parameter which user want to extract. Parameters are contained in the parameter block of each Stan file in the path: `inst/extdata`.

Details

If an estimate is an array, then this function extract estimated parameters preserving an array format. The `rstan` also has such function, i.e., `rstan::get_posterior_mean()`. However this function does not extract paramter as an array but coerce to the class matrix.

Value

A list of datalists from the posterior predictive distribution

Examples

```
## Not run:
#=====The first example: MRMC case =====
#=====
#           MRMC case: Extract a estimates from fitted model objects
#=====

# Make a fitted model object of class stanfitExtended
# which is inherited from the S4class stanfit.
# The following example, fitted model is the hierarchical Bayesian FROC model
# which is used to compare modality.

fit <- fit_Bayesian_FROC( ite = 1111 ,
                        summary = FALSE ,
                        dataList = dataList.Chakra.Web.orderd,
                        cha=1
                        )

# Extract one dimensional array "z = z[]",

z <- extract_EAP_by_array(
                                fit, # The above fitted model object
                                z     # One of the parameter in "fit"
                                )

# Extract two dimensional array "AA = AA[ , ]",
```



```

#           name.of.parameter surrounded by double quote is also available
#=====

#       Let fit be the above fitted model object.
#       Then the following two codes are same.

                                extract_EAP_by_array( fit, "A" )

                                extract_EAP_by_array( fit, A )

# Unfortunately, the later case sometimes cause the R CMD check error which said
# that no visible binding, since object A is not defined.
# For example, if we use the later in the functiton: metadata_to_DrawCurve_MRMC
# Then R command said some NOTE that

# > checking R code for possible problems ... NOTE
# metadata_to_DrawCurve_MRMC: no visible binding for global variable 'A'
# Undefined global functions or variables: A

# Revised 2019 Oct 19

# I am not sure, does this package development make me happy?
# Back pain being due to an abnormality in my immune system, which is caused
# my exposure to surfactants or latex (not LaTeX).

## End(Not run)# Revised 2019 Jun 19

```

```
extract_EAP_CI
```

```
MRMC: Extract Estimates of a vector from stanfitExtended object
```

Description

We extract the EAPs and CIs from the stanfitExtended S4 class which is an inherited class of the stanfit S4 class.

Usage

```
extract_EAP_CI(
  StanS4class,
  parameter.name,
```

```

dimension.of.parameter,
dig = 5,
summary = TRUE
)

```

Arguments

StanS4class	An S4 object of the class stanfit. No need that it is the S4 class stanfitExtended .
parameter.name	character vector. E.g., use as "aaa" . for names of parameter described in the parameter block of stan file.
dimension.of.parameter	If parameter aaa is vector, i.e.,aaa[1],aaa[2],...aaa[6] then dimension.of.parameter = 6
dig	A variable to be passed to the function <code>rstan::sampling()</code> of rstan in which it is named <code>...??</code> . A positive integer representing the Significant digits, used in stan Cancellation. Default = 5,
summary	Logical: TRUE of FALSE. Whether to print the verbose summary. If TRUE then verbose summary is printed in the R console. If FALSE, the output is minimal. I regret, this variable name should be verbose.

Details

To validate our model has no bias, that is comparison of true parameters of distributions and EAPs, we have to extract the estimates from the stanfitExtended object. And this function do it.

Value

EAPs, CI.

See Also

[extract_estimates_MPMC](#)

Examples

```

## Not run:
# First we create the following fitted model object of class stanfitExtend.

fit <- fit_Bayesian_FROC(
  BayesianFROC::dataList.Chakra.Web.orderd, # data
  ite = 1111,                               # MCMC iteration
  summary = FALSE                           # vevrose
)

# Second, to extract the EAPs of the parameter z,
# we also have to specify the dimension of vector z as follows.

```

```

extract_EAP_CI(
  fit, # The above fitted model object
  "z", # The parameter name described in parameter block of stan file
  5    # The dimension of vector z
)

# One more example: to extract the EAPs of the parameter dz,
# we also have to specify its dimension of vector dz as follows.

list.of.dz <-extract_EAP_CI(fit,"dz",4)

# One more example: to extract the EAPs of the parameter w,
# we also have to specify its dimension of vector w as follows.

list.w <-extract_EAP_CI(fit,"w",1)

# Note that this function can extract only parameter of "vector" and not "array" !!
# To extract such array please use "extract_estimates_MRMC()"
# which extract all parameters from a hierarchical Bayesian model
# estimated from user data. So, this function is no longer meaningless,
# and I will delete this.

# I forgot where I use this function
# 2019.05.21 Revised.

#####
#           the following gives convergence seed 2019 Oct 12
#####
#'

f <- fit_Bayesian_FROC( ite = 1111, cha = 1, summary = TRUE, dataList = ddd ,see = 123456)
z <- extract_EAP_CI(f,"z",f@dataList$C )$z.EAP
#usethis::use_data(z)
#usethis package cannot be to use since it is not declared in NAMESPACE.

dz <- extract_EAP_CI(f,"dz",f@dataList$C-1 )$dz.EAP
#usethis::use_data(dz)
#usethis package cannot be to use since it is not declared in NAMESPACE.

## End(Not run)# dottest

```

```
extract_estimates_MRMC
```

MRMC: Extract All Posterior Mean Estimates from stanfitExtended object

Description

Extract Posterior Mean estimates, preserving its format, such as array, vector. From MRMC models, it extract the EAPs and CIs.

Usage

```
extract_estimates_MRMC(StanS4class, dig = 3)
```

Arguments

StanS4class	An S4 object of class <code>stanfitExtended</code> which is an inherited class from the S4 class <code>stanfit</code> . This R object is a fitted model object as a return value of the function <code>fit_Bayesian_FROC()</code> . It can be passed to <code>DrawCurves()</code> , <code>ppp()</code> and ... etc
dig	A variable to be passed to the function <code>rstan::sampling()</code> of rstan in which it is named <code>...??</code> . A positive integer representing the Significant digits, used in stan Cancellation. Default = 5,

Details

To validate our model has no bias, that is comparison of true parameters of distributions and EAPs, we have to extract the estimates from the `stanfitExtended` object. And this function do it.

Value

EAPs, CIs which preserving its format, such as array, vector.

See Also

`extract_EAP_CI()` is used in the function `extract_estimates_MRMC()`.

Examples

```
## Not run:

fit <- fit_Bayesian_FROC(
  BayesianFROC::dataList.Chakra.Web.orderd,
  summary = FALSE,
  ite=111)

EAPs <- extract_estimates_MRMC(fit)
```



```
## End(Not run)# dottest
```

```
extract_parameters_from_replicated_models
      Extract Estimates From Replicated MRMC Model
```

Description

Extract Estimates From Replicated MRMC Model

Usage

```
extract_parameters_from_replicated_models(
  initial.seed = 123,
  mu.truth = BayesianFROC::mu_truth,
  v.truth = BayesianFROC::v_truth,
  z.truth = BayesianFROC::z_truth,
  NI = 200,
  NL = 142,
  ModifiedPoisson = FALSE,
  replication.number = 2,
  summary = FALSE,
  ite = 1111
)
```

Arguments

<code>initial.seed</code>	The variable <code>initial.seed</code> is used to replicate datasets. That is, if you take <code>initial.seed = 1234</code> , then the seed 1234, 1235, 1236, 1237, 1238, etc are for the first replication, the second replication, the third replication, etc. If the <code>n</code> -th model does not converge for some <code>n</code> , then such model has no mean and thus the non-convergent models are omitted to calculate the errors.
<code>mu.truth</code>	array of dimension (M,Q). Mean of the signal distribution of bi-normal assumption.
<code>v.truth</code>	array of dimension (M,Q). Standard Deviation of represents the signal distribution of bi-normal assumption.
<code>z.truth</code>	This is a parameter of the latent Gaussian assumption for the noise distribution.
<code>NI</code>	Number of Images.
<code>NL</code>	Number of Lesions.
<code>ModifiedPoisson</code>	Logical, that is TRUE or FALSE.

If ModifiedPoisson = TRUE, then Poisson rate of false alarm is calculated **per lesion**, and model is fitted so that the FROC curve is an expected curve of points consisting of the pairs of TPF per lesion and FPF **per lesion**.

Similarly,

If ModifiedPoisson = TRUE, then Poisson rate of false alarm is calculated **per image**, and model is fitted so that the FROC curve is an expected curve of points consisting of the pair of TPF per lesion and FPF **per image**.

For more details, see the author's paper in which I explained *per image* and *per lesion*. (for details of models, see [vignettes](#), now, it is omitted from this package, because the size of vignettes are large.)

If ModifiedPoisson = TRUE, then the *False Positive Fraction (FPF)* is defined as follows (F_c denotes the number of false alarms with confidence level c)

$$\frac{F_1 + F_2 + F_3 + F_4 + F_5}{N_L},$$

$$\frac{F_2 + F_3 + F_4 + F_5}{N_L},$$

$$\frac{F_3 + F_4 + F_5}{N_L},$$

$$\frac{F_4 + F_5}{N_L},$$

$$\frac{F_5}{N_L},$$

where N_L is a number of lesions (signal). To emphasize its denominator N_L , we also call it the *False Positive Fraction (FPF) per lesion*.

On the other hand,

if ModifiedPoisson = FALSE (Default), then *False Positive Fraction (FPF)* is given by

$$\frac{F_1 + F_2 + F_3 + F_4 + F_5}{N_I},$$

$$\frac{F_2 + F_3 + F_4 + F_5}{N_I},$$

$$\frac{F_3 + F_4 + F_5}{N_I},$$

$$\frac{F_4 + F_5}{N_I},$$

$$\frac{F_5}{N_I}$$

where N_I is the number of images (trial). To emphasize its denominator N_I , we also call it the *False Positive Fraction (FPF) per image*.

The model is fitted so that the estimated FROC curve can be ragraded as the expected pairs of FPF per image and TPF per lesion (ModifiedPoisson = FALSE)

or as the expected pairs of FPF per image and TPF per lesion (ModifiedPoisson = TRUE)

If ModifiedPoisson = TRUE, then FROC curve means the expected pair of **FPF per lesion** and TPF.

On the other hand, if ModifiedPoisson = FALSE, then FROC curve means the expected pair of **FPF per image** and TPF.

So,data of FPF and TPF are changed thus, a fitted model is also changed whether ModifiedPoisson = TRUE or FALSE. In traditional FROC analysis, it uses only per images (trial). Since we can divide one image into two images or more images, number of trial is not important. And more important is per signal. So, the author also developed FROC theory to consider FROC analysis under per signal. One can see that the FROC curve is rigid with respect to change of a number of images, so, it does not matter whether ModifiedPoisson = TRUE or FALSE. This rigidity of curves means that the number of images is redundant parameter for the FROC trial and thus the author try to exclude it.

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replication.number	For fixed number of lesions, images, the dataset of hits and false alarms are replicated, and the number of replicated datasets are specified by this variable.
summary	Logical: TRUE of FALSE. Whether to print the verbose summary. If TRUE then verbose summary is printed in the R console. If FALSE, the output is minimal. I regret, this variable name should be verbose.
ite	A variable to be passed to the function <code>rstan::sampling()</code> of rstan in which it is named <code>iter</code> . A positive integer representing the number of samples synthesized by Hamiltonian Monte Carlo method, and, Default = 10000.

Value

A list of estimates, posterior means and posterior credible interbals for each model parameter. EAPs and CI interbals.

Examples

```
## Not run:
```

```
list.of.estimates <- extract_parameters_from_replicated_models()
```

```
## End(Not run)
```

```
false_and_its_rate_creator
```

False Alarm Creator for both cases of MRMC and srsc

Description

From threshold, mean and S.D., data of False Alarm are created.

Usage

```
false_and_its_rate_creator(
  z.truth = BayesianFROC::z_truth,
  NI = 333,
  NL = 111,
  ModifiedPoisson = FALSE,
  seed = 12345
)
```

Arguments

`z.truth` Vector of dimension = C represents the thresholds of bi-normal assumption.

`NI` The number of images.

`NL` The number of lesions.

`ModifiedPoisson`

Logical, that is TRUE or FALSE.

If `ModifiedPoisson = TRUE`, then Poisson rate of false alarm is calculated *per lesion*, and model is fitted so that the FROC curve is an expected curve of points consisting of the pairs of TPF per lesion and FPF *per lesion*.

Similarly,

If `ModifiedPoisson = TRUE`, then Poisson rate of false alarm is calculated *per image*, and model is fitted so that the FROC curve is an expected curve of points consisting of the pair of TPF per lesion and FPF *per image*.

For more details, see the author's paper in which I explained *per image* and *per lesion*. (for details of models, see [vignettes](#), now, it is omitted from this package, because the size of vignettes are large.)

If `ModifiedPoisson = TRUE`, then the *False Positive Fraction (FPF)* is defined as follows (F_c denotes the number of false alarms with confidence level c)

$$\frac{F_1 + F_2 + F_3 + F_4 + F_5}{N_L},$$

$$\frac{F_2 + F_3 + F_4 + F_5}{N_L},$$

$$\frac{F_3 + F_4 + F_5}{N_L},$$

$$\frac{F_4 + F_5}{N_L},$$

$$\frac{F_5}{N_L},$$

where N_L is a number of lesions (signal). To emphasize its denominator N_L , we also call it the *False Positive Fraction (FPF) per lesion*.

On the other hand,

if ModifiedPoisson = FALSE (Default), then *False Positive Fraction (FPF)* is given by

$$\frac{F_1 + F_2 + F_3 + F_4 + F_5}{N_I},$$

$$\frac{F_2 + F_3 + F_4 + F_5}{N_I},$$

$$\frac{F_3 + F_4 + F_5}{N_I},$$

$$\frac{F_4 + F_5}{N_I},$$

$$\frac{F_5}{N_I},$$

where N_I is the number of images (trial). To emphasize its denominator N_I , we also call it the *False Positive Fraction (FPF) per image*.

The model is fitted so that the estimated FROC curve can be ragraded as the expected pairs of FPF per image and TPF per lesion (ModifiedPoisson = FALSE)

or as the expected pairs of FPF per image and TPF per lesion (ModifiedPoisson = TRUE)

If ModifiedPoisson = TRUE, then FROC curve means the expected pair of **FPF per lesion** and TPF.

On the other hand, if ModifiedPoisson = FALSE, then FROC curve means the expected pair of **FPF per image** and TPF.

So, data of FPF and TPF are changed thus, a fitted model is also changed whether ModifiedPoisson = TRUE or FALSE. In traditional FROC analysis, it uses only per images (trial). Since we can divide one image into two images or more images, number of trial is not important. And more important is per signal. So, the author also developed FROC theory to consider FROC analysis under per signal. One can see that the FROC curve is rigid with respect to change of a number of images, so, it does not matter whether ModifiedPoisson = TRUE or FALSE. This rigidity of curves means that the number of images is redundant parameter for the FROC trial and thus the author try to exclude it.

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seed The seed for creating a collection of the number of false alarms synthesized by the Poisson distributions using the specified seed.

Details

From threshold, mean and S.D. of the latent Gaussian noise distribution in the bi-normal assumption, data of False Alarm are created. For the process of this drawing false alarm samples, its rate are also created. So, in the return values of the function, the rates for each confidence level is also attached.

Value

A list of vectors, indicating a true parameter and a sample.

A vector indicating a true parameter: False rate from thresholds.

A vector indicating a sample, more precisely, The truth parameter of false alarm rate calculated by true thresholds z and also, one-time drawn samples of false alarms from the calculated false rates.

Examples

```
## Not run:
false.rate <- false_and_its_rate_creator()
```

```
#####
# In SBC, Poisson rate = 0,..so,.. i have to investigate.
#####
```

```
set.seed( 1234 )
```

```
dz <-runif(3,    # sample size
          0.01, # lower bound
          1    # upper bound
```

```
)

w <- rnorm(1,
           0,
           1
          )

z <- z_from_dz(w,dz )

false_and_its_rate_creator(z )

=====
#           Poisson rate is OK
=====

set.seed( 1234 )

dz <-runif(3, # sample size
          0.01, # lower bound
          1 # upper bound
         )

w <- rnorm(1,
           0,
           10 # It cause the poisson rate become small
          )

z <- z_from_dz(w,dz )

false_and_its_rate_creator(z )

=====
# In SBC, Poisson rate is small
=====

set.seed( 1234 )

dz <-runif(3, # sample size
          0.01, # lower bound
          1 # upper bound
         )

w <- rnorm(1,
           0,
```

```

        10 # It cause the poisson rate become small
    )

z <- z_from_dz(w,dz )

false_and_its_rate_creator(z )

#=====
#          Poisson rate = 0
#=====

set.seed( 1234 )

dz <-runif(3, # sample size
          0.01, # lower bound
          10 # It cause the poisson rate become exactly 0 # upper bound
        )

w <- rnorm(1,
          0,
          1
        )

z <- z_from_dz(w,dz )

false_and_its_rate_creator(z )
#'
## End(Not run)

```

```
false_and_its_rate_creator_MRMC
```

MRMC: False Alarm Creator For each Modality and each Reader.

Description

From threshold, mean and S.D., data of False Alarm are created.

Usage

```

false_and_its_rate_creator_MRMC(
  z.truth = BayesianFROC::z_truth,
  NI = 333,
  NL = 111,
  ModifiedPoisson = FALSE,
  seed = 12345,
  M = 5,

```



```

    Q = 4,
    summary = TRUE
)

```

Arguments

z.truth Vector of dimension = C represents the thresholds of bi-normal assumption.

NI The number of images.

NL The number of lesions.

ModifiedPoisson Logical, that is TRUE or FALSE.

If ModifiedPoisson = TRUE, then Poisson rate of false alarm is calculated **per lesion**, and model is fitted so that the FROC curve is an expected curve of points consisting of the pairs of TPF per lesion and FPF **per lesion**.

Similarly,

If ModifiedPoisson = FALSE, then Poisson rate of false alarm is calculated **per image**, and model is fitted so that the FROC curve is an expected curve of points consisting of the pair of TPF per lesion and FPF **per image**.

For more details, see the author's paper in which I explained *per image* and *per lesion*. (for details of models, see **vignettes**, now, it is omitted from this package, because the size of vignettes are large.)

If ModifiedPoisson = TRUE, then the *False Positive Fraction (FPF)* is defined as follows (F_c denotes the number of false alarms with confidence level c)

$$\frac{F_1 + F_2 + F_3 + F_4 + F_5}{N_L},$$

$$\frac{F_2 + F_3 + F_4 + F_5}{N_L},$$

$$\frac{F_3 + F_4 + F_5}{N_L},$$

$$\frac{F_4 + F_5}{N_L},$$

$$\frac{F_5}{N_L},$$

where N_L is a number of lesions (signal). To emphasize its denominator N_L , we also call it the *False Positive Fraction (FPF) per lesion*.

On the other hand,

if ModifiedPoisson = FALSE (Default), then *False Positive Fraction (FPF)* is given by

$$\frac{F_1 + F_2 + F_3 + F_4 + F_5}{N_I},$$

$$\frac{F_2 + F_3 + F_4 + F_5}{N_I},$$

$$\frac{F_3 + F_4 + F_5}{N_I},$$

$$\frac{F_4 + F_5}{N_I},$$

$$\frac{F_5}{N_I},$$

where N_I is the number of images (trial). To emphasize its denominator N_I , we also call it the *False Positive Fraction (FPF) per image*.

The model is fitted so that the estimated FROC curve can be regarded as the expected pairs of FPF per image and TPF per lesion (ModifiedPoisson = FALSE)

or as the expected pairs of FPF per image and TPF per lesion (ModifiedPoisson = TRUE)

If ModifiedPoisson = TRUE, then FROC curve means the expected pair of **FPF per lesion** and TPF.

On the other hand, if ModifiedPoisson = FALSE, then FROC curve means the expected pair of **FPF per image** and TPF.

So, data of FPF and TPF are changed thus, a fitted model is also changed whether ModifiedPoisson = TRUE or FALSE. In traditional FROC analysis, it uses only per images (trial). Since we can divide one image into two images or more images, number of trial is not important. And more important is per signal. So, the author also developed FROC theory to consider FROC analysis under per signal. One can see that the FROC curve is rigid with respect to change of a number of images, so, it does not matter whether ModifiedPoisson = TRUE or FALSE. This rigidity of curves means that the number of images is redundant parameter for the FROC trial and thus the author try to exclude it.

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seed	The seed for creating a collection of the number of false alarms synthesized by the Poisson distributions using the specified seed.
M	Number of modalities
Q	Number of readers
summary	Logical: TRUE or FALSE. Whether to print the verbose summary. If TRUE then verbose summary is printed in the R console. If FALSE, the output is minimal. I regret, this variable name should be verbose.

Details

In our model, false alarm rate does not depend on the readers or modalities. Thus this sampling function merely synthesizes samples from the Poisson distribution of the same false alarm rate. Of course, this same false rate of the Poisson distributions is not desired one. Since we should assume that each reader with different modality should differ. To accomplish this, we have to assume that threshold parameter of Gaussian assumption should depend on the reader and modality. However, such model does not converge in the Hamiltonian Monte Carlo simulation.

Value

Vector for false alarms as an element of list of MRMC data.

Examples

```
## Not run:

false_and_its_rate_creator_MRMC()

## End(Not run)
```

fffaabbb

Package Development tools and memo.

Description

This is for the author of this package. project option build and reload ^ ^ ^ ^

Usage

```
fffaabbb()
```

fit_a_model_to

Fit a model to data

Description

Fit a model to data.

Usage

```
fit_a_model_to(
  dataList,
  number_of_chains_for_MCMC = 1,
  number_of_iterations_for_MCMC = 1111,
  seed_for_MCMC = 1234,
  ...
)
```

Arguments

dataList A list, specifying an FROC data to be fitted a model. It consists of data of numbers of TPs, FPs, lesions, images. .In addition, if in case of mutiple readers or mutiple modalities, then modaity ID and reader ID are included also. The **dataList** will be passed to the function `rstan::sampling()` of **rstan**. This is a variable in the function `rstan::sampling()` in which it is named **data**. For the single reader and a single modality data, the **dataList** is made by the following manner:

```
dataList.Example <-list(
h = c(41,22,14,8,1),# number of hits for each confidence level
f = c(1,2,5,11,13),# number of false alarms for each confidence level

NL = 124,# number of lesions (signals)
NI = 63,# number of images (trials)
C = 5) # number of confidence,.. the author thinks it can be calculated
as the length of h or f ...? ha,why I included this. ha .. should be omitted.
```

Using this object **dataList.Example**, we can apply `fit_Bayesian_FROC()` such as `fit_Bayesian_FROC(dataList.Example)`.

To make this R object **dataList** representing FROC data, this package provides three functions:

- `convertFromJafroc()` If data is a **JAFROC** **xlsx** formulation.
- `dataset_creator_new_version()` Enter TP and FP data **by table** .
- `create_dataset()` Enter TP and FP data by **interactive** manner.

Before fitting a model, we can confirm our dataset is correctly formulated by using the function `viewdata()`.

A Single reader and a single modality (SRSC) case.

In a single reader and a single modality case (**srsc**), **dataList** is a list consisting of **f, h, NL, NI, C** where **f, h** are numeric vectors and **NL, NI, C** are positive integers.

- f** Non-negative integer vector specifying number of false alarms associated with each confidence level. The first component corresponding to the highest confidence level.

h Non-negative integer vector specifying number of Hits associated with each confidence level. The first component corresponding to the highest confidence level.

NL A positive integer, representing Number of Lesions.

NI A positive integer, representing Number of Images.

C A positive integer, representing Number of Confidence level.

The detail of these dataset, see the datasets endowed with this package. 'Note that the maximal number of confidence level, denoted by C, are included, however, Note that confidence level vector `c` should not be specified. If specified, will be ignored, since it is created by `c <-c(rep(C:1))` in the program and do not refer from user input data, where C is the highest number of confidence levels. So, you should write down your hits and false alarms vector so that it is compatible with this automatically created `c` vector.

data Format:

A single reader and a single modality case

NI=63, NL=124 In R console ->	confidence level c	No. of false alarms f	No. of hits h
definitely present	<code>c[1] = 5</code>	<code>f[1] = F₅ = 1</code>	<code>h[1] = H₅ = 41</code>
probably present	<code>c[2] = 4</code>	<code>f[2] = F₄ = 2</code>	<code>h[2] = H₄ = 22</code>
equivocal	<code>c[3] = 3</code>	<code>f[3] = F₃ = 5</code>	<code>h[3] = H₃ = 14</code>
subtle	<code>c[4] = 2</code>	<code>f[4] = F₂ = 11</code>	<code>h[4] = H₂ = 8</code>
very subtle	<code>c[5] = 1</code>	<code>f[5] = F₁ = 13</code>	<code>h[5] = H₁ = 1</code>

* *false alarms* = False Positives = FP

* *hits* = True Positives = TP

Note that in FROC data, all confidence level means *present (diseased, lesion)* case only, no confidence level indicating absent. Since each reader marks his suspicious location only if he thinks lesions are *present*, and marked positions generates the hits or false alarms, *thus* each confidence level represents that lesion is *present*. In the absent case, reader dose not mark any locations and hence, the absent confidence level does not relate this dataset. So, if reader think it is no lesion, then in such case confidence level is not needed.

Note that the first column of confidence level vector `c` should not be specified. If specified, will be ignored, since it is created by `c <-c(rep(C:1))` automatically in the program and do not refer from user input data even if it is specified explicitly, where C is the highest number of confidence levels. So you should check the compatibility of your data and the confidence level vector `c <-c(rep(C:1))` via a table which can be displayed by the function `viewdata()`.

Multiple readers and multiple modalities case, i.e., MRMC case

In case of multiple readers and multiple modalities, i.e., MRMC case, in order to apply the function `fit_Bayesian_FROC()`, dataset represented by an R list object representing FROC data must contain components `m`, `q`, `c`, `h`, `f`, `NL`, `C`, `M`, `Q`.

- `C` A positive integer, representing the **highest** number of confidence level, this is a scalar.
- `M` A positive integer vector, representing the number of **modalities**.
- `Q` A positive integer, representing the number of **readers**.
- `m` A vector of positive integers, representing the **modality ID** vector.
- `q` A vector of positive integers, representing the **reader ID** vector.
- `c` A vector of positive integers, representing the **confidence level**. This vector must be made by `rep(rep(C:1), M*Q)`
- `h` A vector of non-negative integers, representing the number of **hits**.
- `f` A vector of non-negative integers, representing the number of **false alarms**.
- `NL` A positive integer, representing the Total number of **lesions** for all images, this is a scalar.

Note that the maximal number of confidence level (denoted by `C`) are included in the above R object. However, each confidence level vector is not included in the data, because it is created automatically from `C`. To confirm false positives and hits are correctly ordered with respect to the automatically generated confidence vector,

the function `viewdata()` shows the table. Revised 2019 Nov 27 Revised 2019 Dec 5

Example data.

Multiple readers and multiple modalities (i.e., MRMC)

Modality ID	Reader ID	Confidence levels	No. of false alarms	No. of hits.
<code>m</code>	<code>q</code>	<code>c</code>	<code>f</code>	<code>h</code>
1	1	3	20	111
1	1	2	29	55
1	1	1	21	22
1	2	3	6	100
1	2	2	15	44
1	2	1	22	11
2	1	3	6	66
2	1	2	24	55
2	1	1	23	1
2	2	3	5	66
2	2	2	30	55
2	2	1	40	44

* *false alarms* = False Positives = FP
 * *hits* = True Positives = TP

number_of_chains_for_MCMC A positive integer, indicating the number of chains for MCMC. To be passed to the function `rstan::sampling()` of **rstan**.

number_of_iterations_for_MCMC A positive integer, indicating the number of iterations for MCMC. To be passed to the function `rstan::sampling()` of **rstan**.

seed_for_MCMC A positive integer, indicating the seed for MCMC. To be passed to the function `rstan::sampling()` of **rstan**.

... Additional arguments

Details

The author made a function

FROC data to be fitted a model

The following table is a dataset to be fitted a model.

	confidence level	No. of false alarms (FP:False Positive)	No. of hits (TP:True Positive)
<i>definitely</i> present	5	F_5	H_5
<i>probably</i> present	4	F_4	H_4
equivocal	3	F_3	H_3
subtle	2	F_2	H_2
<i>very</i> subtle	1	F_1	H_1

Modeling 1. Traditional way

Define

$$p_c(\theta) := \int_{\theta_c}^{\theta_{c+1}} \text{Gaussian}(z|\mu, \sigma) dz,$$

$$q_c(\theta) := \int_{\theta_c}^{\theta_{c+1}} \frac{d}{dz} \log \Phi(z) dz.$$

Note that $\theta_0 := -\infty$.

We extend the vector from $(H_c)_{c=1,2,\dots,C}$ to $(H_c)_{c=0,1,2,\dots,C}$, where $H_0 := N_L - (H_1 + H_2 + \dots + H_C)$.

Then, we assume

$$(H_c)_{c=0,1,2,\dots,C} \sim \text{Multinomial}((p_c)_{c=0,1,2,\dots,C})$$

and

$$F_c \sim \text{Poisson}(q_c(\theta)N_I).$$

Recall that N_I denotes the number of images (radiographs, such as X-ray films) and N_L the number of lesions (signals, nodules).

`fit_Bayesian_FROC()` which has very redundant variables. So, `fit_a_model_to()` is made by simplifying `fit_Bayesian_FROC()` so that its variables is minimum. To access full details, see the help of `fit_Bayesian_FROC()`.

This function aims to give a simple interface by ignoring unnecessarily parameters of `fit_Bayesian_FROC()`.

Value

An fitted model object of the S4 class named `stanfitExtended` which is an inherited class from `stanfit`.

See Also

`fit_Bayesian_FROC()`

Examples

```
## Not run:

#####
# 1)          Build a data-set
#####

# For a single reader and a single modality case.

data <- list(c=c(3,2,1), # Confidence level. Note that c is ignored.
            h=c(97,32,31), # Number of hits for each confidence level
            f=c(1,14,74), # Number of false alarms for each confidence level

            NL=259, # Number of lesions
            NI=57, # Number of images
            C=3) # Number of confidence level

viewdata(data)

# where,
# c denotes confidence level, i.e., rating of reader.
# 3 = Definitely diseased,
# 2 = subtle,.. diseased
# 1 = very subtle
```



```

#      h denotes number of hits (True Positives: TP) for each confidence level,
#      f denotes number of false alarms (False Positives: FP) for each confidence level,
#      NL denotes number of lesions,
#      NI denotes number of images,

# For example, in the above example data,
# the number of hits with confidence level 3 is 97,
# the number of hits with confidence level 2 is 32,
# the number of hits with confidence level 1 is 31,

# the number of false alarms with confidence level 3 is 1,
# the number of false alarms with confidence level 2 is 14,
# the number of false alarms with confidence level 1 is 74,

#=====
# 2)      Fit an FROC model to the above dataset.
#=====

      fit <- BayesianFROC::fit_a_model_to(
# Dataset to be fiited
      dataList = data,

# To run in time <5s, MCMC iterations too small to obtain reliable estimates
number_of_iterations_for_MCMC = 1111,

# The number of chains, it is better if larger.
number_of_chains_for_MCMC     = 1
      )

#=====
#      fit a FROC model using multinomial distribution
#=====

# The Chakraborty's model is fitted to data named "d"

```

```

fit <- fit_Bayesian_FROC(
  multinomial = TRUE, # <--- here, the model of multinomial is declared
  ite = 1111,
  cha = 1,
  summary = TRUE,
  dataList = d # Example data to be fitted a model
)

```

```
## End(Not run)#dontrun
```

fit_Bayesian_FROC	<i>Fit a model to data</i>
-------------------	----------------------------

Description

Creates a fitted model object of class `stanfitExtended`: an inherited class from the S4 class `stanfit` in **rstan**.

Usage

```

fit_Bayesian_FROC(
  dataList,
  ModifiedPoisson = FALSE,
  prior = -1,
  zz = 1,
  verbose = TRUE,
  print_CI_of_AUC = TRUE,
  multinomial = FALSE,
  model_reparametrized = FALSE,
  Model_MRMC_non_hierarchical = TRUE,
  prototype = FALSE,
  PreciseLogLikelihood = TRUE,
  DrawCurve = length(dataList$m) == 0,
  Drawcol = TRUE,
  summary = TRUE,
  make.csv.file.to.draw.curve = FALSE,
  mesh.for.drawing.curve = 10000,
  significantLevel = 0.7,
  new.imaging.device = TRUE,
  cha = 1,

```

```

ite = 10000,
DrawFROCcurve = TRUE,
DrawAFROCcurve = FALSE,
DrawCFPCTP = TRUE,
dig = 5,
war = floor(ite/5),
see = 1234567,
Null.Hypothesis = FALSE,
...
)

```

Arguments

dataList A list, specifying an FROC data to be fitted a model. It consists of data of numbers of TPs, FPs, lesions, images. In addition, if in case of multiple readers or multiple modalities, then modality ID and reader ID are included also.

The **dataList** will be passed to the function `rstan::sampling()` of **rstan**. This is a variable in the function `rstan::sampling()` in which it is named **data**.

For the single reader and a single modality data, the **dataList** is made by the following manner:

```

dataList.Example <-list(
h = c(41,22,14,8,1),# number of hits for each confidence level
f = c(1,2,5,11,13),# number of false alarms for each confidence level

NL = 124,# number of lesions (signals)
NI = 63,# number of images (trials)
C = 5) # number of confidence, .. the author thinks it can be calculated
as the length of h or f ...? ha,why I included this. ha .. should be omitted.

```

Using this object **dataList.Example**, we can apply `fit_Bayesian_FROC()` such as `fit_Bayesian_FROC(dataList.Example)`.

To make this R object **dataList** representing FROC data, this package provides three functions:

- `convertFromJafroc()` If data is a **JAFROC xlsx** formulation.
- `dataset_creator_new_version()` Enter TP and FP data **by table**.
- `create_dataset()` Enter TP and FP data by **interactive** manner.

Before fitting a model, we can confirm our dataset is correctly formulated by using the function `viewdata()`.

A Single reader and a single modality (SRSC) case.

In a single reader and a single modality case (srsc), **dataList** is a list consisting of **f, h, NL, NI, C** where **f, h** are numeric vectors and **NL, NI, C** are positive integers.

- f Non-negative integer vector specifying number of false alarms associated with each confidence level. The first component corresponding to the highest confidence level.
- h Non-negative integer vector specifying number of Hits associated with each confidence level. The first component corresponding to the highest confidence level.
- NL A positive integer, representing Number of Lesions.
- NI A positive integer, representing Number of Images.
- C A positive integer, representing Number of Confidence level.

The detail of these dataset, see the datasets endowed with this package. Note that the maximal number of confidence level, denoted by C, are included, however, Note that confidence level vector `c` should not be specified. If specified, will be ignored, since it is created by `c <- c(rep(C:1))` in the program and do not refer from user input data, where C is the highest number of confidence levels. So, you should write down your hits and false alarms vector so that it is compatible with this automatically created `c` vector.

data Format:

A single reader and a single modality case

NI=63, NL=124 In R console ->	confidence level c	No. of false alarms f	No. of hits h
definitely present	$c[1] = 5$	$f[1] = F_5 = 1$	$h[1] = H_5 = 41$
probably present	$c[2] = 4$	$f[2] = F_4 = 2$	$h[2] = H_4 = 22$
equivocal	$c[3] = 3$	$f[3] = F_3 = 5$	$h[3] = H_3 = 14$
subtle	$c[4] = 2$	$f[4] = F_2 = 11$	$h[4] = H_2 = 8$
very subtle	$c[5] = 1$	$f[5] = F_1 = 13$	$h[5] = H_1 = 1$

* *false alarms* = False Positives = FP

* *hits* = True Positives = TP

Note that in FROC data, all confidence level means *present (diseased, lesion)* case only, no confidence level indicating absent. Since each reader marks his suspicious location only if he thinks lesions are *present*, and marked positions generates the hits or false alarms, *thus* each confidence level represents that lesion is *present*. In the absent case, reader dose not mark any locations and hence, the absent confidence level does not relate this dataset. So, if reader think it is no lesion, then in such case confidence level is not needed.

Note that the first column of confidence level vector `c` should not be specified. If specified, will be ignored, since it is created by `c <- c(rep(C:1))` automatically in the program and do not refer from user input data even if it is specified explicitly, where C is the highest number of confidence levels. So you

should check the compatibility of your data and the confidence level vector `c` `<-c(rep(C:1))` via a table which can be displayed by the function `viewdata()`.

Multiple readers and multiple modalities case, i.e., MRMC case

In case of multiple readers and multiple modalities, i.e., MRMC case, in order to apply the function `fit_Bayesian_FROC()`, dataset represented by an **R** list object representing FROC data must contain components `m`, `q`, `c`, `h`, `f`, `NL`, `C`, `M`, `Q`.

- `C` A positive integer, representing the **highest** number of confidence level, this is a scalar.
- `M` A positive integer vector, representing the number of **modalities**.
- `Q` A positive integer, representing the number of **readers**.
- `m` A vector of positive integers, representing the **modality ID** vector.
- `q` A vector of positive integers, representing the **reader ID** vector.
- `c` A vector of positive integers, representing the **confidence level**. This vector must be made by `rep(rep(C:1), M*Q)`
- `h` A vector of non-negative integers, representing the number of **hits**.
- `f` A vector of non-negative integers, representing the number of **false alarms**.
- `NL` A positive integer, representing the Total number of **lesions** for all images, this is a scalar.

Note that the maximal number of confidence level (denoted by `C`) are included in the above **R** object. However, each confidence level vector is not included in the data, because it is created automatically from `C`. To confirm false positives and hits are correctly ordered with respect to the automatically generated confidence vector,

the function `viewdata()` shows the table. Revised 2019 Nov 27 Revised 2019 Dec 5

Example data.

Multiple readers and multiple modalities (i.e., MRMC)

Modality ID	Reader ID	Confidence levels	No. of false alarms	No. of hits.
<code>m</code>	<code>q</code>	<code>c</code>	<code>f</code>	<code>h</code>
1	1	3	20	111
1	1	2	29	55
1	1	1	21	22
1	2	3	6	100
1	2	2	15	44
1	2	1	22	11
2	1	3	6	66
2	1	2	24	55
2	1	1	23	1
2	2	3	5	66
2	2	2	30	55

2

2

1

40

44

* *false alarms* = False Positives = FP

* *hits* = True Positives = TP

ModifiedPoisson

Logical, that is TRUE or FALSE.

If ModifiedPoisson = TRUE, then Poisson rate of false alarm is calculated *per lesion*, and model is fitted so that the FROC curve is an expected curve of points consisting of the pairs of TPF per lesion and FPF *per lesion*.

Similarly,

If ModifiedPoisson = TRUE, then Poisson rate of false alarm is calculated *per image*, and model is fitted so that the FROC curve is an expected curve of points consisting of the pair of TPF per lesion and FPF *per image*.

For more details, see the author's paper in which I explained *per image* and *per lesion*. (for details of models, see [vignettes](#), now, it is omitted from this package, because the size of vignettes are large.)

If ModifiedPoisson = TRUE, then the *False Positive Fraction (FPF)* is defined as follows (F_c denotes the number of false alarms with confidence level c)

$$\frac{F_1 + F_2 + F_3 + F_4 + F_5}{N_L},$$

$$\frac{F_2 + F_3 + F_4 + F_5}{N_L},$$

$$\frac{F_3 + F_4 + F_5}{N_L},$$

$$\frac{F_4 + F_5}{N_L},$$

$$\frac{F_5}{N_L},$$

where N_L is a number of lesions (signal). To emphasize its denominator N_L , we also call it the *False Positive Fraction (FPF) per lesion*.

On the other hand,

if ModifiedPoisson = FALSE (Default), then *False Positive Fraction (FPF)* is given by

$$\frac{F_1 + F_2 + F_3 + F_4 + F_5}{N_I},$$

$$\frac{F_2 + F_3 + F_4 + F_5}{N_I},$$

$$\frac{F_3 + F_4 + F_5}{N_I},$$

$$\frac{F_4 + F_5}{N_I},$$

$$\frac{F_5}{N_I},$$

where N_I is the number of images (trial). To emphasize its denominator N_I , we also call it the *False Positive Fraction (FPF) per image*.

The model is fitted so that the estimated FROC curve can be regarded as the expected pairs of FPF per image and TPF per lesion (ModifiedPoisson = FALSE)

or as the expected pairs of FPF per image and TPF per lesion (ModifiedPoisson = TRUE)

If ModifiedPoisson = TRUE, then FROC curve means the expected pair of FPF **per lesion** and TPF.

On the other hand, if ModifiedPoisson = FALSE, then FROC curve means the expected pair of **FPF per image** and TPF.

So, data of FPF and TPF are changed thus, a fitted model is also changed whether ModifiedPoisson = TRUE or FALSE. In traditional FROC analysis, it uses only per images (trial). Since we can divide one image into two images or more images, number of trial is not important. And more important is per signal. So, the author also developed FROC theory to consider FROC analysis under per signal. One can see that the FROC curve is rigid with respect to change of a number of images, so, it does not matter whether ModifiedPoisson = TRUE or FALSE. This rigidity of curves means that the number of images is redundant parameter for the FROC trial and thus the author try to exclude it.

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prior	positive integer, to select the prior
zz	A real number specifying one of the parameter of prior
verbose	A logical, if TRUE, then the redundant summary is printed in R console. If FALSE, it suppresses output from this function.
print_CI_of_AUC	Logical, if TRUE then Credible intervals of AUCs for each modality are plotted.
multinomial	A logical, if TRUE then model is the most classical one using multinomial distribution.
model_reparametrized	A logical, if TRUE, then a model under construction is used.

Model_MRMC_non_hierarchical

A logical. If TRUE, then the model of multiple readers and multiple modalities consists of no hyper parameters. The reason why the author made this parameter is that the hyper parameter make the MCMC posterior samples be unstable. And also, my hierararchical model is not so good in theoretical perspective. Thus, I made this. The Default is TRUE.

prototype

A logical, if TRUE then the model is no longer a generative model. Namely, in generally speaking, a dataset drawn from the model cannot satisfy the condition that the sum of the numbers of hits over all confidence levels is bounded from the above by the number of lesions, namely,

$$\sum_c H_c \leq N_L$$

However, this model (TRUE) is good in the sense that it admits various initial values of MCMC sampling.

if FALSE, then the model is precisely statistical model in the sense that any dataset drawn from the model satisfies that the sum of the number of hits is not greater than the number of lesions, namely,

$$\sum_c H_c \leq N_L.$$

This model is theoretically perfect. However, in the practically, the calculation will generates some undesired results which caused by the so-called floo I forget English :'-D. The flood point??? I forgeeeeeeeeeeeet!! Ha. So, prior synthesizes very small hit rates such as 0.0000000000000001234 and it cause the non accurate calculation such as 0.00000,,,00000123/0.000.....000012345= 0.0012 which becomes hit rate and thus OH No!. Then it synthesizes Bernoulli success rate which is not less than 1 !! To avoid this, the author should develop the theory of prior to avoid this very small numbers, however the author has idea but now it does not success.

If prototype = TRUE, then the model for hits is the following:

$$H_5 \sim \text{Binomial}(p_5, N_L)$$

$$H_4 \sim \text{Binomial}(p_4, N_L)$$

$$H_3 \sim \text{Binomial}(p_3, N_L)$$

$$H_2 \sim \text{Binomial}(p_2, N_L)$$

$$H_1 \sim \text{Binomial}(p_1, N_L)$$

On the other hand, if prototype = FALSE, then the model for hits is the following:

$$H_5 \sim \text{Binomial}(p_5, N_L)$$

$$H_4 \sim \text{Binomial}\left(\frac{p_4}{1 - p_5}, N_L - H_5\right)$$

$$H_3 \sim \text{Binomial}\left(\frac{p_3}{1 - p_5 - p_4}, N_L - H_5 - H_4\right)$$

$$H_2 \sim \text{Binomial}\left(\frac{p_2}{1 - p_5 - p_4 - p_3}, N_L - H_5 - H_4 - H_3\right)$$

$$H_1 \sim \text{Binomial}\left(\frac{p_1}{1 - p_5 - p_4 - p_3 - p_2}, N_L - H_5 - H_4 - H_3 - H_2\right)$$

Each number of lesions is adjusted so that the sum of hits $\sum_c H_c$ is less than the number of lesions (signals, targets) N_L . And hence the model in case of `prototype = FALSE` is a generative model in the sense that it can replicate datasets of FROC arises. Note that the adjustment of the number of lesions in the above manner leads us the adjustment of hit rates. The reason why we use the hit rates such as $\frac{p_2}{1 - p_5 - p_4 - p_3}$ instead of p_c is that it ensures the equality $E[H_c/N_L] = p_c$. This equality is very important. To establish Bayesian FROC theory so that it is compatible to the classical FROC theory, we need the following two equations,

$$E[H_c/N_L] = p_c,$$

$$E[F_c/N_X] = q_c,$$

where E denotes the expectation and N_X is the number of lesion or the number of images and q_c is a false alarm rate, namely, $F_c \sim \text{Poisson}(q_c N_X)$.

Using the above two equations, we can establish the alternative Bayesian FROC theory preserving classical notions and formulas. For the details, please see the author's pre print:

Bayesian Models for ,, for?? I forget my paper title :-D. What the hell!? I forget,... My health is so bad to forget , I forget.

The author did not notice that the prototype is not a generative model. And hence the author revised the model so that the model is exactly generative model.

But the reason why the author remains the prototype model(`prototype = TRUE`) is that the convergence of MCMC sampling in case of MRMC is not good in the current model (`prototype = FALSE`). Because it uses fractions $\frac{p_1}{1 - p_5 - p_4 - p_3 - p_2}$ and which is very dangerous to numerical perspective. For example, if p_1 is very small, then the numerator and denominator of $\frac{p_1}{1 - p_5 - p_4 - p_3 - p_2}$ is very small. Both of them is like 0.000000000000000123.... and such small number causes the non accurate results. So, sometimes, it occurs that $\frac{p_1}{1 - p_5 - p_4 - p_3 - p_2} > 1$ which never occur in the theoretical perspective but unfortunately, in numerically occurs.

SO, now, the author try to avoid such phenomenon by using priors but it now does not success.

Here of course we interpret the terms such as $N_L - H_5 - H_4 - H_3$ as the remained targets after reader get hits. The author thinks it is another manner to do so like $N_L - H_1 - H_2 - H_3$, but it does not be employed. Since the author thinks that the reader will assign his suspicious lesion location from high confidence level and in this view point the author thinks it should be considered that targets are found from the highest confidence suspicious location.

PreciseLogLikelihood

Logical, that is TRUE or FALSE. If `PreciseLogLikelihood = TRUE`(default), then Stan calculates the precise log likelihood with target formulation. If `PreciseLogLikelihood = FALSE`, then Stan calculates the log likelihood by dropping the constant terms

in the likelihood function. In past, I distinct the stan file, one is target formulation and the another is not. But non-target formulation cause some Jacobian warning, thus I made all stanfile with target formulation when I uploaded to CRAN. Thus this variable is now meaningless.

DrawCurve	Logical: TRUE of FALSE. Whether the curve is to be drawn. TRUE or FALSE. If you want to draw the FROC and AFROC curves, then you set DrawCurve =TRUE, if not then DrawCurve =FALSE. The reason why the author make this variable DrawCurve is that it takes long time in MRMC case to draw curves, and thus Default value is FALSE in the case of MRMC data.
Drawcol	Logical: TRUE of FALSE. Whether the (A)FROC curve is to be drawn by using color of dark theme. The Default value is a TRUE.
summary	Logical: TRUE of FALSE. Whether to print the verbose summary. If TRUE then verbose summary is printed in the R console. If FALSE, the output is minimal. I regret, this variable name should be verbose.
make.csv.file.to.draw.curve	Logical: TRUE of FALSE. Whether to create a csv file. If TRUE then csv file is created in your desktop to draw an FROC curve and cumulative hits and false alarms by scatter plot. Default is FALSE since it took times to create csv files.
mesh.for.drawing.curve	A positive large integer, indicating number of dots drawing the curves, Default =10000.
significantLevel	This is a number between 0 and 1. The results are shown if posterior probabilities are greater than this quantity.
new.imaging.device	Logical: TRUE of FALSE. If TRUE (default), then open a new device to draw curve. Using this we can draw curves in same plain by new.imaging.device=FALSE.
cha	A variable to be passed to the function <code>rstan::sampling()</code> of rstan in which it is named chains. A positive integer representing the number of chains generated by Hamiltonian Monte Carlo method, and, Default = 1.
ite	A variable to be passed to the function <code>rstan::sampling()</code> of rstan in which it is named iter. A positive integer representing the number of samples synthesized by Hamiltonian Monte Carlo method, and, Default = 10000.
DrawFROCcurve	Logical: TRUE of FALSE. Whether the FROC curve is to be drawn.
DrawAFROCcurve	Logical: TRUE of FALSE. Whether the AFROC curve is to be drawn.
DrawCFPCTP	Logical: TRUE of FALSE. Whether the CFP and CTP points are to be drawn. CFP: Cumulative false positive per lesion (or image) which is also called False Positive Fraction (FPF). CTP Cumulative True Positive per lesion which is also called True Positive Fraction (TPF)..
dig	A variable to be passed to the function <code>rstan::sampling()</code> of rstan in which it is named . . .??. A positive integer representing the Significant digits, used in stan Cancellation. Default = 5,
war	A variable to be passed to the function <code>rstan::sampling()</code> of rstan in which it is named warmup. A positive integer representing the Burn in period, which must be less than ite. Defaults to war = floor(ite/5)=10000/5=2000,

see	A variable to be passed to the function <code>rstan::sampling()</code> of rstan in which it is named <code>seed</code> . A positive integer representing seed used in stan, Default = 1234567.
Null.Hypothesis	Logical, that is TRUE or FALSE. If <code>Null.or.Alternative.Hypothesis = FALSE</code> (default), then fit the <i>alternative model</i> to <code>dataList</code> (for details of models, see vignettes). If <code>Null.or.Alternative.Hypothesis = TRUE</code> , then fit the <i>null model</i> to <code>dataList</code> (for details of models, see vignettes). Note that the null model is constructed under the null hypothesis that all modality are same observer performance ability. The alternative model is made under the assumption that all modality are not same. The reason why author creates this parameter is to test the null hypothesis by the Bayes factor. But the result of test is not desired one for me. Thus the test is under construction.
...	Additional arguments

Details

Draw MCMC samples using R package: **rstan**

It also plots FROC curves if a single reader and a single modality case. For details, see [vignettes](#)

Build the S4 object by Stan to fit the author's Bayesian models introduced in the author's paper (for details of models, see [vignettes](#)). The output of the `rstan::sampling()` is an object of the S4 class called `stanfit`. But, in this package, we extended the `stanfit` class to an S4 class named `stanfitExtended`. The new S4 class `stanfitExtended` included new slots for sequential analysis. So, the return value of the function is not the S4 class `stanfit` but the new S4 class `stanfitExtended`. Thus, to apply the functions in the **rstan** package for fitted model objects, we have to change the class of the S4 fitted model objects using the function `methods::as()` such as by the code `methods::as(object = fitted.model.object, "stanfit")`.

The following items are main substances of this function.

This function `fit_Bayesian_FROC` is available both a single reader and a single modality case and multiple readers and multiple modality case. Confidence level vector is not required but it is implicitly referred as the decreasing order, For example, if $C=3$, then it would be a form $c=c(3, 2, 1, 3, 2, 1, \dots)$. Even if you write your data according to the order $c=c(1, 2, 3, 1, 2, 3, \dots)$, the program does not consider as your order, but $c=c(3, 2, 1, 3, 2, 1, \dots)$ instead.

Value

An object of class `stanfitExtended` which is an inherited S4 class from the S4 class `stanfit` By `rstan::sampling`, the function fit the author's FROC Bayesian models to user data.

Use this fitted model object for sequential analysis, such as drawing the FROC curve and alternative FROC (AFROC) curves.

Notations and symbols for the **Outputs of a single reader and a single modality case**

In the following, the notations for estimated parameters are shown.

w A real number representing *the lowest threshold* of the Gaussian assumption (bi-normal assumption). so $w=z[1]$.

dz[1] A real number representing *the difference of the first and second threshold* of the Gaussian assumption: $dz[1] := z[2] - z[1]$.

dz[2] A real number representing the difference of the second and third threshold of the Gaussian assumption: $dz[2] := z[3] - z[2]$.

dz[3] A real number representing the difference of the third and fourth threshold of the Gaussian assumption: $dz[3] := z[4] - z[3]$.

...

m A real number representing the *The mean* of the Latent Gaussian distribution for diseased images. In TeX, it denoted by μ

v A positive real number representing the *standard deviation* of the Latent Gaussian distribution for diseased images. In TeX, it will be denoted by σ , not the square of σ .

p[1] A real number representing the Hit rate with confidence level 1.

p[2] A real number representing the Hit rate with confidence level 2.

p[3] A real number representing the Hit rate with confidence level 3.

...

l[1] A positive real number representing the (Cumulative) False positive rate with confidence level 1. In TeX, it will be denoted by λ_1 .

l[2] A positive real number representing the (Cumulative) False positive rate with confidence level 2. In TeX, it will be denoted by λ_2 .

l[3] A positive real number representing the (Cumulative) False positive rate with confidence level 3. In TeX, it will be denoted by λ_3 .

l[4] A positive real number representing the (Cumulative) False positive rate with confidence level 4. In TeX, it will be denoted by λ_4 .

...

d1[1] A positive real number representing the difference $l[1] - l[2]$.

d1[2] A positive real number representing the difference $l[2] - l[3]$.

d1[3] A positive real number representing the difference $l[3] - l[4]$.

...

z[1] A real number representing the lowest threshold of the (Gaussian) bi-normal assumption.

z[2] A real number representing the 2nd threshold of the (Gaussian) bi normal assumption.

z[3] A real number representing the 3rd threshold of the (Gaussian) bi normal assumption.

z[4] A real number representing the fourth threshold of the (Gaussian) bi-normal assumption.

a A real number defined by m/v , please contact the author's paper for detail.

b A real number representing defined by $1/v$, please contact the author's paper for detail.

A A positive real number between 0 and 1, representing AUC, i.e., the area under the alternative ROC curve.

lp__ The logarithmic likelihood of our model for your data.

— **Notations and symbols:** Outputs of Multiple Reader and Multiple Modality case —

w The lowest threshold of the Gaussian assumption (bi-normal assumption). so $w=z[1]$.

dz[1] The difference of the first and second threshold of the Gaussian assumption.

dz[2] The difference of the second and third threshold of the Gaussian assumption.

dz[3] The difference of the third and fourth threshold of the Gaussian assumption.

...

mu The mean of the Latent Gaussian distribution for diseased images.

v The variance of the Latent Gaussian distribution for diseased images.

ppp[1, 1, 1] Hit rate with confidence level 1, modality 1, reader 1.

ppp[2, 1, 1] Hit rate with confidence level 2, modality 1, reader 1.

ppp[3, 1, 1] Hit rate with confidence level 3, modality 1, reader 1.

...

l[1] (Cumulative) False positive rate with confidence level 1.

l[2] (Cumulative) False positive rate with confidence level 2.

l[3] (Cumulative) False positive rate with confidence level 3.

l[4] (Cumulative) False positive rate with confidence level 4.

...

d1[1] This is defined by the difference $l[1] - l[2]$.

d1[2] This is defined by the difference $l[2] - l[3]$.

d1[3] This is defined by the difference $l[3] - l[4]$.

...

z[1] The lowest threshold of the (Gaussian) bi-normal assumption.

z[2] The 2nd threshold of the (Gaussian) bi normal assumption.

z[3] The 3rd threshold of the (Gaussian) bi normal assumption.

z[4] The fourth threshold of the (Gaussian) bi-normal assumption.

aa This is defined by m/v , please see the author's paper for more detail.

bb This is defined by $1/v$, please see the author's paper for more detail.

AA The area under alternative FROC curve associated to reader and modality.

A The area under alternative FROC curve associated to modality.

hyper_v Standard deviation of AA around A.

lp__ The logarithmic likelihood of our model for your data.

References

Bayesian Models for Free-response Receiver Operating Characteristic Analysis; Pre-print See [vi-gnettes](#)

See Also

———— **Before fitting:** *create a dataset*

[convertFromJafroc](#) Convert from JAFROC format xlsx file to the author's format

[dataset_creator_new_version](#) Create an R object which represent user data.

[create_dataset](#) Create an R object which represent user data.

———— **Further sequential analysis: Plot curves** Using the result of fitting a Bayesian FROC model, we can go sequential analysis.

[DrawCurves](#) for drawing free response ROC curves.

———— **Further sequential analysis: Validation of the Model**

[ppp](#) Calculation of a p-value in the Bayesian paradigm.

———— **R objects of example datasets from real world or fictitious:**

[dataList.Chakra.1](#) A list for an example dataset of a single reader and a single modality data. The word Chakra in the dataset name means that it appears in the paper of Chakraborty.

[dataList.Chakra.2](#) A list for an example dataset of a single reader and a single modality data. The word Chakra in the dataset name means that it appears in the paper of Chakraborty.

[dataList.Chakra.3](#) A list for an example dataset of a single reader and a single modality data. The word Chakra in the dataset name means that it appears in the paper of Chakraborty.

[dataList.Chakra.4](#) A list for an example dataset of a single reader and a single modality data. The word Chakra in the dataset name means that it appears in the paper of Chakraborty.

[dataList.high.ability](#) A list for an example dataset of a single reader and a single modality data

[dataList.low.ability](#) A list for an example dataset of a single reader and a single modality data

[dataList.Chakra.Web](#) A list for an example dataset of multiple readers and multiple modalities data. The word Chakra in the dataset name means that it appears in the paper of Chakraborty.

[data.hier.fictitious](#) A list for an example dataset of multiple readers and multiple modalities data

[dataList.High](#) A list for an example dataset of a single reader and a single modality data whose AUC is high.

[dataList.Low](#) A list for an example dataset of a single reader and a single modality data whose AUC is low.

[data.bad.fit](#) A list for an example dataset of a single reader and a single modality data whose fitting is bad, that is chi square is very large. However the MCMC convergence criterion is satisfied with very high quality. Thus the good MCMC convergence does not mean the model is correct. So, to fit a model to this data, we should change the latent Gaussian and differential logarithmic Gaussian to more appropriate distributions for hit and false alarm rate. In theoretically perspective, there is no a prior distribution for hit and false alarm rate. So, if we encounter not good fitting data, then we should change the model, and such change will occur in the latent distributions. The reason why the author saved this data is to show that our model is not unique nor good and gives a future research directions. To tell the truth the author is not interested the FROC theory. My background is mathematics, geometry, pure mathematics. So, I want to go back to my home ground. This program are made to show my

skill for programming or my ability. But, now, I do not think to get job. I want to go back mathematics. Soon, my paper is published which is related Gromov Hausdorff topology. Of course, I will publish this package's theory soon. Please wait.

`dd,ddd,dddd,dddddd,ddddddd` The other datasets, the author like these datasets because name is very simple.

Examples

```
## Not run:
#=====
#                               The 1-st example
#=====
#
#
#                               Making FROC Data and Fitting a Model to the data
#
#                               Notations
#
#                               h = hits = TP = True Positives
#                               f = False alarms = FP = False Positives
#
#=====
#                               1)                               Build a data-set
#=====

BayesianFROC:::clearWorkspace()

# For a single reader and a single modality case.

dat <- list(c=c(3,2,1), # Confidence level. Note that c is ignored.
           h=c(97,32,31), # Number of hits for each confidence level
           f=c(1,14,74), # Number of false alarms for each confidence level

           NL=259, # Number of lesions
           NI=57, # Number of images
           C=3) # Number of confidence level

if (interactive()){ viewdata(dat)}

# where,
# c denotes confidence level, i.e., rating of reader.
# 3 = Definitely diseased,
# 2 = subtle,.. diseased
# 1 = very subtle
# h denotes number of hits (True Positives: TP) for each confidence level,
# f denotes number of false alarms (False Positives: FP) for each confidence level,
# NL denotes number of lesions,
# NI denotes number of images,
```

```

# For example, in the above example data,
# the number of hits with confidence level 3 is 97,
# the number of hits with confidence level 2 is 32,
# the number of hits with confidence level 1 is 31,

# the number of false alarms with confidence level 3 is 1,
# the number of false alarms with confidence level 2 is 14,
# the number of false alarms with confidence level 1 is 74,

#=====
#                               2)      Fit an FROC model to the above dataset.
#=====

fit <- fit_Bayesian_FROC(
      dat,      # dataset
      ite = 1111, #To run in time <5s.
      cha = 1,   # number of chains, it is better more large.
      summary = FALSE
    )

# The return value "fit" is an S4 object of class "stanfitExtended" which is inherited
# from the S4 class "stanfit".

#=====
#                               3) Change the S4 class of fitted model object
# Change the S4 class from "stanfitExtended" to "stanfit" to apply other packages.
# The fitted model object of class "stanfit" is available for the package ggmc, rstan
# Thus, to use such package, we coerce the class into "stanfit" as follows:

# Changing the class from stanfitExtended to stanfit,
# we can apply other package's functions to the resulting object.

#=====

fit.stan <- methods::as(fit,"stanfit")

# Then, return value "fit.stan" is no longer an S4 object of class "stanfitExtended" but
# the S4 object of class "stanfit".

```



```

=====
#           3.1) Apply the functions for the class stanfit
=====

grDevices::dev.new();rstan::stan_hist(fit.stan, bins=33,pars = c("A"))
grDevices::dev.new();rstan::stan_hist(fit.stan, bins=22,pars = c("A"))
grDevices::dev.new();rstan::stan_hist(fit.stan, bins=11,pars = c("A"))

grDevices::dev.off()

# I am not sure why the above stan_hist also works for the new S4 class "stanfitExtended"

# Get pipe operator

`%>%` <- utils::getFromNamespace("%>%", "magrittr")

# Plot about MCMC samples of parameter name "A", representing AUC

# Trace-plot density for parameter "A"
grDevices::dev.new()
  ggmcmc::ggs(fit.stan) %>% ggmcmc::ggs_traceplot(family = "A")
grDevices::dev.off()
# Posterior density for parameter "A"
grDevices::dev.new()
  ggmcmc::ggs(fit.stan) %>% ggmcmc::ggs_density(family = "A")
grDevices::dev.off()

# Auto-correlation for parameter "A"
grDevices::dev.new()
  ggmcmc::ggs(fit.stan) %>% ggmcmc::ggs_autocorrelation(family = "A")
grDevices::dev.off()

# The author does not think the inherited class "stanfitExtended" is good,
# Since the size of object is very redundant and large,
# which caused by the fact that inherited class contains plot data for FROC curve.
# To show the difference of size for the fitted model object of class
# stanfitExtended and stanfit, we execute the following code;

size_of_return_value(fit) - size_of_return_value(methods::as(fit,"stanfit"))

```



```

=====
#
# (1)First, we prepare the data from this package.

      dat <- BayesianFROC::dataList.Chakra.1

# (2)Second, we run fit_Bayesian_FROC() in which the rstan::stan() is implemented.
# with data named "dat" and the author's Bayesian model.

      fit <- fit_Bayesian_FROC(dat,
                             ite = 1111 #To run in time <5s.
                             )

# Now, we get the stan's out put, i.e., an S4 class object named "fit".

# << Minor Comments>>
# More precisely, this is an S4 object of some inherited class (named stanfitExtended)
# which is extended using stan's S4 class named "stanfit".

fit.stan <- methods::as(fit,"stanfit")
# Using the output "fit.stan",

# we can use the functions in the "rstan" package, for example, as follows;

grDevices::dev.new();
  rstan::stan_trace(fit.stan, pars = c("A"))# stochastic process of a posterior estimate
  rstan::stan_hist(fit.stan, pars = c("A")) # Histogram of a posterior estimate
  rstan::stan_rhat(fit.stan, pars = c("A")) # Histogram of rhat for all parameters
  rstan::summary(fit.stan, pars = c("A")) # summary of fit.stan by rstan
grDevices::dev.off()

=====
#
#                               The 3-rd example
#
=====

# Fit a model to a hand made data

# 1) Build the data for a single reader and a single modality case.

```

```

dat <- list(
  c=c(3,2,1), # Confidence level, which is ignored.
  h=c(97,32,31), # Number of hits for each confidence level
  f=c(1,14,74), # Number of false alarms for each confidence level

  NL=259, # Number of lesions
  NI=57, # Number of images
  C=3) # Number of confidence level

# where,
# c denotes confidence level, , each components indicates that
# 3 = Definitely lesion,
# 2 = subtle,
# 1 = very subtle
# That is the high number indicates the high confidence level.
# h denotes number of hits
# (True Positives: TP) for each confidence level,
# f denotes number of false alarms
# (False Positives: FP) for each confidence level,
# NL denotes number of lesions,
# NI denotes number of images,

# 2) Fit and draw FROC and AFROC curves.

fit <- fit_Bayesian_FROC(dat, DrawCurve = TRUE)

# (( REMARK ))
# Changing the hits and false alarms denoted by h and f
# in the above dataset denoted by dat,
# user can fit a model to various datasets and draw corresponding FROC curves.
# Enjoy drawing the curves for various datasets in case of
# a single reader and a single modality data

#=====
# For Prior and Bayesian Update:

# Calculates a posterior mean and variance

# for each parameter
#=====

```

```
# Mean values of posterior samples are used as a point estimates, and
# Although the variance of posteriors receives less attention,
# but to make a prior, we will need the it.
# For, example, if we assume that model parameter m has prior distributed by
# Gaussian, then we have to know the mean and variance to characterize prior.
```

```
e <- rstan::extract(fit)
```

```
# model parameter m and v is a number,
# indicating the mean and variance of signal distribution, respectively.
```

```
stats::var(e$m)
```

```
mean(e$m)
```

```
stats::var(e$v)
```

```
mean(e$v)
```

```
# The model parameter z or dz is a vector, and thus we execute the following;
```

```
# z = ( z[1], z[2], z[3] )
```

```
# dz = ( z[2]-z[1], z[3]-z[2] )
```

```
# `Posterior mean of posterior MCMC samples for parameter z and dz
```

```
apply(e$dz, 2, mean)
```

```
apply(e$z, 2, mean)
```

```
# `Posterior variance of posterior MCMC samples for parameter z and dz
```

```
apply(e$dz, 2, var)
```

```
apply(e$z, 2, var)
```

```
apply(e$d1, 2, mean)
```

```
apply(e$l, 2, mean)
```

```
apply(e$p, 2, mean)
```

```
apply(e$p, 2, var)
```

```
# Revised 2019 Sept 6
```

```
#####  
#                               The 4-th example  
#####  
#
```

```
## Only run examples in interactive R sessions  
if (interactive()) {
```

```
#       1) Build the data interactively,
```

```
        dataList <- create_dataset()
```

```
#Now, as as a return value of create_dataset(), we get the FROC data (list) named dataList.
```

```
#       2) Fit an MRMC or srsc FROC model.
```

```
        fit <- fit_Bayesian_FROC(dataList)
```

```
}## Only run examples in interactive R sessions
```

```

=====
#                                     The 5-th example
=====
# Comparison of the posterior probability for AUC

# In the following, we calculate the probability of the events that
# the AUC of some modality is greater than the AUC of another modality.

=====
#   Posterior Probability for some events of AUCs by using posterior MCMC samples
=====

# This example shows how to use the stanfit (stanfit.Extended) object.
# Using stanfit object, we can extract posterior samples and using these samples,
# we can calculate the posterior probability of research questions.

fit <- fit_Bayesian_FROC(dataList.Chakra.Web.orderd,ite = 1111,summary =FALSE)

#   For example, we shall show the code to compute the posterior probability of the ever
#   that the AUC of modality 1 is larger than that of modality 2:

e <- extract(fit)

# This code means that the MCMC samples are retained in the object e for all parameters.
# For example, the AUC is extracted by the code e$A and it is a two dimensional array.
# The first component indicates the MCMC samples and
# the second component indicate the modality ID.

# For example, the code e$A[,1] means the vector of MCMC samples of the 1 st modality.
# For example, the code e$A[,2] means the vector of MCMC samples of the 2 nd modality.
# For example, the code e$A[,3] means the vector of MCMC samples of the 3 rd modality.
#   To calculate the posterior probability of the ever
#   that the AUC of modality 1 is larger than that of modality 2,
#   we execute the following R script:

mean(e$A[,1] > e$A[,2])

#   Similarly, to compute the posterior probability that
#   the AUC of modality 1 is larger than that of modality 3:

```

```
mean(e$A[,1] > e$A[,3])

# Similarly, to compute the posterior probability that
# the AUC of modality 1 is larger than that of modality 4:

mean(e$A[,1] > e$A[,4])

# Similarly, to compute the posterior probability that
# the AUC of modality 1 is larger than that of modality 5:

mean(e$A[,1] > e$A[,5])

# Similarly, to compute the posterior probability that
# the AUC of modality 1 is larger than that of modality 5 at least 0.01

mean(e$A[,1] > e$A[,5]+0.01)

# Similarly,

mean( e$A[,1] > e$A[,5] + 0.01 )
mean( e$A[,1] > e$A[,5] + 0.02 )
mean( e$A[,1] > e$A[,5] + 0.03 )
mean( e$A[,1] > e$A[,5] + 0.04 )
mean( e$A[,1] > e$A[,5] + 0.05 )
mean( e$A[,1] > e$A[,5] + 0.06 )
mean( e$A[,1] > e$A[,5] + 0.07 )
mean( e$A[,1] > e$A[,5] + 0.08 )

# Since any posterior distribution tends to the Dirac measure whose center is
# true parameter under the assumption that the model is correct in the sense that the
# true distribution is belongs to a family of models.
# Thus using this procedure, we will get
# the true parameter if any more large sample size we can take.

# Close the graphic device to avoid errors in R CMD check.

Close_all_graphic_devices()
```



```

=====
#                                     The 6-th Example for MRMC data
=====

# To draw FROC curves for each modality and each reader, the author provides codes.
# First, we make a fitted object of class stanfitExtended as following manner.

fit <- fit_Bayesian_FROC( ite = 1111,
                        cha = 1,
                        summary = FALSE,
                        Null.Hypothesis = FALSE,
                        dataList = dd # This is a MRMC dataset.
                        )

# Using this fitted model object called fit, we can draw FROC curves for the
# 1-st modality as following manner:

DrawCurves(
# This is a fitted model object
  fit,
# Here, the modality is specified
  modalityID = 1,
# Reader is specified 1,2,3,4
  readerID = 1:4,
# If TRUE, the new imaging device is created and curves are drawn in it.
  new.imaging.device = TRUE
)

# The next codes are quite same, except modality ID and new.imaging.device
# The code that "new.imaging.device = F" means that the curves are drawn using
# the previous imaging device to plot the 1-st and 2-nd modality curves draw in the same
# Plot plain. Drawing in different curves in same plain, we can compare the curve
# of modality. Of course, the interpretation of FROC curve is the ordinal ROC curve,
# that is,
# if curve is upper then the observer performance with its modality is more greater.
# So, please enjoy drawing curves.

DrawCurves(fit,modalityID = 2,readerID = 1:4, new.imaging.device = FALSE)
DrawCurves(fit,modalityID = 3,readerID = 1:4, new.imaging.device = FALSE)
DrawCurves(fit,modalityID = 4,readerID = 1:4, new.imaging.device = FALSE)
DrawCurves(fit,modalityID = 5,readerID = 1:4, new.imaging.device = FALSE)

```

```

Close_all_graphic_devices()

#=====
#                               The 7-th example NON-CONVERGENT CASE 2019 OCT.
#=====

# ff <- fit_Bayesian_FROC( ite = 1111, cha = 1, summary = TRUE, dataList = ddd )

dat <- list(
  c=c(3,2,1),      #Confidence level
  h=c(73703933,15661264,12360003), #Number of hits for each confidence level
  f=c(1738825,53666125 , 254965774), #Number of false alarms for each confidence level

  NL=100000000,    #Number of lesions
  NI=200000000,    #Number of images
  C=3)             #Number of confidence level

# From the examples of the function mu_truth_creator_for_many_readers_MRMC_data()
#=====
#                               Large number of readers cause non-convergence
#=====

  v <- v_truth_creator_for_many_readers_MRMC_data(M=4,Q=6)
m <- mu_truth_creator_for_many_readers_MRMC_data(M=4,Q=6)
d <- create_dataList_MRMC(mu.truth = m,v.truth = v)
# fit <- fit_Bayesian_FROC( ite = 111, cha = 1, summary = TRUE, dataList = d )

plot_FPF_and_TPF_from_a_dataset(d)

#=====
#                               convergence
#=====

```

```

v <- v_truth_creator_for_many_readers_MRMC_data(M=2,Q=21)
m <- mu_truth_creator_for_many_readers_MRMC_data(M=2,Q=21)
d <- create_dataList_MRMC(mu.truth = m,v.truth = v)
# fit <- fit_Bayesian_FROC( ite = 200, cha = 1, summary = TRUE, dataList = d)

plot_FPF_TPF_via_dataframe_with_split_factor(d)
plot_empirical_FROC_curves(d,readerID = 1:21)
#=====
#                               non-convergence
#=====

v <- v_truth_creator_for_many_readers_MRMC_data(M=5,Q=6)
m <- mu_truth_creator_for_many_readers_MRMC_data(M=5,Q=6)
d <- create_dataList_MRMC(mu.truth = m,v.truth = v)
# fit <- fit_Bayesian_FROC( ite = 111, cha = 1, summary = TRUE, dataList = d)

#=====
#                               convergence
#=====

v <- v_truth_creator_for_many_readers_MRMC_data(M=1,Q=36)
m <- mu_truth_creator_for_many_readers_MRMC_data(M=1,Q=36)
d <- create_dataList_MRMC(mu.truth = m,v.truth = v)
# fit <- fit_Bayesian_FROC( ite = 1111, cha = 1, summary = TRUE, dataList = d)

#=====
#                               non-convergence
#=====

v <- v_truth_creator_for_many_readers_MRMC_data(M=1,Q=37)
m <- mu_truth_creator_for_many_readers_MRMC_data(M=1,Q=37)
d <- create_dataList_MRMC(mu.truth = m,v.truth = v)
# fit <- fit_Bayesian_FROC( ite = 111, cha = 1, summary = TRUE, dataList = d)

```

```

=====
#
#                               convergence A single modality and 11 readers
#
=====

v <- v_truth_creator_for_many_readers_MRMC_data(M=1,Q=11)
m <- mu_truth_creator_for_many_readers_MRMC_data(M=1,Q=11)
d <- create_dataList_MRMC(mu.truth = m,v.truth = v)
# fit <- fit_Bayesian_FROC( ite = 1111,
#                           cha = 1,
#                           summary = TRUE,
#                           dataList = d,
#                           see = 123455)
#
## f <-fit
# DrawCurves( summary = FALSE,
#               modalityID = c(1:f@dataList$M),
#               readerID = c(1:f@dataList$Q),
#               StanS4class = f )
#
#
#
#
=====
#
#                               convergence A single modality and 17 readers
#
=====

v <- v_truth_creator_for_many_readers_MRMC_data(M=1,Q=17)
m <- mu_truth_creator_for_many_readers_MRMC_data(M=1,Q=17)
d <- create_dataList_MRMC(mu.truth = m,v.truth = v)
# fit <- fit_Bayesian_FROC( ite = 1111, cha = 1, summary = TRUE, dataList = d,see = 123455)
#
# f <-fit
# DrawCurves( summary = FALSE,   modalityID = c(1:f@dataList$M),
#               readerID = c(1:f@dataList$Q),f )
#
#
# DrawCurves( summary = FALSE,   modalityID = 1,
#               readerID = c(8,9),f )
#
## For readerID 8,9, this model is bad
#
Close_all_graphic_devices()

=====

```

```

#                               convergence 37 readers, 1 modality
#=====

v <- v_truth_creator_for_many_readers_MRMC_data(M=1,Q=37)
m <- mu_truth_creator_for_many_readers_MRMC_data(M=1,Q=37)
d <- create_dataList_MRMC(mu.truth = m,v.truth = v)
# fit <- fit_Bayesian_FROC(see = 2345678, ite = 2000, cha = 1, summary = TRUE, dataList = d)
#
#
# f <-fit
# DrawCurves( summary = FALSE,   modalityID = c(1:f@dataList$M),
#              readerID = c(1:f@dataList$Q),f )
#
#
# DrawCurves( summary = FALSE,   modalityID = 1,
#              readerID = c(8,9),f )

# In the following, consider two readers whose ID are 8 and 15, respectively.
# Obviously, one of them will have high performamce than the other,
# however,
# Sometimes, the FROC curve dose not reflect it,
# Namely, one of the FROC curve is upper than the other
# even if the FPF and TPF are not... WHY??

# DrawCurves( summary = FALSE,   modalityID = 1,
#              readerID = c(8,15),f )
#
Close_all_graphic_devices()

Close_all_graphic_devices()

## End(Not run)# dontrun

```

fit_GUI

Fit with GUI via Shiny

Description

First, please execute, then user will understand what it is. This function is the one of the most important function in this package. I do not assume that the user is familiar with R script but FROC analysis. So, I made this function to provide the Graphical User Interface (GUI) for users. I hope it helps someone in the world.

Usage

```
fit_GUI(display.mode = FALSE)
```

Arguments

`display.mode` Logical, passing to `runApp`. Default is `FALSE` corresponding to "normal", and if `TRUE`, then "showcase" which shows code. The author made this, but it did not work or ignored, that is, showcase did not work. Why???

Value

None

Examples

```
## Not run:  
## Only run examples in interactive R sessions  
if (interactive()) {  
  #No need to consider the variables, it is sufficient in default values.  
  #fit_GUI()  
}### Only run examples in interactive R sessions  
  
## End(Not run)##'
```

`fit_GUI_dashboard` *Fit with GUI via Shiny (Simple version)*

Description

simple is vest

Usage

```
fit_GUI_dashboard(  
  DF = data.frame(h = c(97L, 32L, 31L), f = c(1L, 14L, 74L)),  
  NL.max = 1111,  
  NI.max = 1111,  
  NL.initial = 259,  
  MCMC.chains.max = 4  
)
```

Arguments

DF	A dataframe as an initial data to be fitted a model
NL.max	max number of bins indicating the maximal number in which the number of lesions can move
NI.max	max number of bins indicating the maximal number in which the number of imagegs can move
NL.initial	Natural number indicating the initial number of lesions, Default value =259. The reason why the author made this is in example code, the author made a very strange data in it, the default value = 259 is not satisfies the data format. That is in the example, total number of hits is greater than 259 and it is impossible. So, I have to change the default value.
MCMC.chains.max	max number of bins indicating number of MCMC chains

Details

First, please execute, then user will understand what it is. This function is the one of the most important function in this package. I do not assume that the user is familiar with R script but FROC analysis. So, I made this function to provide the Graphical User Interface (GUI) for users. I hope it helps someone in the world.

Value

None

Author(s)

Issei Tsunoda

Examples

```
## Not run:
## Only run examples in interactive R sessions
if (interactive()) {

#=====
#          1)          Use the default User Interface
#=====
#'

#No need to consider the variables, it is sufficient in default values.

#fit_GUI_dashboard()
```

```

=====
#           2)           Change the User Interface
=====

# We can change the max input of the number of lesions and the max of number of images
#

#fit_GUI_dashboard(NL.max = 2222,
#                   NI.max = 3333)

=====
#           3)           Change the Default value
=====

# fit_GUI_dashboard(
# DF= data.frame( h=dataList.Chakra.4$h,
#                 f=dataList.Chakra.4$f
#                 )
#                 )

# Or equivalently,

# fit_GUI_dashboard(
#     DF= data.frame(
#     h = c(160, 25, 15, 7),
#     f = c( 8, 16, 18, 13)
#     )
# )

=====
#           4)           Change the user Interface
=====

#fit_GUI_dashboard(

#     DF= data.frame(
#     h = c(160, 25, 15, 7),
#     f = c( 8, 16, 18, 13)
#     ),
#
#     NL.max = 1192,
#     NI.max = 794,
#     MCMC.chains.max = 6

```



```
# )  
  
}### Only run examples in interactive R sessions  
  
## End(Not run)
```

fit_GUI_MRMC

Fit with GUI via Shiny in case of MRMC

Description

First, please execute, then user will understand what it is. This function is the one of the most important function in this package. I do not assume the user is familiar with R script but FROC analysis. So, I made this function to provide the Graphical User Interface (GUI) for users. I hope it helps someone in the world.

Usage

```
fit_GUI_MRMC(M = 2, Q = 3, C = 4)
```

Arguments

M	No. of modalities
Q	No. of readers
C	No. of confidence levels revised 2019 Nov. 21

Value

None

fit_GUI_MRMC_new *Fit an MRMC model to data with Shiny GUI*

Description

I love you.

Usage

```
fit_GUI_MRMC_new(M = 2, Q = 3, C = 4)
```

Arguments

M	mo
Q	re
C	con

Details

I need you.

Value

ret

fit_GUI_Shiny *Fit a model with GUI of Shiny*

Description

A graphical user interface (GUI) to fit a model to data.

Usage

```
fit_GUI_Shiny(  
  DF = data.frame(h = c(97L, 32L, 31L), f = c(1L, 14L, 74L)),  
  NL.max = 1111,  
  NI.max = 1111,  
  NL.initial = 259,  
  MCMC.chains.max = 4  
)
```

Arguments

DF	A dataframe as an initial data to be fitted a model
NL.max	max number of bins indicating the maximal number in which the number of lesions can move
NI.max	max number of bins indicating the maximal number in which the number of imagegs can move
NL.initial	Natural number indicating the initial number of lesions, Default value =259. The reason why the author made this is in example code, the author made a very strange data in it, the default value = 259 is not satisfies the data format. That is in the example, total number of hits is greater than 259 and it is impossible. So, I have to change the default value.
MCMC.chains.max	max number of bins indicating number of MCMC chains

Details

First, please execute, then user will understand what it is. This function is the one of the most important function in this package. I do not assume that the user is familiar with R script but FROC analysis. So, I made this function to provide the Graphical User Interface (GUI) for users to avoid CUI (Characteristic User Interface). The GUI is made by the **shiny** package.

Value

None

Author(s)

Issei Tsunoda

Examples

```
## Only run examples in interactive R sessions
if (interactive()) {
#=====
#           1)           Use the default User Interface
#=====
#'

#No need to consider the variables, it is sufficient in default values.

#fit_GUI_Shiny()

#=====
#           2)           Change the User Interface
```

```

=====

# We can change the max input of the number of lesions and the max of number of images
#

fit_GUI_Shiny(NL.max = 2222,
              NI.max = 3333)

=====

#           3)           Change the Default value
=====

fit_GUI_Shiny(
  DF= data.frame( h=dataList.Chakra.4$h,
                 f=dataList.Chakra.4$f
                 )
)

# Or equivalently,

fit_GUI_Shiny(
  DF= data.frame(
    h = c(160, 25, 15, 7),
    f = c( 8, 16, 18, 13)
  )
)

=====

#           4)           Change the user Interface
=====

fit_GUI_Shiny(
  DF= data.frame(
    h = c(160, 25, 15, 7),
    f = c( 8, 16, 18, 13)
  ),
  NL.max = 1192,
  NI.max = 794,
  MCMC.chains.max = 6
)

```

```

=====
#           5) CUI rather than GUI input
=====

#           How to input data using CUI?
#           This example gives an answer.
#

# CUI: Characteristic user interface

# Here, I show the very strange data, that is, the number of hits is all 33
# and replicated 10 times, that is,
# h is substituted by rep(33L,10) indicating 33 33 33 33 33 33 33 33 33 33
# f is also same as h.

fit_GUI_Shiny(NL.initial=555,
              DF =data.frame(
                h= as.integer(rep(33,10)),
                f= as.integer(rep(33,10))
              )
)

# The author made this example since, when I check my program,
# such as whether the color used in polygon() is appropriate or not.

# If user thinks that it is very hard to input hits and false alarms
# by GUI manner, then use this characteristic like manner.

)### Only run examples in interactive R sessions

```

```
fit_GUI_Shiny_MRMC      Fit with GUI via Shiny (in case of MRMC)
```

Description

Fit a Bayesian model with GUI.

Revised 2019 Nov.

Usage

```
fit_GUI_Shiny_MRMC(
  DF = data.frame(m = as.integer(BayesianFROC::dd$m), q =
    as.integer(BayesianFROC::dd$q), c = as.integer(BayesianFROC::dd$c), h =
    as.integer(BayesianFROC::dd$h), f = as.integer(BayesianFROC::dd$f)),
  NL.max = 1111,
  NI.max = 1111,
  NL.initial = 142,
  NI.initial = 199,
  seed.initial.of.MCMC = 237410,
  MCMC.chains.max = 4
)
```

Arguments

DF	A dataframe, consisting of five vectors: reader ID, modality ID, confidence levels, hits, false alarms. initial data to be fitted
NL.max	max number of bins indicating the maximal number in which the number of lesions can move
NI.max	max number of bins indicating the maximal number in which the number of images can move
NL.initial	Natural number indicating the initial number of lesions, Default value =142.
NI.initial	Natural number indicating the initial number of images, Default value =199.
seed.initial.of.MCMC	positive integers indicating the initial seed of MCMC sampling. Default is 1234.
MCMC.chains.max	max number of bins indicating number of MCMC chains

Details

In what follows, we assume that our dataset has more than two readers or modalities, namely, our dataset is MRMC case. The term *imaging modality*, we mean a set of imaging methods such as MRI, CT, PET, etc.

Revised 2019 Nov 25. Revised 2020 Jan

Value

None

Examples

```
## Not run:

### Only run examples in interactive R sessions
if (interactive()) {
```

```
#####  
#           1)           Use the default User Interface  
#####  
#'  
  
#No need to consider the variables, it is sufficient in default values.  
  
fit_GUI_Shiny()  
  
#####  
#           2)           From existing dataset, named ddddd or dddd or ddd  
#####  
  
fit_GUI_Shiny_MRMC(DF=extract_data_frame_from_dataList_MRMC(ddddd))  
fit_GUI_Shiny_MRMC(DF=extract_data_frame_from_dataList_MRMC(dddd))  
fit_GUI_Shiny_MRMC(DF=extract_data_frame_from_dataList_MRMC(ddd))  
  
#####  
#           2)           data of 11 readers and a single modality  
#####  
  
d <- dataset_creator_for_many_Readers(1,11)  
  
fit_GUI_Shiny_MRMC(DF=extract_data_frame_from_dataList_MRMC(d))  
  
#####  
#           see = 2345678           convergence 37readers, 1 modality  
#####  
  
v <- v_truth_creator_for_many_readers_MRMC_data(M=1,Q=37)  
m <- mu_truth_creator_for_many_readers_MRMC_data(M=1,Q=37)
```

```

d <- create_dataList_MRMC(mu.truth = m,v.truth = v)

fit_GUI_Shiny_MRMC(DF=extract_data_frame_from_dataList_MRMC(d),
                  seed.initial.of.MCMC = 2345678,
                  NL.initial = d$NL,
                  NI.initial = d$NI)

#=====
#           2)           From existing dataset, named dddd
#=====

fit_GUI_Shiny_MRMC(DF=extract_data_frame_from_dataList_MRMC(dddd))

# This dataset named dddd is a dataset consisting of
# only a single reader and mutiple modality.
# Such a single reader and mutiple modality case had error caused
# by some reduction of array to vector.
# So, the program was fixed so that such special case is also available
# 2020 Feb 24

# To reflect the information of the number of lesions and images,
# use the following.

fit_GUI_Shiny_MRMC(DF=extract_data_frame_from_dataList_MRMC(dddd),
                  NL.initial = dddd$NL,
                  NI.initial = dddd$NI)

#=====
#                               example
#=====

v <- v_truth_creator_for_many_readers_MRMC_data(M=2,Q=7)
m <- mu_truth_creator_for_many_readers_MRMC_data(M=2,Q=7)
d <- create_dataList_MRMC(mu.truth = m,v.truth = v)
fit_GUI_Shiny_MRMC(DF=extract_data_frame_from_dataList_MRMC(d))

```



```
#####  
#                               non-convergent   example  
#####  
  
v <- v_truth_creator_for_many_readers_MPMC_data(M=3,Q=7)  
m <- mu_truth_creator_for_many_readers_MPMC_data(M=3,Q=7)  
d <- create_dataList_MPMC(mu.truth = m,v.truth = v)  
fit_GUI_Shiny_MPMC(DF=extract_data_frame_from_dataList_MPMC(d),seed.initial.of.MPMC = 23)  
  
}### Only run examples in interactive R sessions  
  
## End(Not run)
```

```
fit_GUI_simple_from_apppp_file  
    Fit with GUI via Shiny
```

Description

First, please execute, then user will understand what it is. This function is the one of the most important function in this package. I do not assume that the user is familiar with R script but FROC analysis. So, I made this function to provide the Graphical User Interface (GUI) for users. I hope it helps someone in the world.

Usage

```
fit_GUI_simple_from_apppp_file(display.mode = FALSE)
```

Arguments

`display.mode` Logical, passing to `runApp`. Default is `FALSE` corresponding to "normal", and if `TRUE`, then "showcase" which shows code. The author made this, but it did not work or ignored, that is, showcase did not work. Why???

Value

None

Author(s)

Issei Tsunoda

Examples

```
## Not run:
## Only run examples in interactive R sessions
if (interactive()) {
  #No need to consider the variables, it is sufficient in default values.
  #fit_GUI_simple_from_apppp_file()

}### Only run examples in interactive R sessions

## End(Not run)##'
```

fit_MRMC

Fit and Draw the FROC models (curves)

Description

Fit and Draw the FROC models (curves).

Usage

```
fit_MRMC(
  dataList,
  DrawCurve = FALSE,
  verbose = TRUE,
  print_CI_of_AUC = TRUE,
  PreciseLogLikelihood = FALSE,
  summary = TRUE,
  dataList.Name = "",
  prior = 1,
  ModifiedPoisson = TRUE,
  mesh.for.drawing.curve = 10000,
  significantLevel = 0.7,
  cha = 1,
  war = floor(ite/5),
  ite = 10000,
  dig = 3,
  see = 1234569,
  Null.Hypothesis = FALSE,
  prototype = FALSE,
  model_reparametrized = FALSE,
  Model_MRMC_non_hierarchical = TRUE,
  zz = 1,
  ...
)
```

Arguments

`dataList`

A list, specifying an FROC data to be fitted a model. It consists of data of numbers of TPs, FPs, lesions, images. .In addition, if in case of mutple readers or mutple modalities, then modaity ID and reader ID are included also.

The `dataList` will be passed to the function `rstan::sampling()` of **rstan**. This is a variable in the function `rstan::sampling()` in which it is named `data`.

For the single reader and a single modality data, the `dataList` is made by the following manner:

```
dataList.Example <-list(
h = c(41,22,14,8,1),# number of hits for each confidence level
f = c(1,2,5,11,13),# number of false alarms for each confidence level

NL = 124,# number of lesions (signals)
NI = 63,# number of images (trials)
C = 5) # number of confidence,.. the author thinks it can be calculated
as the length of h or f ...? ha,why I included this. ha .. should be omitted.
```

Using this object `dataList.Example`, we can apply `fit_Bayesian_FROC()` such as `fit_Bayesian_FROC(dataList.Example)`.

To make this R object `dataList` representing FROC data, this package provides three functions:

- `convertFromJafroc()` If data is a **JAFROC xlsx** formulation.
- `dataset_creator_new_version()` Enter TP and FP data **by table** .
- `create_dataset()` Enter TP and FP data by **interactive** manner.

Before fitting a model, we can confirm our dataset is correctly formulated by using the function `viewdata()`.

A Single reader and a single modality (SRSC) case.

In a single reader and a single modality case (`srsc`), `dataList` is a list consisting of `f,h,NL,NI,C` where `f,h` are numeric vectors and `NL,NI,C` are positive integers.

- `f` Non-negative integer vector specifying number of false alarms associated with each confidence level. The first component corresponding to the highest confidence level.
- `h` Non-negative integer vector specifying number of Hits associated with each confidence level. The first component corresponding to the highest confidence level.
- `NL` A positive integer, representing Number of Lesions.
- `NI` A positive integer, representing Number of Images.
- `C` A positive integer, representing Number of Confidence level.

The detail of these dataset, see the datasets endowed with this package. 'Note that the maximal number of confidence level, denoted by `C`, are included, however, Note that confidence level vector `c` should not be specified. If specified,

will be ignored , since it is created by `c<-c(rep(C:1))` in the program and do not refer from user input data, where C is the highest number of confidence levels. So, you should write down your hits and false alarms vector so that it is compatible with this automatically created c vector.

data Format:

A single reader and a single modality case

NI=63, NL=124 In R console ->	confidence level c	No. of false alarms f	No. of hits h
definitely present	$c[1] = 5$	$f[1] = F_5 = 1$	$h[1] = H_5 = 41$
probably present	$c[2] = 4$	$f[2] = F_4 = 2$	$h[2] = H_4 = 22$
equivocal	$c[3] = 3$	$f[3] = F_3 = 5$	$h[3] = H_3 = 14$
subtle	$c[4] = 2$	$f[4] = F_2 = 11$	$h[4] = H_2 = 8$
very subtle	$c[5] = 1$	$f[5] = F_1 = 13$	$h[5] = H_1 = 1$

* *false alarms* = False Positives = FP

* *hits* = True Positives = TP

Note that in FROC data, all confidence level means *present (diseased, lesion)* case only, no confidence level indicating absent. Since each reader marks his suspicious location only if he thinks lesions are *present*, and marked positions generates the hits or false alarms, *thus* each confidence level represents that lesion is *present*. In the absent case, reader dose not mark any locations and hence, the absent confidence level does not relate this dataset. So, if reader think it is no lesion, then in such case confidence level is not needed.

Note that the first column of confidence level vector `c` should not be specified. If specified, will be ignored , since it is created by `c<-c(rep(C:1))` automatically in the program and do not refer from user input data even if it is specified explicitly, where C is the highest number of confidence levels. So you should check the compatibility of your data and the confidence level vector `c<-c(rep(C:1))` via a table which can be displayed by the function `viewdata()`.

Multiple readers and multiple modalities case, i.e., MRMC case

In case of multiple readers and multiple modalities, i.e., MRMC case, in order to apply the function `fit_Bayesian_FROC()`, dataset represented by an R list object representing FROC data must contain components `m, q, c, h, f, NL, C, M, Q`.

- C A positive integer, representing the **highest** number of confidence level, this is a scalar.
- M A positive integer vector, representing the number of **modalities**.
- Q A positive integer, representing the number of **readers**.

- m A vector of positive integers, representing the **modality ID** vector.
- q A vector of positive integers, representing the **reader ID** vector.
- c A vector of positive integers, representing the **confidence level**. This vector must be made by `rep(rep(C:1), M*Q)`
- h A vector of non-negative integers, representing the number of **hits**.
- f A vector of non-negative integers, representing the number of **false alarms**.
- NL A positive integer, representing the Total number of **lesions** for all images, this is a scalar.

Note that the maximal number of confidence level (denoted by C) are included in the above R object. However, each confidence level vector is not included in the data, because it is created automatically from C. To confirm false positives and hits are correctly ordered with respect to the automatically generated confidence vector,

the function `viewdata()` shows the table. Revised 2019 Nov 27 Revised 2019 Dec 5

Example data.

Multiple readers and multiple modalities (i.e., MRMC)

Modality ID	Reader ID	Confidence levels	No. of false alarms	No. of hits.
m	q	c	f	h
1	1	3	20	111
1	1	2	29	55
1	1	1	21	22
1	2	3	6	100
1	2	2	15	44
1	2	1	22	11
2	1	3	6	66
2	1	2	24	55
2	1	1	23	1
2	2	3	5	66
2	2	2	30	55
2	2	1	40	44

* *false alarms* = False Positives = FP

* *hits* = True Positives = TP

DrawCurve

Logical: TRUE or FALSE. Whether the curve is to be drawn. TRUE or FALSE. If you want to draw the FROC and AFROC curves, then you set DrawCurve =TRUE, if not then DrawCurve =FALSE. The reason why the author make this variable DrawCurve is that it takes long time in MRMC case to draw curves, and thus Default value is FALSE in the case of MRMC data.

verbose	A logical, if TRUE, then the redundant summary is printed in R console. If FALSE, it suppresses output from this function.
print_CI_of_AUC	Logical, if TRUE then Credible intervals of AUCs for each modality are plotted.
PreciseLogLikelihood	Logical, that is TRUE or FALSE. If PreciseLogLikelihood = TRUE(default), then Stan calculates the precise log likelihood with target formulation. If PreciseLogLikelihood = FALSE, then Stan calculates the log likelihood by dropping the constant terms in the likelihood function. In past, I distinct the stan file, one is target formulation and the another is not. But non-target formulation cause some Jacobian warning, thus I made all stanfile with target formulation when I uploaded to CRAN. Thus this variable is now meaningless.
summary	Logical: TRUE of FALSE. Whether to print the verbose summary. If TRUE then verbose summary is printed in the R console. If FALSE, the output is minimal. I regret, this variable name should be verbose.
dataList.Name	This is not for user, but the author for this package development.
prior	positive integer, to select the prior
ModifiedPoisson	<p>Logical, that is TRUE or FALSE.</p> <p>If ModifiedPoisson = TRUE, then Poisson rate of false alarm is calculated <i>per lesion</i>, and model is fitted so that the FROC curve is an expected curve of points consisting of the pairs of TPF per lesion and FPF <i>per lesion</i>.</p> <p>Similarly,</p> <p>If ModifiedPoisson = TRUE, then Poisson rate of false alarm is calculated <i>per image</i>, and model is fitted so that the FROC curve is an expected curve of points consisting of the pair of TPF per lesion and FPF <i>per image</i>.</p> <p>For more details, see the author's paper in which I explained <i>per image</i> and <i>per lesion</i>. (for details of models, see vignettes, now, it is omitted from this package, because the size of vignettes are large.)</p> <p>If ModifiedPoisson = TRUE, then the <i>False Positive Fraction (FPF)</i> is defined as follows (F_c denotes the number of false alarms with confidence level c)</p>

$$\frac{F_1 + F_2 + F_3 + F_4 + F_5}{N_L},$$

$$\frac{F_2 + F_3 + F_4 + F_5}{N_L},$$

$$\frac{F_3 + F_4 + F_5}{N_L},$$

$$\frac{F_4 + F_5}{N_L},$$

$$\frac{F_5}{N_L},$$

where N_L is a number of lesions (signal). To emphasize its denominator N_L , we also call it the *False Positive Fraction (FPF) per lesion*.

On the other hand,

if ModifiedPoisson = FALSE (Default), then *False Positive Fraction (FPF)* is given by

$$\frac{F_1 + F_2 + F_3 + F_4 + F_5}{N_I},$$

$$\frac{F_2 + F_3 + F_4 + F_5}{N_I},$$

$$\frac{F_3 + F_4 + F_5}{N_I},$$

$$\frac{F_4 + F_5}{N_I},$$

$$\frac{F_5}{N_I},$$

where N_I is the number of images (trial). To emphasize its denominator N_I , we also call it the *False Positive Fraction (FPF) per image*.

The model is fitted so that the estimated FROC curve can be regarded as the expected pairs of FPF per image and TPF per lesion (ModifiedPoisson = FALSE)

or as the expected pairs of FPF per image and TPF per lesion (ModifiedPoisson = TRUE)

If ModifiedPoisson = TRUE, then FROC curve means the expected pair of FPF **per lesion** and TPF.

On the other hand, if ModifiedPoisson = FALSE, then FROC curve means the expected pair of **FPF per image** and TPF.

So, data of FPF and TPF are changed thus, a fitted model is also changed whether ModifiedPoisson = TRUE or FALSE. In traditional FROC analysis, it uses only per images (trial). Since we can divide one image into two images or more images, number of trial is not important. And more important is per signal. So, the author also developed FROC theory to consider FROC analysis under per signal. One can see that the FROC curve is rigid with respect to change of a number of images, so, it does not matter whether ModifiedPoisson = TRUE or FALSE. This rigidity of curves means that the number of images is redundant parameter for the FROC trial and thus the author try to exclude it.

Revised 2019 Dec 8 Revised 2019 Nov 25 Revised 2019 August 28

mesh.for.drawing.curve

A positive large integer, indicating number of dots drawing the curves, Default =10000.

significantLevel	This is a number between 0 and 1. The results are shown if posterior probabilities are greater than this quantity.
cha	A variable to be passed to the function <code>rstan::sampling()</code> of rstan in which it is named <code>chains</code> . A positive integer representing the number of chains generated by Hamiltonian Monte Carlo method, and, Default = 1.
war	A variable to be passed to the function <code>rstan::sampling()</code> of rstan in which it is named <code>warmup</code> . A positive integer representing the Burn in period, which must be less than <code>ite</code> . Defaults to <code>war = floor(ite/5)=10000/5=2000</code> ,
ite	A variable to be passed to the function <code>rstan::sampling()</code> of rstan in which it is named <code>iter</code> . A positive integer representing the number of samples synthesized by Hamiltonian Monte Carlo method, and, Default = 10000.
dig	A variable to be passed to the function <code>rstan::sampling()</code> of rstan in which it is named <code>...</code> ?. A positive integer representing the Significant digits, used in stan Cancellation. Default = 5,
see	A variable to be passed to the function <code>rstan::sampling()</code> of rstan in which it is named <code>seed</code> . A positive integer representing seed used in stan, Default = 1234567.
Null.Hypothesis	Logical, that is TRUE or FALSE. If <code>Null.or.Alternative.Hypothesis = FALSE</code> (default), then fit the <i>alternative model</i> to <code>dataList</code> (for details of models, see vignettes). If <code>Null.or.Alternative.Hypothesis = TRUE</code> , then fit the <i>null model</i> to <code>dataList</code> .(for details of models, see vignettes). Note that the null model is constructed under the null hypothesis that all modality are same observer performance ability. The alternative model is made under the assumption that all modality are not same. The reason why author creates this parameter is to test the null hypothesis by the Bayes factor. But the result of test is not desired one for me. Thus the test is under construction.
prototype	A logical, if TRUE then the model is no longer a generative model. Namely, in generally speaking, a dataset drawn from the model cannot satisfy the condition that the sum of the numbers of hits over all confidence levels is bounded from the above by the number of lesions, namely,

$$\sum_c H_c \leq N_L$$

However, this model (TRUE) is good in the sense that it admits various initial values of MCMC sampling.

if FALSE, then the model is precisely statistical model in the sense that any dataset drawn from the model satisfies that the sum of the number of hits is not greater than the number of lesions, namely,

$$\sum_c H_c \leq N_L.$$

This model is theoretically perfect. However, in the practically, the calculation will generates some undesired results which caused by the so-called floor I forget English :-D. The floor point??? I forgeeeeeeeeeeeet!! Ha. So, prior synthesizes very small hit rates such as 0.00000000000000001234 and it cause

the non accurate calculation such as $0.00000,,,00000123/0.000.....000012345=0.0012$ which becomes hit rate and thus OH No!. Then it synthesizes Bernoulli success rate which is not less than 1 !! To avoid this, the author should develop the theory of prior to avoid this very small numbers, however the author has idea but now it does not success.

If prototype = TRUE, then the model for hits is the following:

$$H_5 \sim \text{Binomial}(p_5, N_L)$$

$$H_4 \sim \text{Binomial}(p_4, N_L)$$

$$H_3 \sim \text{Binomial}(p_3, N_L)$$

$$H_2 \sim \text{Binomial}(p_2, N_L)$$

$$H_1 \sim \text{Binomial}(p_1, N_L)$$

On the other hand, if prototype = FALSE, then the model for hits is the following:

$$H_5 \sim \text{Binomial}(p_5, N_L)$$

$$H_4 \sim \text{Binomial}\left(\frac{p_4}{1-p_5}, N_L - H_5\right)$$

$$H_3 \sim \text{Binomial}\left(\frac{p_3}{1-p_5-p_4}, N_L - H_5 - H_4\right)$$

$$H_2 \sim \text{Binomial}\left(\frac{p_2}{1-p_5-p_4-p_3}, N_L - H_5 - H_4 - H_3\right)$$

$$H_1 \sim \text{Binomial}\left(\frac{p_1}{1-p_5-p_4-p_3-p_2}, N_L - H_5 - H_4 - H_3 - H_2\right)$$

Each number of lesions is adjusted so that the sum of hits $\sum_c H_c$ is less than the number of lesions (signals, targets) N_L . And hence the model in case of prototype = FALSE is a generative model in the sense that it can replicate datasets of FROC arises. Note that the adjustment of the number of lesions in the above manner leads us the adjustment of hit rates. The reason why we use the hit rates such as $\frac{p_2}{1-p_5-p_4-p_3}$ instead of p_c is that it ensures the equality $E[H_c/N_L] = p_c$. This equality is very important. To establish Bayesian FROC theory so that it is compatible to the classical FROC theory, we need the following two equations,

$$E[H_c/N_L] = p_c,$$

$$E[F_c/N_X] = q_c,$$

where E denotes the expectation and N_X is the number of lesion or the number of images and q_c is a false alarm rate, namely, $F_c \sim \text{Poisson}(q_c N_X)$.

Using the above two equations, we can establish the alternative Bayesian FROC theory preserving classical notions and formulas. For the details, please see the author's pre print:

Bayesian Models for ,, for?? I forget my paper title :-D. What the hell!? I forget,... My health is so bad to forget , I forget.

The author did not notice that the prototype is not a generative model. And hence the author revised the model so that the model is exactly generative model.

But the reason why the author remains the prototype model(prototype = TRUE) is that the convergence of MCMC sampling in case of MRMC is not good in the current model (prototype = FALSE) . Because it uses fractions $\frac{p_1}{1-p_5-p_4-p_3-p_2}$ and which is very dangerous to numerical perspective. For example, if p_1 is very small, then the numerator and denominator of $\frac{p_1}{1-p_5-p_4-p_3-p_2}$ is very small. Both of them is like 0.000000000000000123.... and such small number causes the non accurate results. So, sometimes, it occurs that $\frac{p_1}{1-p_5-p_4-p_3-p_2} > 1$ which never occur in the theoretical perspective but unfortunately, in numerically occurs.

SO, now, the author try to avoid such phenomenon by using priors but it now does not success.

Here of course we interpret the terms such as $N_L - H_5 - H_4 - H_3$ as the remained targets after reader get hits. The author thinks it is another manner to do so like $N_L - H_1 - H_2 - H_3$, but it does not be employed. Since the author thinks that the reader will assign his suspicious lesion location from high confidence level and in this view point the author thinks it should be considered that targets are found from the highest confidence suspicious location.

model_reparametrized

A logical, if TRUE, then a model under construction is used.

Model_MRMC_non_hierarchical

A logical. If TRUE, then the model of multiple readers and multiple modalities consists of no hyper parameters. The reason why the author made this parameter is that the hyper parameter make the MCMC posterior samples be unstable. And also, my hierarachical model is not so good in theoretical perspective. Thus, I made this. The Default is TRUE.

zz

A real number specifying one of the parameter of prior

...

Additional arguments

fit_MRMC_versionTWO *Fit and Draw the FROC models (curves) version2.*

Description

Fit and Draw the FROC models (curves). This model is aimed to draw a free-response ROC curves for multiple readers and a single modality.

Usage

```
fit_MRMC_versionTWO(
  dataList,
  DrawFROCcurve = TRUE,
```

```

DrawCFPCTP = TRUE,
version = 2,
mesh.for.drawing.curve = 10000,
significantLevel = 0.7,
cha = 1,
war = floor(ite/5),
ite = 10000,
dig = 5,
see = 1234569
)

```

Arguments

dataList A list, specifying an FROC data to be fitted a model. It consists of data of numbers of TPs, FPs, lesions, images. In addition, if in case of mutiple readers or mutiple modalities, then modaity ID and reader ID are included also.

The **dataList** will be passed to the function `rstan::sampling()` of **rstan**. This is a variable in the function `rstan::sampling()` in which it is named **data**.

For the single reader and a single modality data, the **dataList** is made by the following manner:

```

dataList.Example <-list(
h = c(41,22,14,8,1),# number of hits for each confidence level
f = c(1,2,5,11,13),# number of false alarms for each confidence level

NL = 124,# number of lesions (signals)
NI = 63,# number of images (trials)
C = 5) # number of confidence,.. the author thinks it can be calculated
as the length of h or f ...? ha,why I included this. ha .. should be omitted.

```

Using this object **dataList.Example**, we can apply `fit_Bayesian_FROC()` such as `fit_Bayesian_FROC(dataList.Example)`.

To make this R object **dataList** representing FROC data, this package provides three functions:

- `convertFromJafroc()` If data is a **JAFROC xlsx** formulation.
- `dataset_creator_new_version()` Enter TP and FP data **by table** .
- `create_dataset()` Enter TP and FP data by **interactive** manner.

Before fitting a model, we can confirm our dataset is correctly formulated by using the function `viewdata()`.

A Single reader and a single modality (SRSC) case.

In a single reader and a single modality case (srsc), **dataList** is a list consisting of **f,h,NL,NI,C** where **f,h** are numeric vectors and **NL,NI,C** are positive integers.

- f Non-negative integer vector specifying number of false alarms associated with each confidence level. The first component corresponding to the highest confidence level.
- h Non-negative integer vector specifying number of Hits associated with each confidence level. The first component corresponding to the highest confidence level.
- NL A positive integer, representing Number of Lesions.
- NI A positive integer, representing Number of Images.
- C A positive integer, representing Number of Confidence level.

The detail of these dataset, see the datasets endowed with this package. 'Note that the maximal number of confidence level, denoted by C, are included, however, Note that confidence level vector c should not be specified. If specified, will be ignored, since it is created by $c \leftarrow c(\text{rep}(C:1))$ in the program and do not refer from user input data, where C is the highest number of confidence levels. So, you should write down your hits and false alarms vector so that it is compatible with this automatically created c vector.

data Format:

A single reader and a single modality case

NI=63, NL=124 In R console ->	confidence level c	No. of false alarms f	No. of hits h
definitely present	$c[1] = 5$	$f[1] = F_5 = 1$	$h[1] = H_5 = 41$
probably present	$c[2] = 4$	$f[2] = F_4 = 2$	$h[2] = H_4 = 22$
equivocal	$c[3] = 3$	$f[3] = F_3 = 5$	$h[3] = H_3 = 14$
subtle	$c[4] = 2$	$f[4] = F_2 = 11$	$h[4] = H_2 = 8$
very subtle	$c[5] = 1$	$f[5] = F_1 = 13$	$h[5] = H_1 = 1$

* *false alarms* = False Positives = FP

* *hits* = True Positives = TP

Note that in FROC data, all confidence level means *present (diseased, lesion)* case only, no confidence level indicating absent. Since each reader marks his suspicious location only if he thinks lesions are *present*, and marked positions generates the hits or false alarms, *thus* each confidence level represents that lesion is *present*. In the absent case, reader dose not mark any locations and hence, the absent confidence level does not relate this dataset. So, if reader think it is no lesion, then in such case confidence level is not needed.

Note that the first column of confidence level vector c should not be specified. If specified, will be ignored, since it is created by $c \leftarrow c(\text{rep}(C:1))$ automatically in the program and do not refer from user input data even if it is specified explicitly, where C is the highest number of confidence levels. So you

should check the compatibility of your data and the confidence level vector `c` `<-c(rep(C:1))` via a table which can be displayed by the function `viewdata()`.

Multiple readers and multiple modalities case, i.e., MRMC case

In case of multiple readers and multiple modalities, i.e., MRMC case, in order to apply the function `fit_Bayesian_FROC()`, dataset represented by an R list object representing FROC data must contain components `m`, `q`, `c`, `h`, `f`, `NL`, `C`, `M`, `Q`.

- `C` A positive integer, representing the **highest** number of confidence level, this is a scalar.
- `M` A positive integer vector, representing the number of **modalities**.
- `Q` A positive integer, representing the number of **readers**.
- `m` A vector of positive integers, representing the **modality ID** vector.
- `q` A vector of positive integers, representing the **reader ID** vector.
- `c` A vector of positive integers, representing the **confidence level**. This vector must be made by `rep(rep(C:1), M*Q)`
- `h` A vector of non-negative integers, representing the number of **hits**.
- `f` A vector of non-negative integers, representing the number of **false alarms**.
- `NL` A positive integer, representing the Total number of **lesions** for all images, this is a scalar.

Note that the maximal number of confidence level (denoted by `C`) are included in the above R object. However, each confidence level vector is not included in the data, because it is created automatically from `C`. To confirm false positives and hits are correctly ordered with respect to the automatically generated confidence vector,

the function `viewdata()` shows the table. Revised 2019 Nov 27 Revised 2019 Dec 5

Example data.

Multiple readers and multiple modalities (i.e., MRMC)

Modality ID	Reader ID	Confidence levels	No. of false alarms	No. of hits.
<code>m</code>	<code>q</code>	<code>c</code>	<code>f</code>	<code>h</code>
1	1	3	20	111
1	1	2	29	55
1	1	1	21	22
1	2	3	6	100
1	2	2	15	44
1	2	1	22	11
2	1	3	6	66
2	1	2	24	55
2	1	1	23	1
2	2	3	5	66
2	2	2	30	55

2 2 1 40 44

	<p>—</p> <p>* <i>false alarms</i> = False Positives = FP</p> <p>* <i>hits</i> = True Positives = TP</p>
DrawFROCcurve	Logical: TRUE of FALSE. Whether the FROC curve is to be drawn.
DrawCFPCTP	Logical: TRUE of FALSE. Whether the CFP and CTP points are to be drawn. CFP: Cumulative false positive per lesion (or image) which is also called False Positive Fraction (FPF). CTP Cumulative True Positive per lesion which is also called True Positive Fraction (TPF)..
version	2 or 3
mesh.for.drawing.curve	A positive large integer, indicating number of dots drawing the curves, Default =10000.
significantLevel	This is a number between 0 and 1. The results are shown if posterior probabilities are greater than this quantity.
cha	A variable to be passed to the function <code>rstan::sampling()</code> of rstan in which it is named chains. A positive integer representing the number of chains generated by Hamiltonian Monte Carlo method, and, Default = 1.
war	A variable to be passed to the function <code>rstan::sampling()</code> of rstan in which it is named warmup. A positive integer representing the Burn in period, which must be less than ite. Defaults to <code>war = floor(ite/5)=10000/5=2000</code> ,
ite	A variable to be passed to the function <code>rstan::sampling()</code> of rstan in which it is named iter. A positive integer representing the number of samples synthesized by Hamiltonian Monte Carlo method, and, Default = 10000.
dig	A variable to be passed to the function <code>rstan::sampling()</code> of rstan in which it is named <code>...??</code> . A positive integer representing the Significant digits, used in stan Cancellation. Default = 5,
see	A variable to be passed to the function <code>rstan::sampling()</code> of rstan in which it is named seed. A positive integer representing seed used in stan, Default = 1234567.

See Also

Example data:

`BayesianFROC::dataList.one.modality`

This dataset is a single modality dataset with multiple readers.

Examples

```
## Not run:
```

```
#####The first example#####
#(1)First, we prepare the data from this package.

    dat <- BayesianFROC::dataList.one.modality

#(2)Second, we run fit_Bayesian_FROC() in which the rstan::stan() is implemented.
#with data named "dat" and the author's Bayesian model.

#       fit <- fit_MRMC_versionTWO(dat,see = 12,ite=111)

#       It needs a lot of memory and so, in this example we take the small iteration,
#       i.e., ite =2222. However if user execute this, then the ite =30000 is recommended
#       for getting reliable estimates.

#Note that we change the seed from default to 12 to get a convergence model.
#If users encounter the convergence issues,
#then please consider changing the seed like this example.

#The resulting FROC curve means the summarizing curve over all readers

#####The Second example#####
#(1)First, we prepare the data from this package.

    dat <- BayesianFROC::dataList.Chakra.Web

#(2)Second, we run fit_Bayesian_FROC() in which the rstan::stan() is implemented.
#with data named "dat" and the author's Bayesian model.

#       fit <- fit_MRMC_versionTWO(dataList.Chakra.Web ,ite=111)

#The resulting FROC curve means the summarizing curve over all readers

#       It needs a lot of memory and so, in this example we take the small iteration,
#       i.e., ite =2222. However if user execute this, then the ite =30000 is recommended
#       for getting reliable estimates.
```

```

###      Close the graphic device to avoid errors in R CMD check.

if (!grDevices::dev.cur()>=2) {

  for (i in 1:grDevices::dev.cur()-1) {message("The",i,"-th graphic device is omitted.")
    grDevices::dev.off()
  }
}

## End(Not run)#\dontrun

```

```

fit_Null_hypothesis_model_to_
      Fit the null model

```

Description

Fit the null model, representing the null hypothesis that all modalities are same.

Usage

```

fit_Null_hypothesis_model_to_(
  dataList,
  DrawCurve = FALSE,
  PreciseLogLikelihood = FALSE,
  dataList.Name = "",
  ModifiedPoisson = FALSE,
  verbose = TRUE,
  summary = TRUE,
  mesh.for.drawing.curve = 10000,
  significantLevel = 0.7,
  cha = 1,
  war = floor(ite/5),
  ite = 10000,
  dig = 3,
  see = 1234569,
  ...
)

```

Arguments

dataList A list, to be fitted a model. For example, in case of a single reader and a single modality, it consists of f, h, NL, NI, C . The detail of these dataset, see the example data-sets. Note that the maximal number of confidence level, denoted by C , are included, however, should not include its each confidence level in `dataList`

- DrawCurve Logical: TRUE or FALSE. Whether the curve is to be drawn. TRUE or FALSE. If you want to draw the FROC and AFROC curves, then you set DrawCurve =TRUE, if not then DrawCurve =FALSE. The reason why the author make this variable DrawCurve is that it takes long time in MRMC case to draw curves, and thus Default value is FALSE in the case of MRMC data.
- PreciseLogLikelihood Logical, that is TRUE or FALSE. If PreciseLogLikelihood = TRUE(default), then Stan calculates the precise log likelihood with target formulation. If PreciseLogLikelihood = FALSE, then Stan calculates the log likelihood by dropping the constant terms in the likelihood function. In past, I distinct the stan file, one is target formulation and the another is not. But non-target formulation cause some Jacobian warning, thus I made all stanfile with target formulation when I uploaded to CRAN. Thus this variable is now meaningless.
- dataList.Name This is not for user, but the author for this package development.
- ModifiedPoisson

Logical, that is TRUE or FALSE.

If ModifiedPoisson = TRUE, then Poisson rate of false alarm is calculated *per lesion*, and model is fitted so that the FROC curve is an expected curve of points consisting of the pairs of TPF per lesion and FPF *per lesion*.

Similarly,

If ModifiedPoisson = TRUE, then Poisson rate of false alarm is calculated *per image*, and model is fitted so that the FROC curve is an expected curve of points consisting of the pair of TPF per lesion and FPF *per image*.

For more details, see the author's paper in which I explained *per image* and *per lesion*. (for details of models, see *vignettes*, now, it is omitted from this package, because the size of vignettes are large.)

If ModifiedPoisson = TRUE, then the *False Positive Fraction (FPF)* is defined as follows (F_c denotes the number of false alarms with confidence level c)

$$\frac{F_1 + F_2 + F_3 + F_4 + F_5}{N_L},$$

$$\frac{F_2 + F_3 + F_4 + F_5}{N_L},$$

$$\frac{F_3 + F_4 + F_5}{N_L},$$

$$\frac{F_4 + F_5}{N_L},$$

$$\frac{F_5}{N_L},$$

where N_L is a number of lesions (signal). To emphasize its denominator N_L , we also call it the *False Positive Fraction (FPF) per lesion*.

On the other hand,

if `ModifiedPoisson = FALSE` (Default), then *False Positive Fraction (FPF)* is given by

$$\frac{F_1 + F_2 + F_3 + F_4 + F_5}{N_I},$$

$$\frac{F_2 + F_3 + F_4 + F_5}{N_I},$$

$$\frac{F_3 + F_4 + F_5}{N_I},$$

$$\frac{F_4 + F_5}{N_I},$$

$$\frac{F_5}{N_I},$$

where N_I is the number of images (trial). To emphasize its denominator N_I , we also call it the *False Positive Fraction (FPF) per image*.

The model is fitted so that the estimated FROC curve can be regarded as the expected pairs of FPF per image and TPF per lesion (`ModifiedPoisson = FALSE`)

or as the expected pairs of FPF per image and TPF per lesion (`ModifiedPoisson = TRUE`)

If `ModifiedPoisson = TRUE`, then FROC curve means the expected pair of **FPF per lesion** and TPF.

On the other hand, if `ModifiedPoisson = FALSE`, then FROC curve means the expected pair of **FPF per image** and TPF.

So, data of FPF and TPF are changed thus, a fitted model is also changed whether `ModifiedPoisson = TRUE` or `FALSE`. In traditional FROC analysis, it uses only per images (trial). Since we can divide one image into two images or more images, number of trial is not important. And more important is per signal. So, the author also developed FROC theory to consider FROC analysis under per signal. One can see that the FROC curve is rigid with respect to change of a number of images, so, it does not matter whether `ModifiedPoisson = TRUE` or `FALSE`. This rigidity of curves means that the number of images is redundant parameter for the FROC trial and thus the author try to exclude it.

Revised 2019 Dec 8 Revised 2019 Nov 25 Revised 2019 August 28

verbose	A logical, if <code>TRUE</code> , then the redundant summary is printed in R console. If <code>FALSE</code> , it suppresses output from this function.
summary	Logical: <code>TRUE</code> or <code>FALSE</code> . Whether to print the verbose summary. If <code>TRUE</code> then verbose summary is printed in the R console. If <code>FALSE</code> , the output is minimal. I regret, this variable name should be verbose.

mesh.for.drawing.curve	A positive large integer, indicating number of dots drawing the curves, Default =10000.
significantLevel	This is a number between 0 and 1. The results are shown if posterior probabilities are greater than this quantity.
cha	A variable to be passed to the function <code>rstan::sampling()</code> of rstan in which it is named chains. A positive integer representing the number of chains generated by Hamiltonian Monte Carlo method, and, Default = 1.
war	A variable to be passed to the function <code>rstan::sampling()</code> of rstan in which it is named warmup. A positive integer representing the Burn in period, which must be less than ite. Defaults to <code>war = floor(ite/5)=10000/5=2000</code> ,
ite	A variable to be passed to the function <code>rstan::sampling()</code> of rstan in which it is named iter. A positive integer representing the number of samples synthesized by Hamiltonian Monte Carlo method, and, Default = 10000.
dig	A variable to be passed to the function <code>rstan::sampling()</code> of rstan in which it is named <code>...</code> ?. A positive integer representing the Significant digits, used in stan Cancellation. Default = 5,
see	A variable to be passed to the function <code>rstan::sampling()</code> of rstan in which it is named seed. A positive integer representing seed used in stan, Default = 1234567.
...	Additional arguments

fit_ssrc	<i>fit a model to data in the case of A Single reader and A Single modality (src).</i>
----------	--

Description

Build a *fitted model object* in case of **single reader and single modality** data `dataList`. FPF is **per image**.

Usage

```
fit_ssrc(
  dataList,
  prior = -1,
  new.imaging.device = TRUE,
  dataList.Name = "",
  ModifiedPoisson = FALSE,
  model_reparametrized = FALSE,
  verbose = TRUE,
  multinomial = FALSE,
  DrawCurve = TRUE,
  PreciseLogLikelihood = TRUE,
```

```

Drawcol = TRUE,
make.csv.file.to.draw.curve = FALSE,
mesh.for.drawing.curve = 10000,
summary = TRUE,
DrawFROCcurve = TRUE,
DrawAFROCcurve = FALSE,
DrawCFPCTP = TRUE,
cha = 4,
ite = 3000,
dig = 5,
war = floor(ite/5),
see = 1234,
prototype = FALSE,
zz = 2.55,
...
)

```

Arguments

- dataList** A list, to be fitted a model. For example, in case of a single reader and a single modality, it consists of f, h, NL, NI, C . The detail of these dataset, see the example data-sets. Note that the maximal number of confidence level, denoted by C , are included, however, should not include its each confidence level in `dataList`
- prior** positive integer, to select the prior
- new.imaging.device** Logical: TRUE or FALSE. If TRUE (default), then open a new device to draw curve. Using this we can draw curves in same plain by `new.imaging.device=FALSE`.
- dataList.Name** This is not for user, but the author for this package development.
- ModifiedPoisson** Logical, that is TRUE or FALSE.
 If `ModifiedPoisson = TRUE`, then Poisson rate of false alarm is calculated *per lesion*, and model is fitted so that the FROC curve is an expected curve of points consisting of the pairs of TPF per lesion and FPF *per lesion*.
 Similarly,
 If `ModifiedPoisson = TRUE`, then Poisson rate of false alarm is calculated *per image*, and model is fitted so that the FROC curve is an expected curve of points consisting of the pair of TPF per lesion and FPF *per image*.
 For more details, see the author's paper in which I explained *per image* and *per lesion*. (for details of models, see [vignettes](#), now, it is omitted from this package, because the size of vignettes are large.)
 If `ModifiedPoisson = TRUE`, then the *False Positive Fraction (FPF)* is defined as follows (F_c denotes the number of false alarms with confidence level c)

$$\frac{F_1 + F_2 + F_3 + F_4 + F_5}{N_L},$$

$$\frac{F_2 + F_3 + F_4 + F_5}{N_L},$$

$$\frac{F_3 + F_4 + F_5}{N_L},$$

$$\frac{F_4 + F_5}{N_L},$$

$$\frac{F_5}{N_L},$$

where N_L is a number of lesions (signal). To emphasize its denominator N_L , we also call it the *False Positive Fraction (FPF) per lesion*.

On the other hand,

if ModifiedPoisson = FALSE (Default), then *False Positive Fraction (FPF)* is given by

$$\frac{F_1 + F_2 + F_3 + F_4 + F_5}{N_I},$$

$$\frac{F_2 + F_3 + F_4 + F_5}{N_I},$$

$$\frac{F_3 + F_4 + F_5}{N_I},$$

$$\frac{F_4 + F_5}{N_I},$$

$$\frac{F_5}{N_I},$$

where N_I is the number of images (trial). To emphasize its denominator N_I , we also call it the *False Positive Fraction (FPF) per image*.

The model is fitted so that the estimated FROC curve can be regarded as the expected pairs of FPF per image and TPF per lesion (ModifiedPoisson = FALSE)

or as the expected pairs of FPF per image and TPF per lesion (ModifiedPoisson = TRUE)

If ModifiedPoisson = TRUE, then FROC curve means the expected pair of FPF **per lesion** and TPF.

On the other hand, if ModifiedPoisson = FALSE, then FROC curve means the expected pair of **FPF per image** and TPF.

So, data of FPF and TPF are changed thus, a fitted model is also changed whether ModifiedPoisson = TRUE or FALSE. In traditional FROC analysis, it uses only

per images (trial). Since we can divide one image into two images or more images, number of trial is not important. And more important is per signal. So, the author also developed FROC theory to consider FROC analysis under per signal. One can see that the FROC curve is rigid with respect to change of a number of images, so, it does not matter whether ModifiedPoisson = TRUE or FALSE. This rigidity of curves means that the number of images is redundant parameter for the FROC trial and thus the author try to exclude it.

Revised 2019 Dec 8 Revised 2019 Nov 25 Revised 2019 August 28

model_reparametrized	A logical, if TRUE, then a model under construction is used.
verbose	A logical, if TRUE, then the redundant summary is printed in R console. If FALSE, it suppresses output from this function.
multinomial	A logical, if TRUE then model is the most classical one using multinomial distribution.
DrawCurve	Logical: TRUE or FALSE. Whether the curve is to be drawn. TRUE or FALSE. If you want to draw the FROC and AFROC curves, then you set DrawCurve =TRUE, if not then DrawCurve =FALSE. The reason why the author make this variable DrawCurve is that it takes long time in MRMC case to draw curves, and thus Default value is FALSE in the case of MRMC data.
PreciseLogLikelihood	Logical, that is TRUE or FALSE. If PreciseLogLikelihood = TRUE(default), then Stan calculates the precise log likelihood with target formulation. If PreciseLogLikelihood = FALSE, then Stan calculates the log likelihood by dropping the constant terms in the likelihood function. In past, I distinct the stan file, one is target formulation and the another is not. But non-target formulation cause some Jacobian warning, thus I made all stanfile with target formulation when I uploaded to CRAN. Thus this variable is now meaningless.
Drawcol	Logical: TRUE or FALSE. Whether the (A)FROC curve is to be drawn by using color of dark theme. The Default value is a TRUE.
make.csv.file.to.draw.curve	Logical: TRUE or FALSE. Whether to create a csv file. If TRUE then csv file is created in your desktop to draw an FROC curve and cumulative hits and false alarms by scatter plot. Default is FALSE since it took times to create csv files.
mesh.for.drawing.curve	A positive large integer, indicating number of dots drawing the curves, Default =10000.
summary	Logical: TRUE or FALSE. Whether to print the verbose summary. If TRUE then verbose summary is printed in the R console. If FALSE, the output is minimal. I regret, this variable name should be verbose.
DrawFROCcurve	Logical: TRUE or FALSE. Whether the FROC curve is to be drawn.
DrawAFROCcurve	Logical: TRUE or FALSE. Whether the AFROC curve is to be drawn.
DrawCFPCTP	Logical: TRUE or FALSE. Whether the CFP and CTP points are to be drawn. CFP: Cumulative false positive per lesion (or image) which is also called False Positive Fraction (FPF). CTP Cumulative True Positive per lesion which is also called True Positive Fraction (TPF)..

cha	A variable to be passed to the function <code>rstan::sampling()</code> of rstan in which it is named <code>chains</code> . A positive integer representing the number of chains generated by Hamiltonian Monte Carlo method, and, Default = 1.
ite	A variable to be passed to the function <code>rstan::sampling()</code> of rstan in which it is named <code>iter</code> . A positive integer representing the number of samples synthesized by Hamiltonian Monte Carlo method, and, Default = 10000.
dig	A variable to be passed to the function <code>rstan::sampling()</code> of rstan in which it is named <code>...</code> ?. A positive integer representing the Significant digits, used in stan Cancellation. Default = 5,
war	A variable to be passed to the function <code>rstan::sampling()</code> of rstan in which it is named <code>warmup</code> . A positive integer representing the Burn in period, which must be less than <code>ite</code> . Defaults to <code>war = floor(ite/5)=10000/5=2000</code> ,
see	A variable to be passed to the function <code>rstan::sampling()</code> of rstan in which it is named <code>seed</code> . A positive integer representing seed used in stan, Default = 1234567.
prototype	A logical, if TRUE then the model is no longer a generative model. Namely, in generally speaking, a dataset drawn from the model cannot satisfy the condition that the sum of the numbers of hits over all confidence levels is bounded from the above by the number of lesions, namely,

$$\sum_c H_c \leq N_L$$

However, this model (TRUE) is good in the sense that it admits various initial values of MCMC sampling.

if FALSE, then the model is precisely statistical model in the sense that any dataset drawn from the model satisfies that the sum of the number of hits is not greater than the number of lesions, namely,

$$\sum_c H_c \leq N_L.$$

This model is theoretically perfect. However, in the practically, the calculation will generates some undesired results which caused by the so-called floo I forget English :-D. The flood point??? I forgeeeeeeeeeeeet!! Ha. So, prior synthesizes very small hit rates such as 0.0000000000000001234 and it cause the non accurate calculation such as 0.00000,,,00000123/0.000.....000012345= 0.0012 which becomes hit rate and thus OH No!. Then it synthesizes Bernoulli success rate which is not less than 1 !! To avoid this, the author should develop the theory of prior to avoid this very small numbers, however the author has idea but now it does not success.

If `prototype = TRUE`, then the model for hits is the following:

$$H_5 \sim \text{Binomial}(p_5, N_L)$$

$$H_4 \sim \text{Binomial}(p_4, N_L)$$

$$H_3 \sim \text{Binomial}(p_3, N_L)$$

$$H_2 \sim \text{Binomial}(p_2, N_L)$$

$$H_1 \sim \text{Binomial}(p_1, N_L)$$

On the other hand, if `prototype = FALSE`, then the model for hits is the following:

$$H_5 \sim \text{Binomial}(p_5, N_L)$$

$$H_4 \sim \text{Binomial}\left(\frac{p_4}{1 - p_5}, N_L - H_5\right)$$

$$H_3 \sim \text{Binomial}\left(\frac{p_3}{1 - p_5 - p_4}, N_L - H_5 - H_4\right)$$

$$H_2 \sim \text{Binomial}\left(\frac{p_2}{1 - p_5 - p_4 - p_3}, N_L - H_5 - H_4 - H_3\right)$$

$$H_1 \sim \text{Binomial}\left(\frac{p_1}{1 - p_5 - p_4 - p_3 - p_2}, N_L - H_5 - H_4 - H_3 - H_2\right)$$

Each number of lesions is adjusted so that the sum of hits $\sum_c H_c$ is less than the number of lesions (signals, targets) N_L . And hence the model in case of `prototype = FALSE` is a generative model in the sense that it can replicate datasets of FROC arises. Note that the adjustment of the number of lesions in the above manner leads us the adjustment of hit rates. The reason why we use the hit rates such as $\frac{p_2}{1 - p_5 - p_4 - p_3}$ instead of p_c is that it ensures the equality $E[H_c/N_L] = p_c$. This equality is very important. To establish Bayesian FROC theory so that it is compatible to the classical FROC theory, we need the following two equations,

$$E[H_c/N_L] = p_c,$$

$$E[F_c/N_X] = q_c,$$

where E denotes the expectation and N_X is the number of lesion or the number of images and q_c is a false alarm rate, namely, $F_c \sim \text{Poisson}(q_c N_X)$.

Using the above two equations, we can establish the alternative Bayesian FROC theory preserving classical notions and formulas. For the details, please see the author's pre print:

Bayesian Models for ,, for?? I forget my paper title :-D. What the hell!? I forget,... My health is so bad to forget , I forget.

The author did not notice that the `prototype` is not a generative model. And hence the author revised the model so that the model is exactly generative model.

But the reason why the author remains the `prototype` model(`prototype = TRUE`) is that the convergence of MCMC sampling in case of MRMC is not good in the current model (`prototype = FALSE`) . Because it uses fractions $\frac{p_1}{1 - p_5 - p_4 - p_3 - p_2}$ and which is very dangerous to numerical perspective. For example, if p_1 is very small, then the numerator and denominator of $\frac{p_1}{1 - p_5 - p_4 - p_3 - p_2}$ is very small. Both of them is like 0.000000000000000123.... and such small number causes the non accurate results. So, sometimes, it occurs that $\frac{p_1}{1 - p_5 - p_4 - p_3 - p_2} > 1$ which never occur in the theoretical perspective but unfortunately, in numerically occurs.

SO, now, the author try to avoid such phenomenon by using priors but it now does not success.

Here of course we interpret the terms such as $N_L - H_5 - H_4 - H_3$ as the remained targets after reader get hits. The author thinks it is another manner to do so like $N_L - H_1 - H_2 - H_3$, but it does not be employed. Since the author thinks that the reader will assign his suspicious lesion location from high confidence level and in this view point the author thinks it should be considered that targets are found from the highest confidence suspicious location.

zz A real number specifying one of the parameter of prior
 ... Additional arguments

Details

Revised 2019.Jun. 17

Value

An S4 object of class stanfitExtended, which is an inherited S4 class from stanfit.

To change the S4 class, use

Examples

```
## Not run:
#First, prepare the example data from this package.
```

```
dat <- get(data("dataList.Chakra.1"))
```

```
#Second, fit a model to data named "dat"
```

```
fit <- fit_srsc(dat)
```

```
#        Close the graphic device to avoid errors in R CMD check.
```

```
Close_all_graphic_devices()
```

```
## End(Not run)# doctest
```

flatnames *from rstan package*

Description

from rstan package

Usage

```
flatnames(names, dims, col_major = FALSE)
```

Arguments

names	A vector of characters
dims	A positive integer
col_major	A logical

Value

A vector of characters

Author(s)

Some Stan developer, I am not sure,...., who?

Examples

```
flatnames(c("a", "b"), 3)
# [1] "a[1]" "a[2]" "a[3]" "b[1]" "b[2]" "b[3]"
```

flat_one_par	<i>Makes array names</i>
--------------	--------------------------

Description

Makes array names

Usage

```
flat_one_par(n, d, col_major = FALSE)
```

Arguments

n	A character, n is an abbreviation of name
d	A vector of integers, to be passed to seq_array_ind()
col_major	A logical, to be passed to seq_array_ind()

Value

a vector of characters

Author(s)

Some Stan developer, I am not sure,...., who?

Examples

```
a<-flat_one_par("a",1:3)

# > a
# [1] "a[1,1,1]" "a[1,1,2]" "a[1,1,3]" "a[1,2,1]" "a[1,2,2]" "a[1,2,3]"
```

foo	<i>without double quote</i>
-----	-----------------------------

Description

wati

Usage

```
foo(X)
```

Arguments

X	sequence of
---	-------------

 fooo

*taboo or***Description**

wait

Usage

fooo()

 foo_of_a_List_of_Arrays

*Variance of a List of Arrays***Description**

Then the function calculates the variance over all list for each array component.

Usage

foo_of_a_List_of_Arrays(x, name.of.function)

Arguments

x A List of Arrays. The dimension of array is fixed for all list component.

name.of.function

This is an operator, such as mean, var, sum,... Note that user no need to surround the input by "". For example, mean instead of "mean".

Details

Of course variance can change to sum or mean or any other functions whose entry is a vector. One can find this function in the Stack over flow, since I ask there, and thus the example given in here can also find also there. In my hierarchical Bayesian Model, the estimates has the format arrays. For example the hit rate are array whose subscript is confidence level, modality, and reader. So, when one desire to validate the estimates, it needs to calculate such variance of arrays. When I validate the estimates, I used the function.

Value

An array being reduced form use input list of array via user input operator such as mean, var, sum,...

Examples

```
#Suppose that x is the following list of arrays:

a <- array(1,c(2,3,4));
b <- array(2,c(2,3,4));
c <- array(3,c(2,3,4));
d <- array(4,c(2,3,4));
x <- list(a=a,b=b,c=c,d=d)

foo_of_a_List_of_Arrays(x,sum)
foo_of_a_List_of_Arrays(x,mean)
foo_of_a_List_of_Arrays(x,stats::var)

#Note that the component of list can be vectors with fixed same length.

y <- list(c(1,2,3),
          c(11,22,33),
          c(1111,2222,3333))

a <- foo_of_a_List_of_Arrays(y,sum)
```

FROC_curve

FROC curve as an embedding map

Description

FROC curve as an embedding map

Usage

```
FROC_curve(x)
```

Arguments

x A real number moves in domain of FROC curve

Value

none

Examples

```
# I love you!
```

```
from_array_to_vector Transform from an array to a vector
```

Description

Transform a vector into an array

Usage

```
from_array_to_vector(Three.dim.array)
```

Arguments

Three.dim.array

Three dimensional array, such as the number of hits for each confidence level, modality and reader. Or false alarms. Since the author construct the substituting data list as one dimensional (one index) array, it needs to reconstruct to the three indexed array from one dimensional array whose subscript is [confidence level, modality, reader] or vice versa.

Details

In stan files of this package, the number of hits, false alarms and hit rates in binomial assumption for MRMC case are written with **the three indexed array** format. Three index indicates confidence levels, modality ID, reader ID. However, hit data passed to the function `BayesianFROC::fit_Bayesian_FROC()` are written with **the vector**. So, in order to connect these different format, (i.e. vector and array,) the author made this function.

Value

A vector, transformed from three dimensional array.

Examples

```
## Not run:
#=====
#           Practical example
#=====

h.array.etc <- hits_from_thresholds()
h.array.etc$h
```

```

h.vector      <- from_array_to_vector(h.array.etc$h)
h.vector

#=====
#           Educational example 1
#=====

a <- array_easy_example()
a
a.vector <- from_array_to_vector(a)
a.vector

#=====
#           Educational example 2
#=====

a <- array_easy_example(2,3,2)
a
a.vector <- from_array_to_vector(a)
a.vector

# Revised 2019 August 20
# Revised 2020 Jan

## End(Not run)

```

```

get_posterior_variance
      Alternative of rstan::get_posterior_mean()

```

Description

This function is underconstruction. I validate only the example of this function. For MRMC case, I have to write or modify code. 2019 Sept 6

Usage

```
get_posterior_variance(StanS4class, name.of.parameter)
```

Arguments

StanS4class An S4 object of class `stanfitExtended` which is an inherited class from the S4 class `stanfit`. This R object is a fitted model object as a return value of the function `fit_Bayesian_FROC()`.
It can be passed to `DrawCurves()`, `ppp()` and ... etc

name.of.parameter

An parameter name (given as a character string, should not surround by ""). The name of parameter which user want to extract. Parameters are contained in the parameter block of each Stan file in the path: inst/extdata.

Value

variance or posterior parameters, if it is an array, then return is also an array.

Examples

```
## Not run:

fit <- fit_Bayesian_FROC(BayesianFROC::dd,ite = 111)

e <- rstan::extract(fit)

# Check the retrun value is the desired one.

# apply(e$z, 2, var) == get_posterior_variance(fit,z)
# apply(e$mu, c(2,3), var) == get_posterior_variance(fit,mu)
# apply(e$v, c(2,3), var) == get_posterior_variance(fit,v)
# apply(e$ppp, c(2,3,4), var) == get_posterior_variance(fit,ppp)

#This code is OK, but R CMD check might say error cuz the object
# z, mu, v, ppp is not found

# apply(e$z, 2, var) == get_posterior_variance(fit,"z")
# apply(e$mu, c(2,3), var) == get_posterior_variance(fit,"mu")
# apply(e$v, c(2,3), var) == get_posterior_variance(fit,"v")
# apply(e$ppp, c(2,3,4), var) == get_posterior_variance(fit,"ppp")

## End(Not run)#dontrun
```

```
get_samples_from_Posterior_Predictive_distribution
      Synthesizes Samples from Predictive Posterior Distributions (PPD).
```

Description

Synthesizes samples from posterior predictive distributions.

Usage

```
get_samples_from_Posterior_Predictive_distribution(
  StanS4class,
  counter.plot.via.schatter.plot = TRUE,
  new.imaging.device = TRUE,
  upper_x,
  upper_y,
  Colour = TRUE,
  plot.replicated.points = TRUE
)
```

Arguments

StanS4class	An S4 object of class <code>stanfitExtended</code> which is an inherited class from the S4 class <code>stanfit</code> . This R object is a fitted model object as a return value of the function <code>fit_Bayesian_FROC()</code> . It can be passed to <code>DrawCurves()</code> , <code>ppp()</code> and ... etc
counter.plot.via.schatter.plot	Logical: TRUE of FALSE. Whether counter plot via schatter plot is drawn, Default = TRUE.
new.imaging.device	Logical: TRUE of FALSE. If TRUE (default), then open a new device to draw curve. Using this we can draw curves in same plain by <code>new.imaging.device=FALSE</code> .
upper_x	This is a upper bound for the axis of the horisontal coordinate of FROC curve.
upper_y	This is a upper bound for the axis of the vertical coordinate of FROC curve.
Colour	Logical: TRUE of FALSE. whether Colour of curves is dark theme or not.
plot.replicated.points	TRUE or FALSE. If true, then plot replicated points (hits, false alarms) by the scatter plot. This process will takes a long times. So if user has no time, then FALSE will help you.

Details

This methods to draw from the PPD is described in Gelman book, Bayesian Data Analysis. The aim of this function is to evaluate the chi square test statistics as a Bayesian sense. According to Gelman book, the chi square test need the samples from the PPD. So, we use this function to accomplish this task.

Value

A list of datalists from the posterior predictive distribution

Examples

```
## Not run:
```

```
fit <- fit_Bayesian_FROC(
  ite = 1111,
  summary = FALSE ,
  dataList = BayesianFROC::dataList.Chakra.1 )
```

```
##### The first example #####
TPs.FPs <- get_samples_from_Posterior_Predictive_distribution(fit)
```

```
##### The Second Example: Short cut #####
# If user has no time, then plot.replicated.points=FALSE will help you.
# By setting FALSE, the replicated data from the posterior predictive
# distribution does not draw, and hence the running time of function become shorter.
```

```
TPs.FPs <- get_samples_from_Posterior_Predictive_distribution(fit,
  plot.replicated.points = FALSE)
```

```
# Close the graphic device to avoid errors in R CMD check.
```

```
grDevices::dev.new();plot(stats::runif(100),stats::runif(100))
```

```
#####The third example: From Hand made data to fitting #####
# To draw the scatter plots of hits and false alarms synthesized from the posterior
# predictive distribution for the submission to a journal,
# then the colored plot is not appropriate.
# So, by setting the argument Colour = FALSE, the scatter plot colored by black and white.
# we use the resulting plot for submission.
```

```
get_samples_from_Posterior_Predictive_distribution(fit,Colour = FALSE)
```

```
g <-get_samples_from_Posterior_Predictive_distribution(fit)
```

```

x <- g$CFP
y <- g$CTP

plot( hexbin::hexbin(unlist(x),unlist(y)) )

# Close the graphic device to avoid errors in R CMD check.
      Close_all_graphic_devices()

## End(Not run)# dottest

```

ggplotFROC

Draw FROC curves by two parameters a and b

Description

Plot FROC curves based on two parameters a and b.

Usage

```

ggplotFROC(
  a,
  b,
  mesh.for.drawing.curve = 10000,
  upper_x = 1,
  upper_y = 1,
  lower_y = 0,
  dataList,
  StanS4class
)

```

Arguments

- | | |
|------------------------|--|
| a | An arbitrary real number. It is no need to require any assumption, but I use such as $a=\mu/\sigma$, where μ is a mean of signal distribution and σ is its standard deviation in the bi-normal assumption. |
| b | An arbitrary positive real number. I use such as $b=1/\sigma$, where σ is a standard deviation of signal distribution in the bi-normal assumption. |
| mesh.for.drawing.curve | A positive large integer, indicating number of dots drawing the curves, Default =10000. |
| upper_x | A positive real number, indicating the frame size of drawing picture. |

upper_y A positive real number, indicating the frame size of drawing picture.

lower_y A positive real number, indicating the frame size of drawing picture.

dataList A list, specifying an FROC data to be fitted a model. It consists of data of numbers of TPs, FPs, lesions, images. .In addition, if in case of mutiple readers or mutiple modalities, then modaity ID and reader ID are included also.

The `dataList` will be passed to the function `rstan::sampling()` of **rstan**. This is a variable in the function `rstan::sampling()` in which it is named `data`.

For the single reader and a single modality data, the `dataList` is made by the following manner:

```
dataList.Example <- list(
  h = c(41,22,14,8,1), # number of hits for each confidence level
  f = c(1,2,5,11,13), # number of false alarms for each confidence level

  NL = 124, # number of lesions (signals)
  NI = 63, # number of images (trials)
  C = 5) # number of confidence, .. the author thinks it can be calculated
as the length of h or f ...? ha, why I included this. ha .. should be omitted.
```

Using this object `dataList.Example`, we can apply `fit_Bayesian_FROC()` such as `fit_Bayesian_FROC(dataList.Example)`.

To make this R object `dataList` representing FROC data, this package provides three functions:

```
convertFromJafroc() If data is a JAFROC xlsx formulation.
dataset_creator_new_version() Enter TP and FP data by table .
create_dataset() Enter TP and FP data by interactive manner.
```

Before fitting a model, we can confirm our dataset is correctly formulated by using the function `viewdata()`.

A Single reader and a single modality (SRSC) case.

In a single reader and a single modality case (srsc), `dataList` is a list consisting of `f, h, NL, NI, C` where `f, h` are numeric vectors and `NL, NI, C` are positive integers.

- f Non-negative integer vector specifying number of false alarms associated with each confidence level. The first component corresponding to the highest confidence level.
- h Non-negative integer vector specifying number of Hits associated with each confidence level. The first component corresponding to the highest confidence level.
- NL A positive integer, representing Number of Lesions.
- NI A positive integer, representing Number of Images.
- C A positive integer, representing Number of Confidence level.

The detail of these dataset, see the datasets endowed with this package. Note that the maximal number of confidence level, denoted by C , are included, however, Note that confidence level vector c should not be specified. If specified, will be ignored, since it is created by $c \leftarrow c(\text{rep}(C:1))$ in the program and do not refer from user input data, where C is the highest number of confidence levels. So, you should write down your hits and false alarms vector so that it is compatible with this automatically created c vector.

data Format:

A single reader and a single modality case

NI=63, NL=124 In R console ->	confidence level c	No. of false alarms f	No. of hits h
definitely present	$c[1] = 5$	$f[1] = F_5 = 1$	$h[1] = H_5 = 41$
probably present	$c[2] = 4$	$f[2] = F_4 = 2$	$h[2] = H_4 = 22$
equivocal	$c[3] = 3$	$f[3] = F_3 = 5$	$h[3] = H_3 = 14$
subtle	$c[4] = 2$	$f[4] = F_2 = 11$	$h[4] = H_2 = 8$
very subtle	$c[5] = 1$	$f[5] = F_1 = 13$	$h[5] = H_1 = 1$

* *false alarms* = False Positives = FP

* *hits* = True Positives = TP

Note that in FROC data, all confidence level means *present* (*diseased, lesion*) case only, no confidence level indicating absent. Since each reader marks his suspicious location only if he thinks lesions are *present*, and marked positions generates the hits or false alarms, *thus* each confidence level represents that lesion is *present*. In the absent case, reader dose not mark any locations and hence, the absent confidence level does not relate this dataset. So, if reader think it is no lesion, then in such case confidence level is not needed.

Note that the first column of confidence level vector c should not be specified. If specified, will be ignored, since it is created by $c \leftarrow c(\text{rep}(C:1))$ automatically in the program and do not refer from user input data even if it is specified explicitly, where C is the highest number of confidence levels. So you should check the compatibility of your data and the confidence level vector $c \leftarrow c(\text{rep}(C:1))$ via a table which can be displayed by the function `viewdata()`.

Multiple readers and multiple modalities case, i.e., MRMC case

In case of multiple readers and multiple modalities, i.e., MRMC case, in order to apply the function `fit_Bayesian_FROC()`, dataset represented by an R list object representing FROC data must contain components $m, q, c, h, f, NL, C, M, Q$.

C A positive integer, representing the **highest** number of confidence level, this is a scalar.

- M A positive integer vector, representing the number of **modalities**.
 Q A positive integer, representing the number of **readers**.
 m A vector of positive integers, representing the **modality ID** vector.
 q A vector of positive integers, representing the **reader ID** vector.
 c A vector of positive integers, representing the **confidence level**. This vector must be made by `rep(rep(C:1), M*Q)`
 h A vector of non-negative integers, representing the number of **hits**.
 f A vector of non-negative integers, representing the number of **false alarms**.
 NL A positive integer, representing the Total number of **lesions** for all images, this is a scalar.

Note that the maximal number of confidence level (denoted by C) are included in the above R object. However, each confidence level vector is not included in the data, because it is created automatically from C. To confirm false positives and hits are correctly ordered with respect to the automatically generated confidence vector,

the function `viewdata()` shows the table. Revised 2019 Nov 27 Revised 2019 Dec 5

Example data.

Multiple readers and multiple modalities (i.e., MRMC)

Modality ID	Reader ID	Confidence levels	No. of false alarms	No. of hits.
m	q	c	f	h
1	1	3	20	111
1	1	2	29	55
1	1	1	21	22
1	2	3	6	100
1	2	2	15	44
1	2	1	22	11
2	1	3	6	66
2	1	2	24	55
2	1	1	23	1
2	2	3	5	66
2	2	2	30	55
2	2	1	40	44

* *false alarms* = False Positives = FP

* *hits* = True Positives = TP

StanS4class

An S4 object of class `stanfitExtended` which is an inherited class from the S4 class `stanfit`. This R object is a fitted model object as a return value of the function `fit_Bayesian_FROC()`.

It can be passed to `DrawCurves()`, `ppp()` and ... etc

ggplotFROC.EAP

Draw FROC curves by two parameters a and b

Description

Plot FROC curves based on two parameters a and b.

Usage

```
ggplotFROC.EAP(
  a,
  b,
  mesh.for.drawing.curve = 10000,
  upper_x = 1,
  upper_y = 1,
  lower_y = 0,
  dataList,
  StanS4class
)
```

Arguments

- a An arbitrary real number. It is no need to require any assumption, but I use such as $a=\mu/\sigma$, where μ is a mean of signal distribution and σ is its standard deviation in the bi-normal assumption.
- b An arbitrary positive real number. I use such as $b=1/\sigma$, where σ is a standard deviation of signal distribution in the bi-normal assumption.
- mesh.for.drawing.curve A positive large integer, indicating number of dots drawing the curves, Default =10000.
- upper_x A positive real number, indicating the frame size of drawing picture.
- upper_y A positive real number, indicating the frame size of drawing picture.
- lower_y A positive real number, indicating the frame size of drawing picture.
- dataList A list, specifying an FROC data to be fitted a model. It consists of data of numbers of TPs, FPs, lesions, images. .In addition, if in case of mutple readers or mutple modalities, then modality ID and reader ID are included also.
The `dataList` will be passed to the function `rstan::sampling()` of **rstan**. This is a variable in the function `rstan::sampling()` in which it is named `data`.
For the single reader and a single modality data, the `dataList` is made by the following manner:
`dataList.Example <-list(`
`h = c(41,22,14,8,1),# number of hits for each confidence level`

```
f = c(1,2,5,11,13),# number of false alarms for each confidence level
```

```
NL = 124,# number of lesions (signals)
```

```
NI = 63,# number of images (trials)
```

```
C = 5) # number of confidence, .. the author thinks it can be calculated
as the length of h or f ...? ha,why I included this. ha .. should be omitted.
```

Using this object `dataList.Example`, we can apply `fit_Bayesian_FROC()` such as `fit_Bayesian_FROC(dataList.Example)`.

To make this R object `dataList` representing FROC data, this package provides three functions:

`convertFromJafroc()` If data is a **JAFROC xlsx** formulation.

`dataset_creator_new_version()` Enter TP and FP data **by table** .

`create_dataset()` Enter TP and FP data by **interactive** manner.

Before fitting a model, we can confirm our dataset is correctly formulated by using the function `viewdata()`.

A Single reader and a single modality (SRSC) case.

In a single reader and a single modality case (`srs`), `dataList` is a list consisting of `f`, `h`, `NL`, `NI`, `C` where `f`, `h` are numeric vectors and `NL`, `NI`, `C` are positive integers.

`f` Non-negative integer vector specifying number of false alarms associated with each confidence level. The first component corresponding to the highest confidence level.

`h` Non-negative integer vector specifying number of Hits associated with each confidence level. The first component corresponding to the highest confidence level.

`NL` A positive integer, representing Number of Lesions.

`NI` A positive integer, representing Number of Images.

`C` A positive integer, representing Number of Confidence level.

The detail of these dataset, see the datasets endowed with this package. 'Note that the maximal number of confidence level, denoted by `C`, are included, however, Note that confidence level vector `c` should not be specified. If specified, will be ignored, since it is created by `c <-c(rep(C:1))` in the program and do not refer from user input data, where `C` is the highest number of confidence levels. So, you should write down your hits and false alarms vector so that it is compatible with this automatically created `c` vector.

data Format:

A single reader and a single modality case

	confidence level	No. of false alarms	No. of hits
NI=63,NL=124			
In R console ->	<code>c</code>	<code>f</code>	<code>h</code>

definitely present	$c[1] = 5$	$f[1] = F_5 = 1$	$h[1] = H_5 = 41$
probably present	$c[2] = 4$	$f[2] = F_4 = 2$	$h[2] = H_4 = 22$
equivocal	$c[3] = 3$	$f[3] = F_3 = 5$	$h[3] = H_3 = 14$
subtle	$c[4] = 2$	$f[4] = F_2 = 11$	$h[4] = H_2 = 8$
very subtle	$c[5] = 1$	$f[5] = F_1 = 13$	$h[5] = H_1 = 1$

* *false alarms* = False Positives = FP

* *hits* = True Positives = TP

Note that in FROC data, all confidence level means *present* (*diseased, lesion*) case only, no confidence level indicating absent. Since each reader marks his suspicious location only if he thinks lesions are *present*, and marked positions generates the hits or false alarms, *thus* each confidence level represents that lesion is *present*. In the absent case, reader dose not mark any locations and hence, the absent confidence level does not relate this dataset. So, if reader think it is no lesion, then in such case confidence level is not needed.

Note that the first column of confidence level vector c should not be specified. If specified, will be ignored , since it is created by $c \leftarrow c(\text{rep}(C:1))$ automatically in the program and do not refer from user input data even if it is specified explicitly, where C is the highest number of confidence levels. So you should check the compatibility of your data and the confidence level vector $c \leftarrow c(\text{rep}(C:1))$ via a table which can be displayed by the function `viewdata()`.

Multiple readers and multiple modalities case, i.e., MRMC case

In case of multiple readers and multiple modalities, i.e., MRMC case, in order to apply the function `fit_Bayesian_FROC()`, dataset represented by an R list object representing FROC data must contain components $m, q, c, h, f, NL, C, M, Q$.

- C A positive integer, representing the **highest** number of confidence level, this is a scalar.
- M A positive integer vector, representing the number of **modalities**.
- Q A positive integer, representing the number of **readers**.
- m A vector of positive integers, representing the **modality ID** vector.
- q A vector of positive integers, representing the **reader ID** vector.
- c A vector of positive integers, representing the **confidence level**. This vector must be made by $\text{rep}(\text{rep}(C:1), M*Q)$
- h A vector of non-negative integers, representing the number of **hits**.
- f A vector of non-negative integers, representing the number of **false alarms**.
- NL A positive integer, representing the Total number of **lesions** for all images, this is a scalar.

Note that the maximal number of confidence level (denoted by C) are included in the above R object. However, each confidence level vector is not included in the

data, because it is created automatically from C. To confirm false positives and hits are correctly ordered with respect to the automatically generated confidence vector,

the function `viewdata()` shows the table. Revised 2019 Nov 27 Revised 2019 Dec 5

Example data.

Multiple readers and multiple modalities (i.e., MRMC)

Modality ID	Reader ID	Confidence levels	No. of false alarms	No. of hits.
m	q	c	f	h
1	1	3	20	111
1	1	2	29	55
1	1	1	21	22
1	2	3	6	100
1	2	2	15	44
1	2	1	22	11
2	1	3	6	66
2	1	2	24	55
2	1	1	23	1
2	2	3	5	66
2	2	2	30	55
2	2	1	40	44

* *false alarms* = False Positives = FP

* *hits* = True Positives = TP

StanS4class An S4 object of class `stanfitExtended` which is an inherited class from the S4 class `stanfit`. This R object is a fitted model object as a return value of the function `fit_Bayesian_FROC()`.

It can be passed to `DrawCurves()`, `ppp()` and ... etc

give_name_srsc_CFP_CTP_vector

Give a Name For CTP CFP vector

Description

Give a Name for a vector representing cumulative true positives (CTPs) or cumulative false positives (CFPs).

Usage

```
give_name_srsc_CFP_CTP_vector(
  vector,
  CFP.or.CTP = "CFP",
  ModifiedPoisson = FALSE
)
```

Arguments

vector A vector representing cumulative true positives (CTPs) or cumulative false positives (CFPs).

CFP.or.CTP "CFP" or "CTP". Default value is "CFP".

ModifiedPoisson

Logical, that is TRUE or FALSE.

If `ModifiedPoisson = TRUE`, then Poisson rate of false alarm is calculated *per lesion*, and model is fitted so that the FROC curve is an expected curve of points consisting of the pairs of TPF per lesion and FPF *per lesion*.

Similarly,

If `ModifiedPoisson = TRUE`, then Poisson rate of false alarm is calculated *per image*, and model is fitted so that the FROC curve is an expected curve of points consisting of the pair of TPF per lesion and FPF *per image*.

For more details, see the author's paper in which I explained *per image* and *per lesion*. (for details of models, see [vignettes](#), now, it is omitted from this package, because the size of vignettes are large.)

If `ModifiedPoisson = TRUE`, then the *False Positive Fraction (FPF)* is defined as follows (F_c denotes the number of false alarms with confidence level c)

$$\frac{F_1 + F_2 + F_3 + F_4 + F_5}{N_L},$$

$$\frac{F_2 + F_3 + F_4 + F_5}{N_L},$$

$$\frac{F_3 + F_4 + F_5}{N_L},$$

$$\frac{F_4 + F_5}{N_L},$$

$$\frac{F_5}{N_L},$$

where N_L is a number of lesions (signal). To emphasize its denominator N_L , we also call it the *False Positive Fraction (FPF) per lesion*.

On the other hand,

if ModifiedPoisson = FALSE (Default), then *False Positive Fraction (FPF)* is given by

$$\frac{F_1 + F_2 + F_3 + F_4 + F_5}{N_I},$$

$$\frac{F_2 + F_3 + F_4 + F_5}{N_I},$$

$$\frac{F_3 + F_4 + F_5}{N_I},$$

$$\frac{F_4 + F_5}{N_I},$$

$$\frac{F_5}{N_I},$$

where N_I is the number of images (trial). To emphasize its denominator N_I , we also call it the *False Positive Fraction (FPF) per image*.

The model is fitted so that the estimated FROC curve can be ragraded as the expected pairs of FPF per image and TPF per lesion (ModifiedPoisson = FALSE)

or as the expected pairs of FPF per image and TPF per lesion (ModifiedPoisson = TRUE)

If ModifiedPoisson = TRUE, then FROC curve means the expected pair of FPF **per lesion** and TPF.

On the other hand, if ModifiedPoisson = FALSE, then FROC curve means the expected pair of **FPF per image** and TPF.

So,data of FPF and TPF are changed thus, a fitted model is also changed whether ModifiedPoisson = TRUE or FALSE. In traditional FROC analysis, it uses only per images (trial). Since we can divide one image into two images or more images, number of trial is not important. And more important is per signal. So, the author also developed FROC theory to consider FROC analysis under per signal. One can see that the FROC curve is rigid with respect to change of a number of images, so, it does not matter whether ModifiedPoisson = TRUE or FALSE. This rigidity of curves means that the number of images is redundant parameter for the FROC trial and thus the author try to exclude it.

Revised 2019 Dec 8 Revised 2019 Nov 25 Revised 2019 August 28

Details

Some function in this package give the return values of vectors representing the CFP or CTPs. Using this function, we specify what the components of vector means. This is important since its order is not deterministic, that is, its order give two case, one is decreasing and one is increasing order. So, to avoid such confusion, the name should be specified. Of course this function is no needed for user to know or to use it.

Value

A vector representing cumulative true positives (CTPs) or cumulative false positives (CFPs) with its name.

Examples

```
h <- BayesianFROC::dataList.Chakra.1$h
NL <- BayesianFROC::dataList.Chakra.1$NL
CTP.vector <- cumsum(h)/NL
CTP.vector.with.name <- give_name_srsc_CFP_CTP_vector(CTP.vector)
```

give_name_srsc_data *Give a name for srsc data list component*

Description

By specifying the data, the names are given for each component vectors.

Usage

```
give_name_srsc_data(dataList)
```

Arguments

dataList A list, specifying an FROC data to be fitted a model. It consists of data of numbers of TPs, FPs, lesions, images. .In addition, if in case of mutiple readers or mutiple modalities, then modaiaty ID and reader ID are included also.

The **dataList** will be passed to the function `rstan::sampling()` of **rstan**. This is a variable in the function `rstan::sampling()` in which it is named **data**.

For the single reader and a single modality data, the **dataList** is made by the following manner:

```
dataList.Example <-list(
h = c(41,22,14,8,1),# number of hits for each confidence level
f = c(1,2,5,11,13),# number of false alarms for each confidence level

NL = 124,# number of lesions (signals)
NI = 63,# number of images (trials)
C = 5) # number of confidence,.. the author thinks it can be calculated
as the length of h or f ...? ha,why I included this. ha .. should be omitted.
```

Using this object `dataList.Example`, we can apply `fit_Bayesian_FROC()` such as `fit_Bayesian_FROC(dataList.Example)`.

To make this R object `dataList` representing FROC data, this package provides three functions:

- `convertFromJafroc()` If data is a **JAFROC xlsx** formulation.
- `dataset_creator_new_version()` Enter TP and FP data **by table**.
- `create_dataset()` Enter TP and FP data by **interactive** manner.

Before fitting a model, we can confirm our dataset is correctly formulated by using the function `viewdata()`.

A Single reader and a single modality (SRSC) case.

In a single reader and a single modality case (srsc), `dataList` is a list consisting of `f, h, NL, NI, C` where `f, h` are numeric vectors and `NL, NI, C` are positive integers.

- `f` Non-negative integer vector specifying number of false alarms associated with each confidence level. The first component corresponding to the highest confidence level.
- `h` Non-negative integer vector specifying number of Hits associated with each confidence level. The first component corresponding to the highest confidence level.
- `NL` A positive integer, representing Number of Lesions.
- `NI` A positive integer, representing Number of Images.
- `C` A positive integer, representing Number of Confidence level.

The detail of these dataset, see the datasets endowed with this package. Note that the maximal number of confidence level, denoted by `C`, are included, however, Note that confidence level vector `c` should not be specified. If specified, will be ignored, since it is created by `c <- c(rep(C:1))` in the program and do not refer from user input data, where `C` is the highest number of confidence levels. So, you should write down your hits and false alarms vector so that it is compatible with this automatically created `c` vector.

data Format:

A single reader and a single modality case

NI=63, NL=124 In R console ->	confidence level c	No. of false alarms f	No. of hits h
definitely present	$c[1] = 5$	$f[1] = F_5 = 1$	$h[1] = H_5 = 41$
probably present	$c[2] = 4$	$f[2] = F_4 = 2$	$h[2] = H_4 = 22$
equivocal	$c[3] = 3$	$f[3] = F_3 = 5$	$h[3] = H_3 = 14$
subtle	$c[4] = 2$	$f[4] = F_2 = 11$	$h[4] = H_2 = 8$
very subtle	$c[5] = 1$	$f[5] = F_1 = 13$	$h[5] = H_1 = 1$

* *false alarms* = False Positives = FP

* *hits* = True Positives = TP

Note that in FROC data, all confidence level means *present* (*diseased, lesion*) case only, no confidence level indicating absent. Since each reader marks his suspicious location only if he thinks lesions are *present*, and marked positions generates the hits or false alarms, *thus* each confidence level represents that lesion is *present*. In the absent case, reader dose not mark any locations and hence, the absent confidence level does not relate this dataset. So, if reader think it is no lesion, then in such case confidence level is not needed.

Note that the first column of confidence level vector `c` should not be specified. If specified, will be ignored, since it is created by `c<-c(rep(C:1))` automatically in the program and do not refer from user input data even if it is specified explicitly, where `C` is the highest number of confidence levels. So you should check the compatibility of your data and the confidence level vector `c<-c(rep(C:1))` via a table which can be displayed by the function `viewdata()`.

Multiple readers and multiple modalities case, i.e., MRMC case

In case of multiple readers and multiple modalities, i.e., MRMC case, in order to apply the function `fit_Bayesian_FROC()`, dataset represented by an `R` list object representing FROC data must contain components `m, q, c, h, f, NL, C, M, Q`.

- `C` A positive integer, representing the **highest** number of confidence level, this is a scalar.
- `M` A positive integer vector, representing the number of **modalities**.
- `Q` A positive integer, representing the number of **readers**.
- `m` A vector of positive integers, representing the **modality** ID vector.
- `q` A vector of positive integers, representing the **reader** ID vector.
- `c` A vector of positive integers, representing the **confidence level**. This vector must be made by `rep(rep(C:1), M*Q)`
- `h` A vector of non-negative integers, representing the number of **hits**.
- `f` A vector of non-negative integers, representing the number of **false alarms**.
- `NL` A positive integer, representing the Total number of **lesions** for all images, this is a scalar.

Note that the maximal number of confidence level (denoted by `C`) are included in the above `R` object. However, each confidence level vector is not included in the data, because it is created automatically from `C`. To confirm false positives and hits are correctly ordered with respect to the automatically generated confidence vector,

the function `viewdata()` shows the table. Revised 2019 Nov 27 Revised 2019 Dec 5

Example data.

Multiple readers and multiple modalities (i.e., MRMC)

Modality ID m	Reader ID q	Confidence levels c	No. of false alarms f	No. of hits. h
1	1	3	20	111
1	1	2	29	55
1	1	1	21	22
1	2	3	6	100
1	2	2	15	44
1	2	1	22	11
2	1	3	6	66
2	1	2	24	55
2	1	1	23	1
2	2	3	5	66
2	2	2	30	55
2	2	1	40	44

* *false alarms* = False Positives = FP
 * *hits* = True Positives = TP

Details

This is only available on singular reader and single modality case, not available on MRMC case.

Examples

```

#>dataList.Chakra.2
#f
#[1] 4 13 44
#
#$h
#[1] 122 31 20
#
#fNL
#[1] 269
#
#fNI
#[1] 57
#
#fC
#[1] 3

```

```
dataList.with.name <- give_name_srsc_data(dataList.Chakra.2)
```



```

#> dataList.with.name
# $f
# F(3) F(2) F(1)
# 4 13 44
#
# $h
# H(3) H(2) H(1)
# 122 31 20
#
# $NL
# Number of Lesions
# 269
#
# $NI
# Number of Images
# 57
#
# $C
# Number of Confidence levels
# 3

## Not run:
# dottest

```

hits_creator_from_rate

MRMC Dataset Creator From Hit Rate.

Description

From hit rates, data of hits are created.

Usage

```
hits_creator_from_rate(NL = 252, seed = 123, p.truth = BayesianFROC::p_truth)
```

Arguments

NL	Number of Lesions.
seed	The seed for creating data consisting of the number of hits synthesized by the binomial distributions with the specified seed.
p.truth	Array of dimension (C, M, Q), where C = number of confidence levels, M = number of modalities, Q = number of readers.

Details

Random variables of hits are distributed as follows.

$$h_{5,m,r} \sim \text{Binomial}(p_{5,m,r}, N_L),$$

then $h_{4,m,r}$ should be drawn from the binomial distribution with remaining targets

$$h_{4,m,r} \sim \text{Binomial}\left(\frac{p_{4,m,r}}{1 - p_{5,m,r}}, N_L - h_{5,m,r}\right).$$

Similarly,

$$h_{3,m,r} \sim \text{Binomial}\left(\frac{p_{3,m,r}}{1 - p_{5,m,r} - p_{4,m,r}}, N_L - h_{5,m,r} - h_{4,m,r}\right).$$

$$h_{2,m,r} \sim \text{Binomial}\left(\frac{p_{2,m,r}}{1 - p_{5,m,r} - p_{4,m,r} - p_{3,m,r}}, N_L - h_{5,m,r} - h_{4,m,r} - h_{3,m,r}\right).$$

$$h_{1,m,r} \sim \text{Binomial}\left(\frac{p_{1,m,r}}{1 - p_{5,m,r} - p_{4,m,r} - p_{3,m,r} - p_{2,m,r}}, N_L - h_{5,m,r} - h_{4,m,r} - h_{3,m,r} - h_{2,m,r}\right).$$

p. truth is an array representing $p_{c,m,r}$. By specifying the array p. truth (and hence $p_{c,m,r}$), with the above model, we can calculate hit data $h_{c,m,r}$ for each c, m, r .

Value

Hits Data, an array of dimension [Confidence,Modality,Reader].

Examples

```
## Not run:
#=====
#2019 Sept 6 1) Using the default hit values, hit data are created as follows;
#=====
```

```
hits <- hits_creator_from_rate()
```

```
#=====
#2019 Sept 6 2) If user want to use their own hit rates, then use the following codes:
#=====
```

```

h <- hits_creator_from_rate(

NL=252,
seed =123,
p.truth =
array(c(
  c(0.03,0.13,0.2,0.3,0.4,   #for M=1 Q=1
    0.04,0.23,0.3,0.4,0.5) , #for M=2 Q=1 ,

  c(0.05,0.33,0.4,0.5,0.6,   #for M=1 Q=2
    0.06,0.43,0.5,0.6,0.7) , #for M=2 Q=2 ,

  c(0.07,0.53,0.6,0.7,0.8,   #for M=1 Q=3
    0.08,0.63,0.7,0.8,0.9)   #for M=2 Q=3 ,
  ),

dim = c(5,2,3) #C M Q
)#array

)

```

```

=====
#2019 Sept 6 3)  If user want to use their own hit rates, then use the following codes:
=====

```

```

h <- hits_creator_from_rate(

NL=252,
seed =123,
p.truth =
array(c(

  c(0.03,0.1,0.2,0.3,0.4,   #for M=1 Q=1
    0.04,0.2,0.3,0.4,0.5,   #for M=2 Q=1
    0.05,0.3,0.4,0.5,0.6),  #for M=3 Q=1

  c(0.05,0.33,0.4,0.5,0.6,   #for M=1 Q=2
    0.06,0.43,0.5,0.6,0.7,   #for M=2 Q=2
    0.05,0.3,0.4,0.5,0.6),   #for M=3 Q=2

```

```

    c(0.07,0.53,0.6,0.7,0.8, #for M=1 Q=3
      0.08,0.63,0.7,0.8,0.9, #for M=2 Q=3
      0.05,0.3,0.4,0.5,0.6) #for M=3 Q=3

  ),

dim = c(5,3,3) #C M Q

)#array

)

#=====
#2019 Sept 6 3) Only one reader
#=====

h <- hits_creator_from_rate(

NL=252,
seed =123,
p.truth =
array(c(

    c(0.03,0.1,0.2,0.3,0.4, #for M=1 Q=1
      0.04,0.2,0.3,0.4,0.5, #for M=2 Q=1
      0.05,0.3,0.4,0.5,0.6) #for M=3 Q=1

    ),

dim = c(5,3,1) #C M Q

)#array

)

#=====
#
#=====

#=====The third example=====

# The hits rate cannot take any values, since there is a trend that a hit rate of
# a higher confidence level is a higher. So, If it is difficult for user to create

```

```

# a true hit rates, then by taking estimates as true parameters,
# user can replicate datasets.
# To do so, work follow is first fitting, secondly extracting estimates,
# thirdly apply this function (hits_creator_from_rate() ).

# * Fitting

fit <- fit_Bayesian_FROC(
  dataList.Chakra.Web.orderd,
  ite = 1111, # For simplicity, we take small MCMC samples.
  summary =FALSE)

# * Extracting

estimates <- extract_estimates_MRMC(fit)

ppp <- estimates$ppp.EAP

# Note that ppp is an array
# whose dimension is constituted by number of confidence levels, modalities, readers.

# * Replicating as an true values is ppp

hits <- hits_creator_from_rate(p.truth = ppp )

# <<Remark>>
# ppp is an array. ignoring its indices, we can write that

# hits ~ Binomial(ppp, NL)

# Where NL is a number of lesions.

# By writing its component explicitly, we can write

# Hits[c,m,r] ~ Binomial(ppp[c,m,r], NL)

# Where c means the c-th confidence level,
# m means the m-th modality,
# r means the r-th reader.

## End(Not run)# dottest

```

Description

From the parameter of the bi-normal assumptions, hits and false alarms are generated.

Usage

```
hits_false_alarms_creator_from_thresholds(
  replicate.datset = 3,
  ModifiedPoisson = FALSE,
  mean.truth = 0.6,
  sd.truth = 5.3,
  z.truth = c(-0.8, 0.7, 2.38),
  NL = 259,
  NI = 57,
  summary = TRUE,
  initial.seed = 12345
)
```

Arguments

replicate.datset

A Number indicate that how many you replicate dataset from user's specified dataset.

ModifiedPoisson

Logical, that is TRUE or FALSE.

If ModifiedPoisson = TRUE, then Poisson rate of false alarm is calculated *per lesion*, and model is fitted so that the FROC curve is an expected curve of points consisting of the pairs of TPF per lesion and FPF *per lesion*.

Similarly,

If ModifiedPoisson = TRUE, then Poisson rate of false alarm is calculated *per image*, and model is fitted so that the FROC curve is an expected curve of points consisting of the pair of TPF per lesion and FPF *per image*.

For more details, see the author's paper in which I explained *per image* and *per lesion*. (for details of models, see [vignettes](#), now, it is omitted from this package, because the size of vignettes are large.)

If ModifiedPoisson = TRUE, then the *False Positive Fraction (FPF)* is defined as follows (F_c denotes the number of false alarms with confidence level c)

$$\frac{F_1 + F_2 + F_3 + F_4 + F_5}{N_L},$$

$$\frac{F_2 + F_3 + F_4 + F_5}{N_L},$$

$$\frac{F_3 + F_4 + F_5}{N_L},$$

$$\frac{F_4 + F_5}{N_L},$$

$$\frac{F_5}{N_L},$$

where N_L is a number of lesions (signal). To emphasize its denominator N_L , we also call it the *False Positive Fraction (FPF) per lesion*.

On the other hand,

if ModifiedPoisson = FALSE (Default), then *False Positive Fraction (FPF)* is given by

$$\frac{F_1 + F_2 + F_3 + F_4 + F_5}{N_I},$$

$$\frac{F_2 + F_3 + F_4 + F_5}{N_I},$$

$$\frac{F_3 + F_4 + F_5}{N_I},$$

$$\frac{F_4 + F_5}{N_I},$$

$$\frac{F_5}{N_I},$$

where N_I is the number of images (trial). To emphasize its denominator N_I , we also call it the *False Positive Fraction (FPF) per image*.

The model is fitted so that the estimated FROC curve can be regarded as the expected pairs of FPF per image and TPF per lesion (ModifiedPoisson = FALSE)

or as the expected pairs of FPF per image and TPF per lesion (ModifiedPoisson = TRUE)

If ModifiedPoisson = TRUE, then FROC curve means the expected pair of FPF **per lesion** and TPF.

On the other hand, if ModifiedPoisson = FALSE, then FROC curve means the expected pair of **FPF per image** and TPF.

So, data of FPF and TPF are changed thus, a fitted model is also changed whether ModifiedPoisson = TRUE or FALSE. In traditional FROC analysis, it uses only per images (trial). Since we can divide one image into two images or more images, number of trial is not important. And more important is per signal. So, the author also developed FROC theory to consider FROC analysis under per signal. One can see that the FROC curve is rigid with respect to change of a number of images, so, it does not matter whether ModifiedPoisson = TRUE or FALSE. This rigidity of curves means that the number of images is redundant parameter for the FROC trial and thus the author try to exclude it.

Revised 2019 Dec 8 Revised 2019 Nov 25 Revised 2019 August 28

<code>mean.truth</code>	This is a parameter of the latent Gaussian assumption for the noise distribution.
<code>sd.truth</code>	This is a parameter of the latent Gaussian assumption for the noise distribution.
<code>z.truth</code>	This is a parameter of the latent Gaussian assumption for the noise distribution.
<code>NL</code>	Number of Lesions.
<code>NI</code>	Number of Images.
<code>summary</code>	Logical: TRUE of FALSE. Whether to print the verbose summary. If TRUE then verbose summary is printed in the R console. If FALSE, the output is minimal. I regret, this variable name should be verbose.
<code>initial.seed</code>	Replicated datasets are created using a continuous sequence of seeds and its initial seed is specified by this argument. For example, if you choose <code>initial.seed = 12300</code> , then the replicated datasets are created from using the sequence of seeds: 12301,12302,12303,12304,...

Details

From the fixed parameters of bi-normal assumptions, we replicate data, that is, we draw the data from the distributions whose parameters are known. Especially, we interest the hits and false alarms since the number of images, lesions and confidence level is same for all replications. So, it is sufficient to check the hits and false alarms.

Value

Datasets Including Hits and False Alarms

Examples

```
## Not run:
#=====The first example=====
#      Replication of Data from Fixed ( specified) Parameters.

a <- hits_false_alarms_creator_from_thresholds(replicate.datset = 1)

# Extract the first replicated dataset:

a[[1]]$NL
a[[1]]$NI
a[[1]]$f
a[[1]]$h
a[[1]]$C

#=====The second example=====
#      Replication of Data from Fixed ( specified) Parameters.

b <- hits_false_alarms_creator_from_thresholds(replicate.datset = 2)

# Extract the first replicated dataset:
```



```
b[[1]]$NL
b[[1]]$NI
b[[1]]$f
b[[1]]$h
b[[1]]$C

# Extract the second replicated dataset:

b[[2]]$NL
b[[2]]$NI
b[[2]]$f
b[[2]]$h
b[[2]]$C

#=====The Third example=====
#      Replication of Data from Fixed ( specified) Parameters.

c <- hits_false_alarms_creator_from_thresholds(replicate.datset = 3)

# Extract the first replicated dataset:

c[[1]]$NL
c[[1]]$NI
c[[1]]$f
c[[1]]$h
c[[1]]$C

# Extract the second replicated dataset:

c[[2]]$NL
c[[2]]$NI
c[[2]]$f
c[[2]]$h
c[[2]]$C

# Extract the third replicated dataset:

c[[3]]$NL
c[[3]]$NI
c[[3]]$f
c[[3]]$h
c[[3]]$C

## End(Not run)# dottest
```

hits_from_thresholds *MRMC Hit Creator from thresholds, mean and S.D.*

Description

From threshold, mean and S.D., data of hit rate are created.

Usage

```
hits_from_thresholds(
  z.truth = BayesianFROC::z_truth,
  mu.truth = BayesianFROC::mu_truth,
  v.truth = BayesianFROC::v_truth,
  NL = 252,
  seed = 123
)
```

Arguments

z.truth	Vector of dimension = C represents the thresholds of bi-normal assumption.
mu.truth	array of dimension (M,Q). Mean of the signal distribution of bi-normal assumption.
v.truth	array of dimension (M,Q). Standard Deviation of represents the signal distribution of bi-normal assumption.
NL	Number of Lesions.
seed	The seed for creating data consisting of the number of hits synthesized by the binomial distributions with the specified seed.

Value

Hits Data for MRMC. The reason that hits is multiple reader and multiple modalities arise from the multiple indices of mean and S.D. of signal distribution of the bi-normal assumption.

Examples

```
## Not run:
hits.rate.p <-hits_from_thresholds()

## End(Not run)#dontrun
```

hits_rate_creator *MRMC Hit Rates Creator from Thresholds, Mean and S.D.*

Description

From thresholds, data of hit rate are created.

Note that the return values has changed from p (in \mathbb{R} notation:ppp) to

$$hitrate_c := \frac{p_c(\theta)}{1 - p_C(\theta) - p_{C-1}(\theta) - \dots - p_{c+1}(\theta)}$$

Usage

```
hits_rate_creator(
  z.truth = BayesianFROC::z_truth,
  mu.truth = BayesianFROC::mu_truth,
  v.truth = BayesianFROC::v_truth,
  is_hit_rate_adjusted = FALSE
)
```

Arguments

`z.truth` Vector of dimension = C represents the thresholds of bi-normal assumption.

`mu.truth` array of dimension (M,Q). Mean of the signal distribution of bi-normal assumption.

`v.truth` array of dimension (M,Q). Standard Deviation of represents the signal distribution of bi-normal assumption.

`is_hit_rate_adjusted`
whether the return value is a vector of

$$p_c(\theta)$$

or

$$hitrate_c := \frac{p_c(\theta)}{1 - p_C(\theta) - p_{C-1}(\theta) - \dots - p_{c+1}(\theta)}$$

The former is the default (FALSE) and the later is returned if `is_hit_rate_adjusted=TRUE`.

Value

A vector of the hit rate:

$$hitrate_c := \frac{p_c(\theta)}{1 - p_C(\theta) - p_{C-1}(\theta) - \dots - p_{c+1}(\theta)}$$

Do not confuse the old version ppp which is an array with three indices: ppp[C, M, Q].

Examples

```

## Not run:
#=====The first example=====

#   Using default values for hit rates, we can create a data of hits as follows:

      hits.rate <-hits_rate_creator()

#=====The second example=====

#   Using the hit rate from the hits_rate_creator(), we can get the hits data:

      hits_creator_from_rate(p.truth =hits_rate_creator() )

#=====The remark for example=====

# The author does not show how to specify the hit rates or threshods.
# For the details of it, please see the default values of such a quantities.

#=====The 4-th example=====

      p.truth.array <- hits_rate_creator()

#=====
#2019 Sept 6
#=====

## End(Not run)# dottest

```

```

hit_rate_adjusted_from_the_vector_p
      hit rate adjusted from a vector p

```

Description

hit rate adjusted from a vector p

Usage

```
hit_rate_adjusted_from_the_vector_p(p_vector)
```

Arguments

p_vector A vector

Value

A vector

Examples

```

p <- c(1,2,3)
a <- hit_rate_adjusted_from_the_vector_p( p )
a

# [1] -0.25 -1.00  3.00

a[3] == 3
a[2] == p[2]/(1-p[3])
a[1] == p[1]/(1-p[3]-p[2])

```

```

#=====
#                               application in the function ppp_srsc in this package
#=====

```

Not run:

```

f <- fit_Bayesian_FROC( dataList = d )
e <-rstan::extract(f)

q<-e$p[1,]
hit_rate_adjusted_from_the_vector_p(q)
t(apply(e$p,hit_rate_adjusted_from_the_vector_p,MARGIN = 1))[1,]
q<-e$p[2,]
hit_rate_adjusted_from_the_vector_p(q)
t(apply(e$p,hit_rate_adjusted_from_the_vector_p,MARGIN = 1))[2,]

```

End(Not run)

```
initial_values_specification_for_stan_in_case_of_MRMC
```

Initial values for HMC (Hamiltonian Monte Carlo Markov Chains)

Description

An internal function.

Usage

```
initial_values_specification_for_stan_in_case_of_MRMC(dataList)
```

Arguments

`dataList` A list, specifying an FROC data to be fitted a model. It consists of data of numbers of TPs, FPs, lesions, images. .In addition, if in case of mutiple readers or mutiple modalities, then modaity ID and reader ID are included also. The `dataList` will be passed to the function `rstan::sampling()` of **rstan**. This is a variable in the function `rstan::sampling()` in which it is named `data`. For the single reader and a single modality data, the `dataList` is made by the following manner:

```
dataList.Example <-list(
h = c(41,22,14,8,1),# number of hits for each confidence level
f = c(1,2,5,11,13),# number of false alarms for each confidence level

NL = 124,# number of lesions (signals)
NI = 63,# number of images (trials)
C = 5) # number of confidence,.. the author thinks it can be calculated
as the length of h or f ...? ha,why I included this. ha .. should be omitted.
```

Using this object `dataList.Example`, we can apply `fit_Bayesian_FROC()` such as `fit_Bayesian_FROC(dataList.Example)`.

To make this R object `dataList` representing FROC data, this package provides three functions:

- [convertFromJafroc\(\)](#) If data is a **JAFROC xlsx** formulation.
- [dataset_creator_new_version\(\)](#) Enter TP and FP data **by table** .
- [create_dataset\(\)](#) Enter TP and FP data by **interactive** manner.

Before fitting a model, we can confirm our dataset is correctly formulated by using the function [viewdata\(\)](#).

A Single reader and a single modality (SRSC) case.

In a single reader and a single modality case (`srsc`), `dataList` is a list consisting of `f,h,NL,NI,C` where `f,h` are numeric vectors and `NL,NI,C` are positive integers.

- f Non-negative integer vector specifying number of false alarms associated with each confidence level. The first component corresponding to the highest confidence level.
- h Non-negative integer vector specifying number of Hits associated with each confidence level. The first component corresponding to the highest confidence level.
- NL A positive integer, representing Number of Lesions.
- NI A positive integer, representing Number of Images.
- C A positive integer, representing Number of Confidence level.

The detail of these dataset, see the datasets endowed with this package. Note that the maximal number of confidence level, denoted by C, are included, however, Note that confidence level vector c should not be specified. If specified, will be ignored, since it is created by $c \leftarrow c(\text{rep}(C:1))$ in the program and do not refer from user input data, where C is the highest number of confidence levels. So, you should write down your hits and false alarms vector so that it is compatible with this automatically created c vector.

data Format:

A single reader and a single modality case

NI=63, NL=124 In R console ->	confidence level c	No. of false alarms f	No. of hits h
definitely present	$c[1] = 5$	$f[1] = F_5 = 1$	$h[1] = H_5 = 41$
probably present	$c[2] = 4$	$f[2] = F_4 = 2$	$h[2] = H_4 = 22$
equivocal	$c[3] = 3$	$f[3] = F_3 = 5$	$h[3] = H_3 = 14$
subtle	$c[4] = 2$	$f[4] = F_2 = 11$	$h[4] = H_2 = 8$
very subtle	$c[5] = 1$	$f[5] = F_1 = 13$	$h[5] = H_1 = 1$

* *false alarms* = False Positives = FP

* *hits* = True Positives = TP

Note that in FROC data, all confidence level means *present (diseased, lesion)* case only, no confidence level indicating absent. Since each reader marks his suspicious location only if he thinks lesions are *present*, and marked positions generates the hits or false alarms, *thus* each confidence level represents that lesion is *present*. In the absent case, reader dose not mark any locations and hence, the absent confidence level does not relate this dataset. So, if reader think it is no lesion, then in such case confidence level is not needed.

Note that the first column of confidence level vector c should not be specified. If specified, will be ignored, since it is created by $c \leftarrow c(\text{rep}(C:1))$ automatically in the program and do not refer from user input data even if it is specified explicitly, where C is the highest number of confidence levels. So you

should check the compatibility of your data and the confidence level vector `c <-c(rep(C:1))` via a table which can be displayed by the function `viewdata()`.

Multiple readers and multiple modalities case, i.e., MRMC case

In case of multiple readers and multiple modalities, i.e., MRMC case, in order to apply the function `fit_Bayesian_FROC()`, dataset represented by an R list object representing FROC data must contain components `m, q, c, h, f, NL, C, M, Q`.

- `C` A positive integer, representing the **highest** number of confidence level, this is a scalar.
- `M` A positive integer vector, representing the number of **modalities**.
- `Q` A positive integer, representing the number of **readers**.
- `m` A vector of positive integers, representing the **modality ID** vector.
- `q` A vector of positive integers, representing the **reader ID** vector.
- `c` A vector of positive integers, representing the **confidence level**. This vector must be made by `rep(rep(C:1), M*Q)`
- `h` A vector of non-negative integers, representing the number of **hits**.
- `f` A vector of non-negative integers, representing the number of **false alarms**.
- `NL` A positive integer, representing the Total number of **lesions** for all images, this is a scalar.

Note that the maximal number of confidence level (denoted by `C`) are included in the above R object. However, each confidence level vector is not included in the data, because it is created automatically from `C`. To confirm false positives and hits are correctly ordered with respect to the automatically generated confidence vector,

the function `viewdata()` shows the table. Revised 2019 Nov 27 Revised 2019 Dec 5

Example data.

Multiple readers and multiple modalities (i.e., MRMC)

Modality ID <code>m</code>	Reader ID <code>q</code>	Confidence levels <code>c</code>	No. of false alarms <code>f</code>	No. of hits. <code>h</code>
1	1	3	20	111
1	1	2	29	55
1	1	1	21	22
1	2	3	6	100
1	2	2	15	44
1	2	1	22	11
2	1	3	6	66
2	1	2	24	55
2	1	1	23	1
2	2	3	5	66
2	2	2	30	55

2	2	1	40	44
---	---	---	----	----

* *false alarms* = False Positives = FP
 * *hits* = True Positives = TP

Details

This attempt failed, that is, I cannot specify the initial values so that the `rstan::sampling()` does not say the following:

Rejecting initial value:

Log probability evaluates to $\log(0)$, i.e. negative infinity.

Stan can't start sampling from this initial value.

Value

Initial values specification. See the detailed documentation for the `init` argument in `stan()`.

Examples

```

init <- initial_values_specification_for_stan_in_case_of_MRMC(dataList.Chakra.Web)

# Where init is the variable of the rstan::stan() or rstan::sampling()

```

install_imports	<i>Installer.</i>
-----------------	-------------------

Description

This is an installer for required packages in this package. To install this package BayesianFROC, we use the package `xlsx` which require the Java. So, if use buy a new computer and and it does not have installed the Java, then please install Java.

Usage

```
install_imports()
```

inv_Phi	<i>Inverse function of the Cumulative distribution function $\Phi(x)$ of the Standard Gaussian. where x is a real number.</i>
---------	---

Description

The author is confused `stats::qnorm()` with `stats::pnorm()` and thus he made this.

Usage

```
inv_Phi(x)
```

Arguments

`x` A real. To be passed to the function `stats::qnorm()`

Details

In Stan file, it is `inv_Phi()` and not `inv_phi`.

Since $\Phi(x)$ is monotonic, it follows that $\frac{d}{dx}\Phi^{-1} = (\frac{d}{dx}\Phi)^{-1} > 0$, and thus $\Phi^{-1}(x)$ is also monotonic.

Value

A real number: $\Phi^{-1}(x)$

See Also

[Phi\(\)](#), [Phi_inv\(\)](#)

Examples

```
x <- runif(100)
Phi_inv(x) == stats::qnorm(x)
inv_Phi(x) == stats::qnorm(x)
```

make_TeX	<i>Make a TeX file for summary</i>
----------	------------------------------------

Description

Under Construction... “This only inner funtion, in the future I run this in the [fit_Bayesian_FROC\(\)](#)).

Usage

```
make_TeX()
```

Value

TeX file reflected the analysis

make_true_parameter_MRMC	<i>Make a true model parameter and include it in this package</i>
--------------------------	---

Description

Make a true model parameter and include it in this package

Usage

```
make_true_parameter_MRMC(StanS4class)
```

Arguments

StanS4class An S4 object of class [stanfitExtended](#) which is an inherited class from the S4 class `stanfit`. This R object is a fitted model object as a return value of the function [fit_Bayesian_FROC\(\)](#).

It can be passed to [DrawCurves\(\)](#), [ppp\(\)](#) and ... etc

```
metadata_srcsc_per_image
```

Create metadata for MRMC data.

Description

The so-called *false positive fraction (FPF)* and the *true positive fraction (TPF)* are calculated from the number of hits (True Positives: TPs) and the number of false alarms (False Positives: FPs)

Usage

```
metadata_srcsc_per_image(dataList, ModifiedPoisson)
```

Arguments

dataList A list, should include m, q, c, h, f, NL, C, M, Q which means
 c should be created by `c<-c(rep(C:1))`, where C is the number of confidence levels. So, you should write down your hits and false alarms vector so that it is compatible with this automatically created c vector.
 h means the number of hits
 f means the number of false alarm
 NL means the Total number of lesions for all images
 C means the highest number of confidence level

ModifiedPoisson

Logical, that is TRUE or FALSE.

If ModifiedPoisson = TRUE, then Poisson rate of false alarm is calculated ***per lesion***, and model is fitted so that the FROC curve is an expected curve of points consisting of the pairs of TPF per lesion and FPF ***per lesion***.

Similarly,

If ModifiedPoisson = TRUE, then Poisson rate of false alarm is calculated ***per image***, and model is fitted so that the FROC curve is an expected curve of points consisting of the pair of TPF per lesion and FPF ***per image***.

For more details, see the author's paper in which I explained *per image* and *per lesion*. (for details of models, see **vignettes**, now, it is omitted from this package, because the size of vignettes are large.)

If ModifiedPoisson = TRUE, then the *False Positive Fraction (FPF)* is defined as follows (F_c denotes the number of false alarms with confidence level c)

$$\frac{F_1 + F_2 + F_3 + F_4 + F_5}{N_L},$$

$$\frac{F_2 + F_3 + F_4 + F_5}{N_L},$$

$$\frac{F_3 + F_4 + F_5}{N_L},$$

$$\frac{F_4 + F_5}{N_L},$$

$$\frac{F_5}{N_L},$$

where N_L is a number of lesions (signal). To emphasize its denominator N_L , we also call it the *False Positive Fraction (FPF) per lesion*.

On the other hand,

if ModifiedPoisson = FALSE (Default), then *False Positive Fraction (FPF)* is given by

$$\frac{F_1 + F_2 + F_3 + F_4 + F_5}{N_I},$$

$$\frac{F_2 + F_3 + F_4 + F_5}{N_I},$$

$$\frac{F_3 + F_4 + F_5}{N_I},$$

$$\frac{F_4 + F_5}{N_I},$$

$$\frac{F_5}{N_I},$$

where N_I is the number of images (trial). To emphasize its denominator N_I , we also call it the *False Positive Fraction (FPF) per image*.

The model is fitted so that the estimated FROC curve can be regarded as the expected pairs of FPF per image and TPF per lesion (ModifiedPoisson = FALSE)

or as the expected pairs of FPF per image and TPF per lesion (ModifiedPoisson = TRUE)

If ModifiedPoisson = TRUE, then FROC curve means the expected pair of **FPF per lesion** and TPF.

On the other hand, if ModifiedPoisson = FALSE, then FROC curve means the expected pair of **FPF per image** and TPF.

So, data of FPF and TPF are changed thus, a fitted model is also changed whether ModifiedPoisson = TRUE or FALSE. In traditional FROC analysis, it uses only

per images (trial). Since we can divide one image into two images or more images, number of trial is not important. And more important is per signal. So, the author also developed FROC theory to consider FROC analysis under per signal. One can see that the FROC curve is rigid with respect to change of a number of images, so, it does not matter whether ModifiedPoisson = TRUE or FALSE. This rigidity of curves means that the number of images is redundant parameter for the FROC trial and thus the author try to exclude it.

Revised 2019 Dec 8 Revised 2019 Nov 25 Revised 2019 August 28

Details

From data of number of hits (True Positive: TP) and false alarms (False Positive: FP), we calculate the number of cumulative false positives (FPF) and cumulative hits (TPF).

Because there are three subscripts, reader, modality, and image, we create array format and vector format etc...

Value

A metadata such as number of cumulative false alarms and hits to create and draw the curve.

Examples

```
## Not run:
#=====
#                               TP and FP
#=====

dat <- BayesianFROC::dataList.Chakra.Web

#=====
#                               Calculates TPF and FPF from TP and FP
#=====

metadata_srsc_per_image(dat)

# Revised 2019 Nov.

## End(Not run)# dottest
```

 metadata_to_DrawCurve_MRMC

Create metadata for MRMC data

Description

From data of number of hits and false alarms, we calculate the number of cumulative false positives and hits. Since there are three subscripts, reader, modality, and image, we create array format and vector format etc...

Usage

```
metadata_to_DrawCurve_MRMC(StanS4class, mesh.for.drawing.curve = 5000)
```

Arguments

StanS4class An S4 object of class `stanfitExtended` which is an inherited class from the S4 class `stanfit`. This R object is a fitted model object as a return value of the function `fit_Bayesian_FROC()`.

It can be passed to `DrawCurves()`, `ppp()` and ... etc

mesh.for.drawing.curve

A positive large integer, indicating number of dots drawing the curves, Default =10000.

Value

A metadata such as number of cumulative false alarms and hits to create and draw the curve.

 metadata_to_fit_MRMC *Create metadata for MRMC data*

Description

The so-called *false positive fraction (FPF)* and the *true positive fraction (TPF)* are calculated from the number of hits (True Positives: TPs) and the number of false alarms (False Positives: FPs)

Usage

```
metadata_to_fit_MRMC(dataList, ModifiedPoisson = FALSE)
```

Arguments

`dataList` A list, consisting of the following **R** objects: `m`, `q`, `c`, `h`, `f`, `NL`, `C`, `M`, `Q` each of which means from the right

`m` : A vector, indicating the modality ID = 1,2,... which does not include zero.
`q` : A vector, indicating the reader ID = 1,2,... which does not include zero.
`c` : A vector, indicating the confidence = 1,2,... which does not include zero.
`h` : A vector, indicating the number of hits
`f` : A vector, indicating the number of false alarm
`NL` : An positive integer, indicating the number of lesions for all images
`C` : An positive integer, indicating the highest number of confidence level
`M` : An positive integer, indicating the number of modalities
`Q` : An positive integer, indicating the number of readers.
The detail of these dataset, please see the example datasets, e.g. [dd](#).

`ModifiedPoisson`

Logical, that is TRUE or FALSE.

If `ModifiedPoisson = TRUE`, then Poisson rate of false alarm is calculated *per lesion*, and model is fitted so that the FROC curve is an expected curve of points consisting of the pairs of TPF per lesion and FPF *per lesion*.

Similarly,

If `ModifiedPoisson = TRUE`, then Poisson rate of false alarm is calculated *per image*, and model is fitted so that the FROC curve is an expected curve of points consisting of the pair of TPF per lesion and FPF *per image*.

For more details, see the author's paper in which I explained *per image* and *per lesion*. (for details of models, see [vignettes](#), now, it is omitted from this package, because the size of vignettes are large.)

If `ModifiedPoisson = TRUE`, then the *False Positive Fraction (FPF)* is defined as follows (F_c denotes the number of false alarms with confidence level c)

$$\frac{F_1 + F_2 + F_3 + F_4 + F_5}{N_L},$$

$$\frac{F_2 + F_3 + F_4 + F_5}{N_L},$$

$$\frac{F_3 + F_4 + F_5}{N_L},$$

$$\frac{F_4 + F_5}{N_L},$$

$$\frac{F_5}{N_L},$$

where N_L is a number of lesions (signal). To emphasize its denominator N_L , we also call it the *False Positive Fraction (FPF) per lesion*.

On the other hand,

if ModifiedPoisson = FALSE (Default), then *False Positive Fraction (FPF)* is given by

$$\frac{F_1 + F_2 + F_3 + F_4 + F_5}{N_I},$$

$$\frac{F_2 + F_3 + F_4 + F_5}{N_I},$$

$$\frac{F_3 + F_4 + F_5}{N_I},$$

$$\frac{F_4 + F_5}{N_I},$$

$$\frac{F_5}{N_I},$$

where N_I is the number of images (trial). To emphasize its denominator N_I , we also call it the *False Positive Fraction (FPF) per image*.

The model is fitted so that the estimated FROC curve can be regarded as the expected pairs of FPF per image and TPF per lesion (ModifiedPoisson = FALSE)

or as the expected pairs of FPF per image and TPF per lesion (ModifiedPoisson = TRUE)

If ModifiedPoisson = TRUE, then FROC curve means the expected pair of **FPF per lesion** and TPF.

On the other hand, if ModifiedPoisson = FALSE, then FROC curve means the expected pair of **FPF per image** and TPF.

So, data of FPF and TPF are changed thus, a fitted model is also changed whether ModifiedPoisson = TRUE or FALSE. In traditional FROC analysis, it uses only per images (trial). Since we can divide one image into two images or more images, number of trial is not important. And more important is per signal. So, the author also developed FROC theory to consider FROC analysis under per signal. One can see that the FROC curve is rigid with respect to change of a number of images, so, it does not matter whether ModifiedPoisson = TRUE or FALSE. This rigidity of curves means that the number of images is redundant parameter for the FROC trial and thus the author try to exclude it.

Revised 2019 Dec 8 Revised 2019 Nov 25 Revised 2019 August 28

Details

To fit a model to data, we need a hit data and false data formulated by both an array and a vector.

It also calculates the so-called False Positive Fractions (FPF) (resp. True Positive Fractions (TPF)) which are cumulative sums of false alarms (resp. hits) over number of lesions or images.

From data of number of hits and false alarms, we calculate the number of cumulative false positives and hits per image or lesion, in other words, *False Positive Fraction (FPF)* and *True Positive Fraction (TPF)*. Since there are three subscripts, *reader*, *modality*, and *image*, we can create array format or vector format etc...

Abbreviations

FPF: false positive fraction

TPF: true positive fraction

hit : True Positive = TP

false alarms: False Positive = FP

The traditionally, the so-called FPF;False Positive Fraction and TPT:True Positive Fraction are used. Recall that our data format:

A single reader and a single modality case

NI, NL	confidence level	No. of false alarms (FP:False Positive)	No. of hits (TP:True Positive)
<i>definitely</i> present	5	F_5	H_5
<i>probably</i> present	4	F_4	H_4
equivocal	3	F_3	H_3
subtle	2	F_2	H_2
<i>very</i> subtle	1	F_1	H_1

FPF is defined as follows;

$$\begin{aligned}
 FPF(5) &:= \frac{F_5}{NI}, \\
 FPF(4) &:= \frac{F_4 + F_5}{NI}, \\
 FPF(3) &:= \frac{F_3 + F_4 + F_5}{NI}, \\
 FPF(2) &:= \frac{F_2 + F_3 + F_4 + F_5}{NI}, \\
 FPF(1) &:= \frac{F_1 + F_2 + F_3 + F_4 + F_5}{NI}.
 \end{aligned}$$

TPF is defined as follows;

$$\begin{aligned}
 TPF(5) &:= \frac{H_5}{NL}, \\
 TPF(4) &:= \frac{H_4 + H_5}{NL}, \\
 TPF(3) &:= \frac{H_3 + H_4 + H_5}{NL}, \\
 TPF(2) &:= \frac{H_2 + H_3 + H_4 + H_5}{NL}, \\
 TPF(1) &:= \frac{H_1 + H_2 + H_3 + H_4 + H_5}{NL}.
 \end{aligned}$$

Value

A list, which includes arrays and vectors. A metadata such as number of cumulative false alarms and hits to create and draw the curve.

The *False Positive Fraction (FPF)* and *True Positive Fraction (TPF)* are also calculated.

The components of list *I rediscover it at 2019 Jun 18, I am not sure it is useful? 2019 Dec 8*

- harray An array of hit, dimension [C,M,Q], where C,M,Q are a number of confidence level, modalities, readers, respectively.
- farray An array of false alarms, dimension [C,M,Q], where C,M,Q are a number of confidence level, modalities, readers, respectively.
- hharray An array of **cumulative** hits, dimension [C,M,Q], where C,M,Q are a number of confidence level, modalities, readers, respectively.
- ffarray An array of **cumulative** false alarms, dimension [C,M,Q], where C,M,Q are a number of confidence level, modalities, readers, respectively.
- hharrayN An array of TPF, dimension [C,M,Q], where C,M,Q are a number of confidence level, modalities, readers, respectively.
- ffarrayN An array of FPF, dimension [C,M,Q], where C,M,Q are a number of confidence level, modalities, readers, respectively.
- h An vector of hit, dimension [C*M*Q], where C,M,Q are a number of confidence level, modalities, readers, respectively.
- f An vector of false alarms, dimension [C*M*Q], where C,M,Q are a number of confidence level, modalities, readers, respectively.
- hh An vector of **cumulative** hits, dimension [C*M*Q], where C,M,Q are a number of confidence level, modalities, readers, respectively.
- ff An vector of **cumulative** false alarms, dimension [C*M*Q], where C,M,Q are a number of confidence level, modalities, readers, respectively.
- hhN An vector of TPF, dimension [C*M*Q], where C,M,Q are a number of confidence level, modalities, readers, respectively.
- ffN An vector of FPF, dimension [C*M*Q], where C,M,Q are a number of confidence level, modalities, readers, respectively.

Revised Nov. 21

Examples

```

=====
#
#           First, we prepare the data endowed with this package.
#
=====

dat <- get(data("dataList.Chakra.Web"))

#=====
#
#           #Calculate FPFs and TPFs and etc.
#
=====

a <- metadata_to_fit_MRMC(dat)

#Now, we get a meta-data object named "a".

#=====
#
#           Check of Definiion
#
=====

a$hh/dat$NL == a$hhN

# Since all of aboves are TRUE, the hhN is a TPF per NL.

#=====
#
#           Plot a FPFs and TPFs
#
=====
#'

FPF = a$ffN
TPF = a$hhN

dark_theme()
plot(FPF, TPF)

#=====
#
#           Plot a FPFs and TPFs via ggplot
#
=====

length(dat$f)==length(FPF)

```

```
q <- dat$q
m <- dat$m
df <- data.frame(FPF,
                 TPF,
                 m,
                 q
                 )

# ggplot2::ggplot(df, aes(x = FPF, y = TPF, colour = q, group = m)) + ggplot2::geom_point()

# Revised 2019 Jun 18, Revised 2019 Sept 9
```

mu

Mean of signal: parameter of an MRMC model

Description

A posterior mean of the model parameter for data [ddd](#) as an example of truth parameter.

Author(s)

Issei Tsunoda <tsunoda.issei1111@gmail.com >

See Also

`make_true_parameter_MRMC`

Examples

```
#> BayesianFROC::mu

#[,1]      [,2]      [,3]      [,4]
#[1,] 1.914686 0.7933306 1.526482 0.9543375
#[2,] 2.008008 1.2005846 2.081756 1.0197703
#[3,] 1.532117 0.5851726 1.513018 0.8879678

# [modality, reader]
```

mu_truth	<i>Mean of signal: parameter of an MRMC model</i>
----------	---

Description

A posterior mean of the model parameter for data `ddd` as an example of truth parameter.

Details

Mean Rate data of some MRMC data to use as a default value of the function `hits_creator_from_rate`. This is an array obtained from estimates of some data contained in this package. To simulate a replication of dataset, the default values should be used from an actual values. Thus the author prepare this data.

Author(s)

Issei Tsunoda <tsunoda.issei1111@gmail.com >

See Also

`hits_creator_from_rate`

Examples

```
#> mu_truth
#
#      [,1]      [,2]      [,3]      [,4]
#[1,] 1.730751 0.8298189 1.334771 0.6386057
#[2,] 1.812523 1.1889223 1.883562 0.7185546
#[3,] 1.319588 0.6062924 1.248589 0.5458920

# [modality, reader]
```

mu_truth_creator_for_many_readers_MRMC_data
mu of MRMC model paramter

Description

mu of MRMC model paramter

Usage

```
mu_truth_creator_for_many_readers_MRMC_data(M, Q)
```

Arguments

M An integer, indicating a number of modalities
 Q An integer, indicating a number of readers

Value

An array, representing a mu of MRMC model paramter

Examples

```
m <- mu_truth_creator_for_many_readers_MRMC_data(M=4,Q=50)

## Not run:

#=====
#           Large number of readers or modalities causes non-convergence MCMC
#=====

v <- v_truth_creator_for_many_readers_MRMC_data(M=4,Q=6)
m <- mu_truth_creator_for_many_readers_MRMC_data(M=4,Q=6)
d <- create_dataList_MRMC(mu.truth = m,v.truth = v)
#fit <- fit_Bayesian_FROC( ite = 1111, cha = 1, summary = TRUE, dataList = d )

#plot_FPF_and_TPF_from_a_dataset(fit@dataList)

#=====
#           convergence
#=====
```

```
v <- v_truth_creator_for_many_readers_MRMC_data(M=2,Q=21)
m <- mu_truth_creator_for_many_readers_MRMC_data(M=2,Q=21)
d <- create_dataList_MRMC(mu.truth = m,v.truth = v)
#fit <- fit_Bayesian_FROC( ite = 200, cha = 1, summary = TRUE, dataList = d)

#=====
#                               non-convergence
#=====

v <- v_truth_creator_for_many_readers_MRMC_data(M=5,Q=6)
m <- mu_truth_creator_for_many_readers_MRMC_data(M=5,Q=6)
d <- create_dataList_MRMC(mu.truth = m,v.truth = v)
# fit <- fit_Bayesian_FROC( ite = 111, cha = 1, summary = TRUE, dataList = d)

#=====
#                               convergence
#=====

v <- v_truth_creator_for_many_readers_MRMC_data(M=1,Q=36)
m <- mu_truth_creator_for_many_readers_MRMC_data(M=1,Q=36)
d <- create_dataList_MRMC(mu.truth = m,v.truth = v)
#fit <- fit_Bayesian_FROC( ite = 2000, cha = 1, summary = TRUE, dataList = d)

#=====
#                               non-convergence
#=====

v <- v_truth_creator_for_many_readers_MRMC_data(M=1,Q=37)
m <- mu_truth_creator_for_many_readers_MRMC_data(M=1,Q=37)
d <- create_dataList_MRMC(mu.truth = m,v.truth = v)
# fit <- fit_Bayesian_FROC( ite = 111, cha = 1, summary = TRUE, dataList = d)
```



```
## End(Not run)
```

```
m_q_c_vector_from_M_Q_C
```

```
Creates vectors: m, q, c from integers: M, Q, C
```

Description

Makes m, q, c vectors from a collection of three integers M, Q, C, where three vectors m, q, c denotes modality ID, reader ID, confidence level, respectively.

Usage

```
m_q_c_vector_from_M_Q_C(M, Q, C)
```

Arguments

M	A positive integer, representing modality ID
Q	A positive integer, representing reader ID
C	A positive integer, representing confidence level

Details

My research is not supported any found, I am completely independent and only my own or my parents are supported my research. No internet, poor condition, I made this. I must go on until journal accepts my manuscripts.

I am not happy to spent with FROC analysis, since it is not my interest. I want to research pure mathematics. I do not want to waste a time. I do not want to waste a time in hospital or plurigo nodularis. When I become happy? This program helps me? With great pain at 2019 Sept. 2019 Sept. 8

Value

A data-frame, including three vectors, which are named m, q, c representing modality ID and reader ID and confidence level, respectively.

For example, the resulting object of a `<-m_q_c_vector_from_M_Q_C(2, 3, 4)` is given by

```
> a
```

m	q	c
1	1	4
1	1	3
1	1	2
1	1	1
1	2	4
1	2	3
1	2	2
1	2	1
1	3	4
1	3	3
1	3	2
1	3	1
2	1	4
2	1	3
2	1	2
2	1	1
2	2	4
2	2	3
2	2	2
2	2	1
2	3	4
2	3	3
2	3	2
2	3	1

Examples

```

=====
#                               Create a ID vectors
=====

a <- m_q_c_vector_from_M_Q_C(2,3,4)

a$m
a$q
a$c

=====
#                               validation of this function
=====
#'

a <- m_q_c_vector_from_M_Q_C(5,4,5)

```

```
a$m == dd$m
a$c == dd$c
a$q == dd$q
```

p

*Hit Rate: parameter of an MRMC model***Description**

A posterior mean of the model parameter for data `ddd` as an example of truth parameter.

Author(s)

Issei Tsunoda <tsunoda.issei1111@gmail.com >

See Also

`make_true_parameter_MRMC`

`pairs_plot_if_divergent_transition_occurred`

Pairs plot for divergent transition

Description

If divergent transition occurs, the author often forget the variable `par` or `pars`. So, I made this to avoid such confusion.

Usage

```
pairs_plot_if_divergent_transition_occurred(
  StanS4class,
  character.representing.paramter = "z"
)
```

Arguments

`StanS4class` An S4 object of class `stanfitExtended` which is an inherited class from the S4 class `stanfit`. This R object is a fitted model object as a return value of the function `fit_Bayesian_FROC()`.

It can be passed to `DrawCurves()`, `ppp()` and ... etc

`character.representing.paramter`

Character, surrounded by "", indicating the paramter of model.

Examples

```
## Not run:
\dontrun{

# Create a fitted model object of class stanfitExtended inherited from stanfit.

fit <- fit_Bayesian_FROC( ite = 1111,
                        summary = FALSE,
                        cha = 1,
                        Null.Hypothesis = FALSE,
                        dataList = dd )

# Pairs plot to examine the divergent transition.

if (interactive()){grDevices::dev.new()}
  pairs_plot_if_divergent_transition_occurred(fit)
if (interactive()){grDevices::dev.off()}

}

## End(Not run)
```

pause

Pause for Demo

Description

Pause if and only if `interactive() = TRUE`.

Usage

```
pause(simple = FALSE)
```

Arguments

`simple` A logical. If false, then verbose.
`pause()`

Phi *The Cumulative distribution function $\Phi(x)$ of the Standard Gaussian, namely, mean = 0 and variance = 1.*

Description

$$\Phi(x) := \int_{-\infty}^x \frac{1}{\sqrt{2\pi}} e^{-\frac{x^2}{2}}$$

Usage

Phi(x)

Arguments

x A real. To be passed to the function `stats::pnorm()`

Value

$\Phi(x) := \int_{-\infty}^x \text{Gaussian}(z|0,1)dz$

See Also

[Phi_inv\(\)](#)

Examples

```
#####
#           1)           validation of this function
#####
#'
  x<-0.2
  Phi(x)==stats::pnorm(x)

#####
#           1)           Build the data
#####
#'

a <- 0.1;
NX <- 222;
x <- runif(100,-11,11)
y <- Phi_inv(exp(a/NX) *Phi(x))-x
plot(x,y)

a <- 0.1;
NX <- 222;
```

```
x <- runif(100,0,11)
y <- Phi_inv(exp(a/NX) *Phi(x))-x
plot(x,y)
```

```
a <- 0.1;
NX <- 222;
x <- runif(100,2,4)
y <- Phi_inv(exp(a/NX) *Phi(x))-x
plot(x,y)
```

```
a <- 0.01;
NX <- 222;
x <- runif(100,2,4);
y <- Phi_inv(exp(a/NX) *Phi(x))-x
plot(x,y)
```

```
a <- 0.01;
NX <- 222;
x <- runif(100,3.5,4);
y <- Phi_inv(exp(a/NX) *Phi(x))-x
plot(x,y)
```

Phi_inv	<i>Inverse function of the Cumulative distribution function $\Phi(x)$ of the Standard Gaussian. where x is a real number.</i>
---------	---

Description

The author is confused stats::qnorm() with stats::pnorm() and thus he made this.

Usage

```
Phi_inv(x)
```

Arguments

x A real. To be passed to the function stats::qnorm()

Details

In Stan file, it is inv_Phi() and not inv_phi.

Since $\Phi(x)$ is monotonic, it follows that $\frac{d}{dx}\Phi^{-1} = \left(\frac{d}{dx}\Phi\right)^{-1} > 0$, and thus $\Phi^{-1}(x)$ is also monotonic.

Value

A real number: $\Phi^{-1}(x)$

See Also

[Phi\(\)](#), [inv_Phi\(\)](#)

Examples

```
x <- runif(100)
Phi_inv(x) == stats::qnorm(x)
inv_Phi(x) == stats::qnorm(x)
```

plot,stanfitExtended,missing-method
A generic function plot()

Description

A generic function plot()

Usage

```
## S4 method for signature 'stanfitExtended,missing'
plot(x, y, ...)
```

Arguments

x	An R object of the S4 class (stanfitExtended)
y	An R object of the S4 class <code>methods::missing-class</code> .
...	Additional arguments

plotFROC

Draw FROC curves by two parameters a and b

Description

Plot FROC curves based on two parameters a and b.

Usage

```
plotFROC(
  a,
  b,
  mesh.for.drawing.curve = 10000,
  upper_x = 1,
  upper_y = 1,
  lower_y = 0
)
```

Arguments

- | | |
|------------------------|--|
| a | An arbitrary real number. It is no need to require any assumption, but I use such as $a=\mu/\sigma$, where μ is a mean of signal distribution and σ is its standard deviation in the bi-normal assumption. |
| b | An arbitrary positive real number. I use such as $b=1/\sigma$, where σ is a standard deviation of signal distribution in the bi-normal assumption. |
| mesh.for.drawing.curve | A positive large integer, indicating number of dots drawing the curves, Default =10000. |
| upper_x | A positive real number, indicating the frame size of drawing picture. |
| upper_y | A positive real number, indicating the frame size of drawing picture. |
| lower_y | A positive real number, indicating the frame size of drawing picture. |

Details

FROC curve is the alternative notion of ROC curve in signal detection theory.

The definition of FROC curve is

$$(x(t), y(t)) = (t, 1 - \Phi(b * \Phi^{-1}(\exp(-t)) - a))$$

where, $\Phi()$ is the cumulative distribution function of the standard Gaussian distribution and $\Phi^{-1}()$ is its inverse mapping.

Revised 2019 Nov 27

Examples

```
dark_theme()

plotFROC(0.1,0.2)
```

```
plot_curve_and_hit_rate_and_false_rate_simultaneously
      Curve and signal distribution and noise  $d \log \Phi$  for a single reader
      and a single modality
```

Description

Draws FROC curve and signal and noise (noise distribution is the differential of the logarithmic of the cumulative standard Gaussian denoted by $d \log \Phi$) are drawn in a **same** plain. The author of this pacakage developed the FROC theory, and find that the noise distribution is not the so-called bi normal assumption. But instead, we use the differential logarithmic Gaussian for the noise distribution.

Note that MRMC data is not allowed.

Usage

```
plot_curve_and_hit_rate_and_false_rate_simultaneously(StanS4class)
```

Arguments

`StanS4class` An S4 object of class `stanfitExtended` which is an inherited class from the S4 class `stanfit`. This R object is a fitted model object as a return value of the function `fit_Bayesian_FROC()`.
It can be passed to `DrawCurves()`, `ppp()` and ... etc

Details

This function is made to pass this plot to Shiny.

With pain from all my body, but today 2019 July 23 is good. Neuralgia or muscle aches makes my feeling down and down. If I can transform into Anpanman, then I want to give my head.

I fails, this is very small plot, so I cannot use this function for my package. I will remove this function or extende plot region for more comfortable exhibition.

Value

None

See Also[DrawCurves](#)[draw_latent_noise_distribution](#)**Examples**

```

## Not run:

#=====
#           1)           Build the data
#=====

# For singler reader and single modality case.

dat <- list(c=c(3,2,1), #Confidence level. Note that c is ignored.
           h=c(97,32,31), #Number of hits for each confidence level
           f=c(1,14,74), #Number of false alarms for each confidence level

           NL=259, #Number of lesions
           NI=57, #Number of images
           C=3) #Number of confidence level

# where,
# c denotes confidence level, i.e., rating of reader.
# 3 = Definitely deseased,
# 2 = subtle,.. deseased
# 1 = very subtle
# h denotes number of hits (True Positives: TP) for each confidence level,
# f denotes number of false alarms (False Positives: FP) for each confidence level,
# NL denotes number of lesions,
# NI denotes number of images,

# For example, in the above example data,
# the number of hits with confidence level 3 is 97,
# the number of hits with confidence level 2 is 32,
# the number of hits with confidence level 1 is 31,

# the number of false alarms with confidence level 3 is 1,
# the number of false alarms with confidence level 2 is 14,
# the number of false alarms with confidence level 1 is 74,

#-----
#           2)           Fit a model to the above data-set
#-----

```

#Since dataset named dat are a single reader and a single modality,
#the function build the such model by running the following code.

```
fit <- BayesianFROC::fit_Bayesian_FROC(
  dat,      # dataset
  ite=1111, #To run in time <5s.
  cha=1     # number of chains, it is better more large.
)
```

```
#-----
#           3) Draw the FROC curve and signal and noise (logarithmic Gaussian)
#-----
```

```
# Using fitted model object of class stanfitExtended, we can draw curves.
```

```
plot_curve_and_hit_rate_and_false_rate_simultaneously(fit)
```

```
## End(Not run)
```

plot_empirical_FROC_curves

*Plot empirical FROC Curves by traditional ways of **ggplot2***

Description

Plot empirical FROC Curves.

Usage

```
plot_empirical_FROC_curves(
  dataList.MRMC,
  ModifiedPoisson = FALSE,
  colored_by_modality = TRUE,
  numbered_by_modality = TRUE,
  cex = 1.3,
```

```

modalityID = c(1, dataList.MRMC$M),
readerID = c(1, dataList.MRMC$Q)
)

```

Arguments

`dataList.MRMC` A list, indicating FROC data of MRMC. See also `dataList` which is a variable of the function `fit_Bayesian_FROC()`.

`ModifiedPoisson`

Logical, that is TRUE or FALSE.

If `ModifiedPoisson = TRUE`, then Poisson rate of false alarm is calculated *per lesion*, and model is fitted so that the FROC curve is an expected curve of points consisting of the pairs of TPF per lesion and FPF *per lesion*.

Similarly,

If `ModifiedPoisson = TRUE`, then Poisson rate of false alarm is calculated *per image*, and model is fitted so that the FROC curve is an expected curve of points consisting of the pair of TPF per lesion and FPF *per image*.

For more details, see the author's paper in which I explained *per image* and *per lesion*. (for details of models, see [vignettes](#), now, it is omitted from this package, because the size of vignettes are large.)

If `ModifiedPoisson = TRUE`, then the *False Positive Fraction (FPF)* is defined as follows (F_c denotes the number of false alarms with confidence level c)

$$\frac{F_1 + F_2 + F_3 + F_4 + F_5}{N_L},$$

$$\frac{F_2 + F_3 + F_4 + F_5}{N_L},$$

$$\frac{F_3 + F_4 + F_5}{N_L},$$

$$\frac{F_4 + F_5}{N_L},$$

$$\frac{F_5}{N_L},$$

where N_L is a number of lesions (signal). To emphasize its denominator N_L , we also call it the *False Positive Fraction (FPF) per lesion*.

On the other hand,

if `ModifiedPoisson = FALSE` (Default), then *False Positive Fraction (FPF)* is given by

$$\frac{F_1 + F_2 + F_3 + F_4 + F_5}{N_I},$$

$$\frac{F_2 + F_3 + F_4 + F_5}{N_I},$$

$$\frac{F_3 + F_4 + F_5}{N_I},$$

$$\frac{F_4 + F_5}{N_I},$$

$$\frac{F_5}{N_I},$$

where N_I is the number of images (trial). To emphasize its denominator N_I , we also call it the *False Positive Fraction (FPF) per image*.

The model is fitted so that the estimated FROC curve can be regarded as the expected pairs of FPF per image and TPF per lesion (ModifiedPoisson = FALSE)

or as the expected pairs of FPF per image and TPF per lesion (ModifiedPoisson = TRUE)

If ModifiedPoisson = TRUE, then FROC curve means the expected pair of FPF **per lesion** and TPF.

On the other hand, if ModifiedPoisson = FALSE, then FROC curve means the expected pair of **FPF per image** and TPF.

So, data of FPF and TPF are changed thus, a fitted model is also changed whether ModifiedPoisson = TRUE or FALSE. In traditional FROC analysis, it uses only per images (trial). Since we can divide one image into two images or more images, number of trial is not important. And more important is per signal. So, the author also developed FROC theory to consider FROC analysis under per signal. One can see that the FROC curve is rigid with respect to change of a number of images, so, it does not matter whether ModifiedPoisson = TRUE or FALSE. This rigidity of curves means that the number of images is redundant parameter for the FROC trial and thus the author try to exclude it.

Revised 2019 Dec 8 Revised 2019 Nov 25 Revised 2019 August 28

colored_by_modality

A logical, if TRUE, then the color in the scatter plot means modality ID. If not, then the each color in the scatter plot indicates reader ID.

numbered_by_modality

A logical, if TRUE, then the number in the scatter plot means modality ID. If not, then the each number in the scatter plot indicates reader ID.

cex

A positive real number, specifying the size of dots in the resulting plot.

modalityID

A vector of integer, specifying modality ID to be drawn.

readerID

A vector of integer, specifying reader ID to be drawn.

Value

An object made by ggplot2, I am not sure what it is.

Examples

```
#####
#                               The 1-st example
#####
```

```
plot_empirical_FROC_curves(dd,readerID = 1:4,modalityID = 1:5)
plot_empirical_FROC_curves(dd,readerID = 1,modalityID = c(4,3))
plot_empirical_FROC_curves(dd,readerID = 2,modalityID = c(4,3))
plot_empirical_FROC_curves(dd,readerID = 3,modalityID = c(4,3))
plot_empirical_FROC_curves(dd,readerID = 4,modalityID = c(4,3))
```

```
#####
#                               The example
#####
```

```
v <- v_truth_creator_for_many_readers_MRMC_data(M=2,Q=37)
m <- mu_truth_creator_for_many_readers_MRMC_data(M=2,Q=37)
d <- create_dataList_MRMC(mu.truth = m,v.truth = v)
```

```
plot_empirical_FROC_curves(d,readerID = 1:14,modalityID = 1:2)
```

```
plot_empirical_FROC_curves(d,readerID = 1:24,modalityID = 1:2)
```

```
plot_empirical_FROC_curves(d,readerID = 1:34,modalityID = 1:2)
```

```
#####
#                               The example
#####
```

```
v <- v_truth_creator_for_many_readers_MRMC_data(M=2,Q=7)
m <- mu_truth_creator_for_many_readers_MRMC_data(M=2,Q=7)
d <- create_dataList_MRMC(mu.truth = m,v.truth = v)
```

```

plot_empirical_FROC_curves(d,readerID = 1,modalityID = 1:2)
plot_empirical_FROC_curves(d,readerID = 2,modalityID = 1:2)
plot_empirical_FROC_curves(d,readerID = 3,modalityID = 1:2)
plot_empirical_FROC_curves(d,readerID = 4,modalityID = 1:2)
plot_empirical_FROC_curves(d,readerID = 5,modalityID = 1:2)
plot_empirical_FROC_curves(d,readerID = 6,modalityID = 1:2)
plot_empirical_FROC_curves(d,readerID = 7,modalityID = 1:2)

#=====
#                               The example
#=====

plot_empirical_FROC_curves(dd)
plot_empirical_FROC_curves(dd,modalityID = c(3,5))
plot_empirical_FROC_curves(dd,modalityID = c(3,5),readerID = c(1,4))
plot_empirical_FROC_curves(dd,modalityID = c(3,5),readerID = c(1,3))
plot_empirical_FROC_curves(dd,modalityID = c(3,5),readerID = c(1,2,3))
plot_empirical_FROC_curves(dd,modalityID = c(3,5),readerID = c(1,2,3))
plot_empirical_FROC_curves(dd,modalityID = c(3,5),readerID = c(3))
plot_empirical_FROC_curves(dd,modalityID = c(3,5),readerID = c(1,2,3))
plot_empirical_FROC_curves(dd,modalityID = c(3,5),readerID = c(1,2))
plot_empirical_FROC_curves(dd,modalityID = c(3,5),readerID = c(2))
plot_empirical_FROC_curves(dd,modalityID = c(3),readerID = c(2))
plot_empirical_FROC_curves(dd,modalityID = c(5),readerID = c(2))

```

plot_FPF_and_TPF_from_a_dataset

Plot FPF and TPF from MRMC data

Description

From data (srsc or MRMC), empirical FROC is plotted, namely FPF and TPF.

Usage

```
plot_FPF_and_TPF_from_a_dataset(dataList, ModifiedPoisson = FALSE)
```

Arguments

`dataList`

A list, specifying an FROC data to be fitted a model. It consists of data of numbers of TPs, FPs, lesions, images. .In addition, if in case of mutple readers or mutple modalities, then modaity ID and reader ID are included also.

The `dataList` will be passed to the function `rstan::sampling()` of **rstan**. This is a variable in the function `rstan::sampling()` in which it is named `data`.

For the single reader and a single modality data, the `dataList` is made by the following manner:

```
dataList.Example <-list(
h = c(41,22,14,8,1),# number of hits for each confidence level
f = c(1,2,5,11,13),# number of false alarms for each confidence level

NL = 124,# number of lesions (signals)
NI = 63,# number of images (trials)
C = 5) # number of confidence,.. the author thinks it can be calculated
as the length of h or f ...? ha,why I included this. ha .. should be omitted.
```

Using this object `dataList.Example`, we can apply `fit_Bayesian_FROC()` such as `fit_Bayesian_FROC(dataList.Example)`.

To make this R object `dataList` representing FROC data, this package provides three functions:

- `convertFromJafroc()` If data is a **JAFROC xlsx** formulation.
- `dataset_creator_new_version()` Enter TP and FP data **by table** .
- `create_dataset()` Enter TP and FP data by **interactive** manner.

Before fitting a model, we can confirm our dataset is correctly formulated by using the function `viewdata()`.

A Single reader and a single modality (SRSC) case.

In a single reader and a single modality case (`srsc`), `dataList` is a list consisting of `f,h,NL,NI,C` where `f,h` are numeric vectors and `NL,NI,C` are positive integers.

- `f` Non-negative integer vector specifying number of false alarms associated with each confidence level. The first component corresponding to the highest confidence level.
- `h` Non-negative integer vector specifying number of Hits associated with each confidence level. The first component corresponding to the highest confidence level.
- `NL` A positive integer, representing Number of Lesions.
- `NI` A positive integer, representing Number of Images.
- `C` A positive integer, representing Number of Confidence level.

The detail of these dataset, see the datasets endowed with this package. 'Note that the maximal number of confidence level, denoted by `C`, are included, however, Note that confidence level vector `c` should not be specified. If specified,

will be ignored , since it is created by `c<-c(rep(C:1))` in the program and do not refer from user input data, where C is the highest number of confidence levels. So, you should write down your hits and false alarms vector so that it is compatible with this automatically created c vector.

data Format:

A single reader and a single modality case

NI=63, NL=124 In R console ->	confidence level c	No. of false alarms f	No. of hits h
definitely present	$c[1] = 5$	$f[1] = F_5 = 1$	$h[1] = H_5 = 41$
probably present	$c[2] = 4$	$f[2] = F_4 = 2$	$h[2] = H_4 = 22$
equivocal	$c[3] = 3$	$f[3] = F_3 = 5$	$h[3] = H_3 = 14$
subtle	$c[4] = 2$	$f[4] = F_2 = 11$	$h[4] = H_2 = 8$
very subtle	$c[5] = 1$	$f[5] = F_1 = 13$	$h[5] = H_1 = 1$

* *false alarms* = False Positives = FP

* *hits* = True Positives = TP

Note that in FROC data, all confidence level means *present (diseased, lesion)* case only, no confidence level indicating absent. Since each reader marks his suspicious location only if he thinks lesions are *present*, and marked positions generates the hits or false alarms, *thus* each confidence level represents that lesion is *present*. In the absent case, reader dose not mark any locations and hence, the absent confidence level does not relate this dataset. So, if reader think it is no lesion, then in such case confidence level is not needed.

Note that the first column of confidence level vector c should not be specified. If specified, will be ignored , since it is created by `c<-c(rep(C:1))` automatically in the program and do not refer from user input data even if it is specified explicitly, where C is the highest number of confidence levels. So you should check the compatibility of your data and the confidence level vector `c<-c(rep(C:1))` via a table which can be displayed by the function `viewdata()`.

Multiple readers and multiple modalities case, i.e., MRMC case

In case of multiple readers and multiple modalities, i.e., MRMC case, in order to apply the function `fit_Bayesian_FROC()`, dataset represented by an R list object representing FROC data must contain components m, q, c, h, f, NL, C, M, Q.

- C A positive integer, representing the **highest** number of confidence level, this is a scalar.
- M A positive integer vector, representing the number of **modalities**.
- Q A positive integer, representing the number of **readers**.

- m A vector of positive integers, representing the **modality** ID vector.
- q A vector of positive integers, representing the **reader** ID vector.
- c A vector of positive integers, representing the **confidence level**. This vector must be made by `rep(rep(C:1), M*Q)`
- h A vector of non-negative integers, representing the number of **hits**.
- f A vector of non-negative integers, representing the number of **false alarms**.
- NL A positive integer, representing the Total number of **lesions** for all images, this is a scalar.

Note that the maximal number of confidence level (denoted by C) are included in the above R object. However, each confidence level vector is not included in the data, because it is created automatically from C. To confirm false positives and hits are correctly ordered with respect to the automatically generated confidence vector,

the function `viewdata()` shows the table. Revised 2019 Nov 27 Revised 2019 Dec 5

Example data.

Multiple readers and multiple modalities (i.e., MRMC)

Modality ID	Reader ID	Confidence levels	No. of false alarms	No. of hits.
m	q	c	f	h
1	1	3	20	111
1	1	2	29	55
1	1	1	21	22
1	2	3	6	100
1	2	2	15	44
1	2	1	22	11
2	1	3	6	66
2	1	2	24	55
2	1	1	23	1
2	2	3	5	66
2	2	2	30	55
2	2	1	40	44

* *false alarms* = False Positives = FP

* *hits* = True Positives = TP

ModifiedPoisson

Logical, that is TRUE or FALSE.

If ModifiedPoisson = TRUE, then Poisson rate of false alarm is calculated *per lesion*, and model is fitted so that the FROC curve is an expected curve of points consisting of the pairs of TPF per lesion and FPF *per lesion*.

Similarly,

If `ModifiedPoisson = TRUE`, then Poisson rate of false alarm is calculated **per image**, and model is fitted so that the FROC curve is an expected curve of points consisting of the pair of TPF per lesion and FPF **per image**.

For more details, see the author's paper in which I explained *per image* and *per lesion*. (for details of models, see **vignettes**, now, it is omitted from this package, because the size of vignettes are large.)

If `ModifiedPoisson = TRUE`, then the *False Positive Fraction (FPF)* is defined as follows (F_c denotes the number of false alarms with confidence level c)

$$\frac{F_1 + F_2 + F_3 + F_4 + F_5}{N_L},$$

$$\frac{F_2 + F_3 + F_4 + F_5}{N_L},$$

$$\frac{F_3 + F_4 + F_5}{N_L},$$

$$\frac{F_4 + F_5}{N_L},$$

$$\frac{F_5}{N_L},$$

where N_L is a number of lesions (signal). To emphasize its denominator N_L , we also call it the *False Positive Fraction (FPF) per lesion*.

On the other hand,

if `ModifiedPoisson = FALSE` (Default), then *False Positive Fraction (FPF)* is given by

$$\frac{F_1 + F_2 + F_3 + F_4 + F_5}{N_I},$$

$$\frac{F_2 + F_3 + F_4 + F_5}{N_I},$$

$$\frac{F_3 + F_4 + F_5}{N_I},$$

$$\frac{F_4 + F_5}{N_I},$$

$$\frac{F_5}{N_I},$$


```
plot_FPF_and_TPF_from_a_dataset(dd)
```

```
Close_all_graphic_devices()
```

```
plot_FPF_TPF_via_dataframe_with_split_factor
```

Scatter Plot of FPFs and TPFs via Splitting Factor

Description

Make a factor vector by which we plot FPF and TPF.

Usage

```
plot_FPF_TPF_via_dataframe_with_split_factor(
  dataList.MRMC,
  ModifiedPoisson = FALSE,
  colored_by_modality = TRUE,
  numbered_by_modality = TRUE,
  cex = 1.3
)
```

Arguments

`dataList.MRMC` A list, indicating FROC data of MRMC. See also `dataList` which is a variable of the function `fit_Bayesian_FROC()`.

`ModifiedPoisson`

Logical, that is TRUE or FALSE.

If `ModifiedPoisson = TRUE`, then Poisson rate of false alarm is calculated *per lesion*, and model is fitted so that the FROC curve is an expected curve of points consisting of the pairs of TPF per lesion and FPF *per lesion*.

Similarly,

If `ModifiedPoisson = TRUE`, then Poisson rate of false alarm is calculated *per image*, and model is fitted so that the FROC curve is an expected curve of points consisting of the pair of TPF per lesion and FPF *per image*.

For more details, see the author's paper in which I explained *per image* and *per lesion*. (for details of models, see [vignettes](#), now, it is omitted from this package, because the size of vignettes are large.)

If `ModifiedPoisson = TRUE`, then the *False Positive Fraction (FPF)* is defined as follows (F_c denotes the number of false alarms with confidence level c)

$$\frac{F_1 + F_2 + F_3 + F_4 + F_5}{N_L},$$

$$\frac{F_2 + F_3 + F_4 + F_5}{N_L},$$

$$\frac{F_3 + F_4 + F_5}{N_L},$$

$$\frac{F_4 + F_5}{N_L},$$

$$\frac{F_5}{N_L},$$

where N_L is a number of lesions (signal). To emphasize its denominator N_L , we also call it the *False Positive Fraction (FPF) per lesion*.

On the other hand,

if ModifiedPoisson = FALSE (Default), then *False Positive Fraction (FPF)* is given by

$$\frac{F_1 + F_2 + F_3 + F_4 + F_5}{N_I},$$

$$\frac{F_2 + F_3 + F_4 + F_5}{N_I},$$

$$\frac{F_3 + F_4 + F_5}{N_I},$$

$$\frac{F_4 + F_5}{N_I},$$

$$\frac{F_5}{N_I},$$

where N_I is the number of images (trial). To emphasize its denominator N_I , we also call it the *False Positive Fraction (FPF) per image*.

The model is fitted so that the estimated FROC curve can be regarded as the expected pairs of FPF per image and TPF per lesion (ModifiedPoisson = FALSE)

or as the expected pairs of FPF per image and TPF per lesion (ModifiedPoisson = TRUE)

If ModifiedPoisson = TRUE, then FROC curve means the expected pair of FPF **per lesion** and TPF.

On the other hand, if `ModifiedPoisson = FALSE`, then FROC curve means the expected pair of **FPF per image** and TPF.

So, data of FPF and TPF are changed thus, a fitted model is also changed whether `ModifiedPoisson = TRUE` or `FALSE`. In traditional FROC analysis, it uses only per images (trial). Since we can divide one image into two images or more images, number of trial is not important. And more important is per signal. So, the author also developed FROC theory to consider FROC analysis under per signal. One can see that the FROC curve is rigid with respect to change of a number of images, so, it does not matter whether `ModifiedPoisson = TRUE` or `FALSE`. This rigidity of curves means that the number of images is redundant parameter for the FROC trial and thus the author try to exclude it.

Revised 2019 Dec 8 Revised 2019 Nov 25 Revised 2019 August 28

`colored_by_modality`

A logical, if `TRUE`, then the color in the scatter plot means modality ID. If not, then the each color in the scatter plot indicates reader ID.

`numbered_by_modality`

A logical, if `TRUE`, then the number in the scatter plot means modality ID. If not, then the each number in the scatter plot indicates reader ID.

`cex`

A positive real number, specifying the size of dots in the resulting plot.

Value

A dataframe, which is added TPF and FPF, etc into `dataList.MRMC`.

Added Vectors as Contents of the Data-frame

CFP A vector of *Cumulative False Positive*

CTP A vector of *Cumulative True Positive*

TPF A vector of *True Positive Fraction*

FPF A vector of *False Positive Fraction* per image or per lesion according to the logical variable `ModifiedPoisson`

factor What this means is trivial.

Vectors as Contents of the Data-frame `dataList.MRMC`

`c` A vector of positive integers, representing the **confidence level**. This vector must be made by `rep(rep(C:1), M*Q)`

`m` A vector of positive integers, representing the **modality** ID vector.

`q` A vector of positive integers, representing the **reader** ID vector.

`h` A vector of non-negative integers, representing the number of **hits**.

`f` A vector of non-negative integers, representing the number of **false alarm**.

Examples

```
#=====
#                               The 1st example
```

```

=====

v <- v_truth_creator_for_many_readers_MRMC_data(M=1,Q=37)
m <- mu_truth_creator_for_many_readers_MRMC_data(M=1,Q=37)
d <- create_dataList_MRMC(mu.truth = m,v.truth = v)

plot_FPF_TPF_via_dataframe_with_split_factor(d,
  colored_by_modality = TRUE,
  numbered_by_modality = TRUE)

plot_FPF_TPF_via_dataframe_with_split_factor(d,
  colored_by_modality = FALSE,
  numbered_by_modality = TRUE)

plot_FPF_TPF_via_dataframe_with_split_factor(d,
  colored_by_modality = TRUE,
  numbered_by_modality = FALSE)

plot_FPF_TPF_via_dataframe_with_split_factor(d,
  colored_by_modality = FALSE,
  numbered_by_modality = FALSE)

=====
#                                     The 2-nd example
=====
#
v <- v_truth_creator_for_many_readers_MRMC_data(M=2,Q=37)
m <- mu_truth_creator_for_many_readers_MRMC_data(M=2,Q=37)
d <- create_dataList_MRMC(mu.truth = m,v.truth = v)

plot_FPF_TPF_via_dataframe_with_split_factor(d,
  colored_by_modality = TRUE,
  numbered_by_modality = TRUE)

plot_FPF_TPF_via_dataframe_with_split_factor(d,
  colored_by_modality = FALSE,
  numbered_by_modality = TRUE)

plot_FPF_TPF_via_dataframe_with_split_factor(d,
  colored_by_modality = TRUE,
  numbered_by_modality = FALSE)

plot_FPF_TPF_via_dataframe_with_split_factor(d,
  colored_by_modality = FALSE,
  numbered_by_modality = FALSE)

```



```

=====
#
#                               The 3rd example
#
=====

v <- v_truth_creator_for_many_readers_MRMC_data(M=3,Q=7)
m <- mu_truth_creator_for_many_readers_MRMC_data(M=3,Q=7)
d <- create_dataList_MRMC(mu.truth = m,v.truth = v)

plot_FPF_TPF_via_dataframe_with_split_factor(d,
  colored_by_modality = TRUE,
  numbered_by_modality = TRUE)

plot_FPF_TPF_via_dataframe_with_split_factor(d,
  colored_by_modality = FALSE,
  numbered_by_modality = TRUE)

plot_FPF_TPF_via_dataframe_with_split_factor(d,
  colored_by_modality = TRUE,
  numbered_by_modality = FALSE)

plot_FPF_TPF_via_dataframe_with_split_factor(d,
  colored_by_modality = FALSE,
  numbered_by_modality = FALSE)
=====
#
#                               The 4th example
#
=====

plot_FPF_TPF_via_dataframe_with_split_factor( dataList.MRMC = dd,
                                              colored_by_modality = TRUE,
                                              numbered_by_modality = TRUE)

=====
#
#                               The 5th example
#
=====

## Not run:
a <- plot_FPF_TPF_via_dataframe_with_split_factor(dd)

p <- ggplot2::ggplot(a, ggplot2::aes(FPF, TPF,
                                   group = factor(factor),
                                   colour = factor(m)) ) +
  ggplot2::geom_line(size = 1.4)
print(p)

```

```

=====
#                               The 6th example
=====

a <- plot_FPF_TPF_via_dataframe_with_split_factor(dd,cex = 1.8)

=====
#                               The 7th example
=====

# Plot empirical FROC curve whose modality is specified as following manner

a <- plot_FPF_TPF_via_dataframe_with_split_factor(dd)
aa <- a[a$m == c(2,3), ]

p <- ggplot2::ggplot(aa, ggplot2::aes(FPF, TPF,
                                     group = factor(factor),
                                     colour = factor(m)) ) +
  ggplot2::geom_line(size = 1.4)
print(p)

# Plot empirical FROC curve whose modality is specified as following manner

a <- plot_FPF_TPF_via_dataframe_with_split_factor(dd)
aa <- a[a$m %in% c(4,3), ]

p <- ggplot2::ggplot(aa, ggplot2::aes(FPF, TPF,
                                     group = factor(factor),
                                     colour = factor(m)) ) +
  ggplot2::geom_line(size = 1.4)
print(p)

# Plot empirical FROC curve whose modality is specified as following manner

a <- plot_FPF_TPF_via_dataframe_with_split_factor(dd)
aa <- a[a$m %in% c(3,4), ]

p <- ggplot2::ggplot(aa, ggplot2::aes(FPF, TPF,
                                     group = factor(factor),
                                     colour = factor(m)) ) +
  ggplot2::geom_line(size = 1.4)
print(p)

```

```
# Close_all_graphic_devices()
## End(Not run)#dontrun
```

```
plot_test      # Definition of a method for the inherited class stanfitExtended from
               stanfit
```

Description

This is a function for a method in the generic function plot.

Usage

```
plot_test(x)
```

Arguments

x This is an object of an S4 class named stanfitExtended which is an inherited S4 class from the stanfit S4 class in the rstan package.

```
pnorm_or_qnorm      pnorm or qnorm
```

Description

The author is stupid, so he is confused pnorm() and qnorm().

Thu author always forget which is cumulative distribution of Gaussia, so I made this and this tells me which is mmy desired one. In this package, I often use $\Phi()$ for the standard Gaussian, and it is pnorm(). I am very confuse, since probability density has initial alphabet p, but pnorm() is not it.

Usage

```
pnorm_or_qnorm()
```

 ppp

MRMC or srsc: Posterior Predictive P value (PPP) for MRMC or srsc.

Description

PPP for chi square goodness of fit statistic.

Usage

```
ppp(StanS4class, Colour = TRUE, dark_theme = TRUE, plot = TRUE, summary = TRUE)
```

Arguments

StanS4class	An S4 object of class <code>stanfitExtended</code> which is an inherited class from the S4 class <code>stanfit</code> . This R object is a fitted model object as a return value of the function <code>fit_Bayesian_FROC()</code> . It can be passed to <code>DrawCurves()</code> , <code>ppp()</code> and ... etc
Colour	Logical: TRUE or FALSE. whether Colour of curves is dark theme or not.
dark_theme	TRUE or FALSE
plot	Logical, whether replicated datasets are drawn.
summary	Logical: TRUE or FALSE. Whether to print the verbose summary. If TRUE then verbose summary is printed in the R console. If FALSE, the output is minimal. I regret, this variable name should be verbose.

Details

I hate the notion of p value and this is the motivation that I developed new FROC theory. However, I cannot overcome the traditional bitch. I hate statistics since p value is bitch, monotonically decreases when the sample size is large. In some papers, I forget the name, but in some papers, one pointed out that the frequentist p values precisely coincides some posterior probability of some event (I forget this but such as mean1 is greater than mean2).

In some suitable condition, I conjecture that Bayesian p value coincides to frequentist p value in some sense such as analytically or its expectation of a posterior or etc or large MCMC samples. So, p value is bitch and bitch and bitch. I emphasize that notion of p value is bitch and its background is unknown. In suitable condition, frequentist p value bitch is equal to a probability of some event measured by posterior. So,... Bayesian method cannot break the traditional frequentist bitch. Bayesian and frequentist are all bitch!! Of course, intuitively, it is good. But, the theoretically, it does not satisfies naturalist.

Value

A positive number between zero and one, indicating Posterior Predictive P value (PPP). In addition, it plots replicated datasets which are used to calculate a ppp.

Examples

```
## Not run:

# The 1-st example: MRMC data
#=====
#                               1) Fit a Model to MRMC Data
#=====

fit <- fit_Bayesian_FROC( ite = 111, dataList = ddd )

#=====
# 2) Evaluate Posterior Predictive P value for the Goodness of Fit
#=====

ppp(fit)

# If this quantity, namely a p value, is greater,
# then we may say that our goodness of fit is better. (accept the null hypothesis)
# In the traditional procedure, if p-value is less than 0.05 or 0.01 then we reject
# the null hypothesis that our model fit to data well.

# Of course, even if p-values is small, we should not ignore our result.
# P value bitch is not so clear what it does and in frequentist methods,
# we experienced p value is bitch with respect to sample size.
# So, in Bayesian context, this bitch might be bitch with respect to ...
# Anyway, but ha...many statisticians like this bitch.
```

```

# The 2-nd example uses data named d
#=====
#                               1) Fit a Model to Data
#=====

                                fitt <- fit_Bayesian_FROC( ite = 111, dataList = d )

#=====
# 2) Evaluate Posterior Predictive P value for the Goodness of Fit
#=====

                                ppp(fitt)

# If this quantity is greater, then we may say that our model is better.
# I made this ppp at 2019 August 25.

#=====
#                               PPP is problematic
#=====

# Consider the dataset:

dat <- list(c=c(4,3,2,1), # Confidence level. Note that c is ignored.
           h=c(77,97,32,31), # Number of hits for each confidence level
           f=c(77,1,14,74), # Number of false alarms for each confidence level

           NL=259, # Number of lesions
           NI=57, # Number of images
           C=4) # Number of confidence level#

# Fit a model to the data

                                fit <- fit_Bayesian_FROC(dat,ite=111)

```

```
# calculate p value

ppp(fit)

# Then we can see that FPF and TPF are far from FROC curve, but p value is not
# so small, and thus in this case, ppp is not the desired one for us.

# In our model, we need monotonicity condition, namely
#
#   h[1] > h[2] > h[3] > h[4]
#   f[1] < f[2] < f[3] < f[4]
#
# However the above dataset is far from this condition, and it would relate the
# above undesired p value.
#   Revised 2019 Sept 7
# Of course it is no need to satisfy this monotonicity precisely, but good data
# should satisfy.
# Since doctor should not wrong (false positive) diagnosis with his high confidence.

## End(Not run)
```

ppp_MRMC

MRMC: Posterior Predictive P value (PPP) for MRMC,

Description

PPP for chi square goodness of fit statistic

Usage

ppp_MRMC(

```

StanS4class,
summary = TRUE,
replicate.number.from.model.for.each.MCMC.sample = 2
)

```

Arguments

StanS4class An S4 object of class `stanfitExtended` which is an inherited class from the S4 class `stanfit`. This R object is a fitted model object as a return value of the function `fit_Bayesian_FROC()`.
It can be passed to `DrawCurves()`, `ppp()` and ... etc

summary Logical: TRUE of FALSE. Whether to print the verbose summary. If TRUE then verbose summary is printed in the R console. If FALSE, the output is minimal. I regret, this variable name should be verbose.

replicate.number.from.model.for.each.MCMC.sample

A positive integer, representing J in the following notation. Now, I think all I needed is love! ttu ttu tututu Love is all I need.

Suppose that

$$\theta_1, \theta_2, \theta_3, \dots, \theta_n$$

is drawn from posterior $\pi(\theta|D)$ of given data D .

Let y_1, y_2, \dots, y_n be samples drawn from

$$y_1 \sim \text{likelihood}(\cdot|\theta_1),$$

$$y_2 \sim \text{likelihood}(\cdot|\theta_2),$$

$$y_3 \sim \text{likelihood}(\cdot|\theta_3),$$

...

$$y_n \sim \text{likelihood}(\cdot|\theta_n),$$

Then the list of return values retains the following:

`chisq_at_observed_data`

$$\chi(D|\theta_1), \chi(D|\theta_2), \chi(D|\theta_3), \dots, \chi(D|\theta_n),$$

`chisq_not_at_observed_data`

$$\chi(y_1|\theta_1), \chi(y_2|\theta_2), \chi(y_3|\theta_3), \dots, \chi(y_n|\theta_n),$$

Logical The i -th component is a logical vector indicating whether

$$\chi(y_2|\theta_2) > \chi(D|\theta_2)$$

is satisfied or not. Oppai ga Ippai. If TRUE, then the inequality holds.

p.value From the component **Logical**, we calculate the so-called *Posterior Predictive P value*. Note that the author hate this notion!! I hate it!! Akkan Beeeee!!!

Details

The author hates the notion of p value and this is the motivation that he developed new theory without p values. However, he cannot overcome the traditional people. he loves mathematics, but he hates statistics. he emphasizes that notion of p value is dangerous (monotonicity w.r.t. sample size) and its background is unknown. Of course, intuitively, it is good. But, the theoretically, it does not ensure some criterion in large sample context.

So, p value said that my effort is rarely admissible, since its p value said that he is small for various datasets. So, this fucking p value said my effort is wrong, or should change model. Unfortunately, my hand aches cannot program more models. Ha,... why many peoply like p value bitch.

Value

A positive number indicates Posterior Predictive P value (ppp).

Examples

```
## Not run:
#####
# 1) Fit a Model to MRMC Data
#####

fit <- fit_Bayesian_FROC( ite = 111, dataList = ddd )

#####
# 1) Evaluate Posterior Predictive P value for the Goodness of Fit
#####

ppp_MRMC(fit)

# If this quantity is greater, then we may say that our model is better.

# I made this ppp at 2019 August 25.

## End(Not run)##'
```

Description

Calculates Posterior Predictive P value for chi square (goodness of fit)

Usage

```
ppp_srsc(
  StanS4class,
  Colour = TRUE,
  dark_theme = TRUE,
  plot = TRUE,
  summary = TRUE,
  replicate.number.from.model.for.each.MCMC.sample = 100
)
```

Arguments

StanS4class An S4 object of class `stanfitExtended` which is an inherited class from the S4 class `stanfit`. This R object is a fitted model object as a return value of the function `fit_Bayesian_FROC()`.

It can be passed to `DrawCurves()`, `ppp()` and ... etc

Colour Logical: TRUE of FALSE. whether Colour of curves is dark theme or not.

dark_theme TRUE or FALSE

plot Logical, whether replicated data are drawn, in the following notation, replicated data are denoted by y_1, y_2, \dots, y_N .

summary Logical: TRUE of FALSE. Whether to print the verbose summary. If TRUE then verbose summary is printed in the R console. If FALSE, the output is minimal. I regret, this variable name should be verbose.

replicate.number.from.model.for.each.MCMC.sample

A positive integer, representing J in the following notation. Now, I think all I needed is love! ttu ttu tututu Love is all I need.

Suppose that

$$\theta_1, \theta_2, \theta_3, \dots, \theta_n$$

is drawn from posterior $\pi(\theta|D)$ of given data D .

Let y_1, y_2, \dots, y_n be samples drawn from

$$y_1 \sim \text{likelihood}(\cdot|\theta_1),$$

$$y_2 \sim \text{likelihood}(\cdot|\theta_2),$$

$$y_3 \sim \text{likelihood}(\cdot|\theta_3),$$

...

$$y_n \sim \text{likelihood}(\cdot|\theta_n),$$

Then the list of return values retains the following:

`chisq_at_observed_data`

$$\chi(D|\theta_1), \chi(D|\theta_2), \chi(D|\theta_3), \dots, \chi(D|\theta_n),$$

chisq_not_at_observed_data

$$\chi(y_1|\theta_1), \chi(y_2|\theta_2), \chi(y_3|\theta_3), \dots, \chi(y_n|\theta_n),$$

Logical The i-th component is a logical vector indicating whether

$$\chi(y_2|\theta_2) > \chi(D|\theta_2)$$

is satisfied or not. Oppai ga Ippai. If TRUE, then the inequality holds.

p.value From the component Logical, we calculate the so-called *Posterior Predictive P value*. Note that the author hate this notion!! I hate it!! Akkan Beeeee!!!

Details

In addition, this function plots replicated datasets from model at each MCMC sample generated by HMC. Using the Hamiltonian Monte Carlo Sampling: HMC. we can draw the MCMC samples of size n , say

$$\theta_1, \theta_2, \theta_3, \dots, \theta_n$$

, namely,

$$\theta_1 \sim \pi(.|D),$$

$$\theta_2 \sim \pi(.|D),$$

$$\theta_3 \sim \pi(.|D),$$

...

$$\theta_n \sim \pi(.|D).$$

where $\pi(\theta|D)$ is the posterior for given data D .

Then, the function plots the following datasets $y_1^1, y_2^1, \dots, y_I^J$.

$$\chi(y_{1,1}|\theta_1), \chi(y_{1,2}|\theta_1), \chi(y_{1,3}|\theta_1), \dots, \chi(y_{1,j}|\theta_1), \dots, \chi(y_{1,J}|\theta_1),$$

$$\chi(y_{2,1}|\theta_2), \chi(y_{2,2}|\theta_2), \chi(y_{2,3}|\theta_2), \dots, \chi(y_{2,j}|\theta_2), \dots, \chi(y_{2,J}|\theta_2),$$

$$\chi(y_{3,1}|\theta_3), \chi(y_{3,2}|\theta_3), \chi(y_{3,3}|\theta_3), \dots, \chi(y_{3,j}|\theta_3), \dots, \chi(y_{3,J}|\theta_3),$$

...

$$\chi(y_{i,1}|\theta_i), \chi(y_{i,2}|\theta_i), \chi(y_{i,3}|\theta_i), \dots, \chi(y_{i,j}|\theta_i), \dots, \chi(y_{i,J}|\theta_i),$$

...

$$\chi(y_{I,1}|\theta_I), \chi(y_{I,2}|\theta_I), \chi(y_{I,3}|\theta_I), \dots, \chi(y_{I,j}|\theta_I), \dots, \chi(y_{I,J}|\theta_I).$$

where $L(.|\theta_i)$ is a likelihood at parameter θ_i .

Let $\chi(y|\theta)$ be a chi square goodness of fit statistics of our hierarchical Bayesian Model

$$\chi(y|\theta) := \sum_{r=1}^R \sum_{m=1}^M \sum_{c=1}^C \left(\frac{(H_{c,m,r} - N_L \times p_{c,m,r})^2}{N_L \times p_{c,m,r}} + \frac{(F_{c,m,r} - (\lambda_c - \lambda_{c+1}) \times N_L)^2}{(\lambda_c - \lambda_{c+1}) \times N_L} \right).$$

and a chi square goodness of fit statistics of our non-hierarchical Bayesian Model

$$\chi(y|\theta) := \sum_{c=1}^C \left(\frac{(H_c - N_L \times p_c)^2}{N_L \times p_c} + \frac{(F_c - (\lambda_c - \lambda_{c+1})) \times N_L]^2}{(\lambda_c - \lambda_{c+1}) \times N_L} \right).$$

where a dataset y denotes $(F_{c,m,r}, H_{c,m,r})$ in MRMC case and (F_c, H_c) in a single reader and a single modality case, and model parameter θ .

Then we can calculate the *posterior predictive p value* for a given dataset y_0 .

$$\begin{aligned} & \int \int I(\chi(y|\theta) > \chi(y_0|\theta)) f(y|\theta) \pi(\theta|y_0) d\theta dy \\ & \approx \int \sum_i I(\chi(y|\theta_i) > \chi(y_0|\theta_i)) f(y|\theta_i) dy \\ & \approx \sum_{j=1}^J \sum_{i=1}^I I(\chi(y_{i,j}|\theta_i) > \chi(y_0|\theta_i)) \end{aligned}$$

When we plot these synthesized data-sets $y_{i,j}$, we use the `jitter()` which adds a small amount of noise to **avoid overlapping points**. For example, `jitter(c(1,1,1,1))` returns values: 1.0161940 1.0175678 0.9862400 0.9986126, which is changed from 1,1,1,1 to be not exactly 1 by adding tiny errors to avoid overlapping. I love you. 2019 August 19 Nowadays, I cannot remove my self from some notion, such as honesty, or pain, or... maybe these thing is no longer with myself. This programm is made to fix previous release calculation. Now, this programm calculates correct p value.

So... I calculate the ppp for MCMC and Graphical User Interface based on Shiny for MRMC, which should be variable such as number of readers, modalities, to generate such ID vectors automatically. Ha,... tired! Boaring, I want to die...t, diet!! Tinko, tinko unko unko. Manko manko. ha.

Leberiya, he will be die, ha... he cannot overcome, very old, old guy. I will get back to meet him. Or I cannot meet him? Liberiya,...very wisdom guy, Ary you already die? I will get back with presents for you. Ball, I have to throgh ball, and he will catch it.

The reason why the author made the plot of data drawn from **Posterior Predictive likelihoods with each MCMC parameters** is to understand our programm is correct, that is, each drawing is very mixed. Ha,... when wright this,... I always think who read it. I love you, Ruikobach. Ruikobach is tiny and tiny, but,... cute. Ruikosan...Ruiko... But he has time only several years. He will die, he lives sufficiently so long, ha.

Using this function, user would get **reliable posterior predictive p values**, Cheers! Pretty Crowd!

We note that the calculation of posterior perdictive p value (PPP) relies on the law of large number. Thus, in order to obtain the relicable PPP, we need to enough large MCMC samples to approximate the double integral of PPP. For example, the MCMC samples is small, then R hat is far from 1 but, the low MCMC samples leads us to incorrect p value which sometimes said that the model is correct even if the R hat criteria reject the MCMC results.

Value

A list, including p value and materials to calculate it.

Author(s)

Issei Tsunoda, Prof. of Curlbus University, Mosquitobus and Gostbus univ. also. My technique of catch mosquitos are excellent, so, I am a prof. ha,, employ me. My health is bad, my life will be over.

Examples

```
## Not run:
```

```
#####
#           1) Create a fitted model object with data named "d"
#####
```

```
fit <- fit_Bayesian_FROC( dataList = d,
                        ite = 222 # to restrict running time, but it is too small
                        )
```

```
#####
#           2) Calculate p value and meta data
#####
```

```
ppp <- ppp_srsc(fit)
```

```
#####
#           3) Extract a p value
#####
```

```
ppp$p.value
```

```
# Revised 2019 August 19
```

```
# Revised 2019 Nov 27
```

```
## End(Not run)
```

```
print,stanfitExtended-method
  A method for a generic function print() for class
  "stanfitExtended"
```

Description

This is a method for print and `stanfitExtended` S4 class.

Usage

```
## S4 method for signature 'stanfitExtended'
print(x)
```

Arguments

`x` An S4 object of class `stanfitExtended` inherited from the class `stanfit` in the `rstan` package.

Examples

```
## Not run:
# How to use a new method for generic function "print".
#=====The First Example=====

#(1)First, we prepare the example data from this package.

      dat <- BayesianFROC::dataList.Chakra.1

# The R object named dat is a list which contains the hits and false alarms representing
# an FROC dataset. To confirm it, the function viewdata() can be used;

      viewdata(dat)

#(2)Second, we run fit_Bayesian_FROC() in which the rstan::sampling() is implemented.
#Fit to data named "dat" the author's Bayesian model by

      fit <- fit_Bayesian_FROC(dat)
```

```
#(3)Thirdly, we obtain the R object fit of S4 class
# named stanfitExtended that is an inherited class from the S4 class stanfit
# defined in the package rstan.
# For the S4 class stanfitExtended defined in this package, we can use
# the generic function print for this new S4 class.
```

```
print(fit)
```

```
# To use the generic function print() as a object of class "stanfit",
# we coerce class of fit into stanfit from stanfitExtended as follows;
```

```
fitt <- methods::as(fit,"stanfit")
```

```
# The R object "fitt" is a fitted model object of class stanfit,
# thus we can also apply the generic function print() as follows:
```

```
print(fitt)
```

```
#####The Second Example#####
```

```
 #(1)First, we prepare the example data from this package.
```

```
dat <- BayesianFROC::dataList.Chakra.Web
```

```
 #(2)Second, we run fit_Bayesian_FROC() in which the rstan::sampling() is implemented.
#Fit to data named "dat" the author's Bayesian model by
```

```
fit <- fit_Bayesian_FROC(dat)
```

```
 #(3)Thirdly, we obtain the R object fit of S4 class
# named stanfitExtended that is an inherited class from the S4 class stanfit
# defined in the package rstan.
```

```
# For the S4 class stanfitExtended defined in this package, we can use  
# the generic function print for this new S4 class.
```

```
print(fit)
```

```
# 2019.05.21 Revised.
```

```
## End(Not run)# doctest
```

```
print_minimal_reproducible_code_in_case_of_MRMC  
Show minimal code in MRMC
```

Description

Now 2020 March, it is available.

Usage

```
print_minimal_reproducible_code_in_case_of_MRMC()
```

Value

NULL ?

Examples

```
print_minimal_reproducible_code_in_case_of_MRMC()
```

print_stanfitExtended *Definition of a method for the inherited class stanfitExtended from stanfit*

Description

This is a function for a method for a generic function print() for class "[stanfitExtended](#)"

Usage

```
print_stanfitExtended(x)
```

Arguments

x This is an R object of an S4 class named [stanfitExtended](#) inherited class from the stanfit in the rstan package.

Details

Print of stanfit has many parameters, but one of them, the AUC is the most important parameter. Thus in particular, we explain how to interpret the print out messages for AUCs.

—— Print of stanfit object —————

* The AUC denoted by AA[modalityID ,readerID] are shown by the function print() with a stanfit object.

* The column of 2.5% and 97.5% means the lower and upper bounds of the 95

* For example, AA[2, 3] means the AUC of the 2 nd modality and the 3 rd reader.

priorResearch *Research for Prior*

Description

The autor investigates prior

Usage

```
priorResearch(z, m = 6, sd = 1, e = 0.01)
```

Arguments

z a real number, indicating θ_c .

m a real number, specifying the mean of signal Gaussian

sd a real number, specifying the standard deviation of signal Gaussian

e a positive real number, indicating ϵ .

Value

A real, to investigate prior

$$\mu + \sigma \Phi^{-1}(1 - \epsilon + \Phi(\frac{\theta_c - \mu}{\sigma})) - \Phi^{-1}(\Phi(\theta) \exp(\epsilon))$$

where, $m = \mu$, $sd = \sigma$, $z = \theta$, $e = \epsilon$.

Examples

```

#=====
#           From this plot, we can evaluate the minimum value of x such that
#           the value is negative.
#=====

x <- runif(100,-1,3 ) # Synthesisze 100 smaples from Uniform(-1,3)
y <- priorResearch(x)

plot(x,y)

```

prior_predictor *Predict some estimates of parameter*

Description

Predict some estimates of parameter

Usage

```
prior_predictor(d = d)
```

Arguments

d A list of data, which can be passed to the fit_Bayesian_FROC.

Value

none

prior_print_MRMC *Print What Prior Are Used*

Description

Prints prior in R console

Usage

```
prior_print_MRMC(prior = 0)
```

Arguments

prior An integer, representing type of Prior

Value

none

Examples

```
prior_print_MRMC()
```

prior_print_srsc *Print What Prior Are Used*

Description

Prints prior in R console

Usage

```
prior_print_srsc(prior = 0)
```

Arguments

prior An integer, representing type of Prior

Value

none

Examples

```
prior_print_srsc()
```

`p_truth`*Hit Rate: parameter of an MRMC model*

Description

A posterior mean of the model parameter for data `ddd` as an example of truth parameter.

Details

Hit Rate data of some MRMC data to use as a default value of the function `hits_creator_from_rate`. This is an array obtained from estimates of some data contained in this package. To simulate a replication of dataset, the default values should be used from an actual values. Thus the author prepare this data.

Author(s)

Issei Tsunoda <tsunoda.issei1111@gmail.com >

See Also

`hits_creator_from_rate`

`p_value_of_the_Bayesian_sense_for_chi_square_goodness_of_fit`*P value for goodness of fit : No longer used in 2019 Oct*

Description

Calculates the p value of the chi-squared test statistic for our model.

Get the Chi square values

$$\chi(D_i|\theta_j)$$

for all possible pairs of synthesized data-sets $D_1, D_2, \dots, D_i, \dots$ and MCMC samples $\theta_1, \theta_2, \dots, \theta_i, \dots$

Usage

```
p_value_of_the_Bayesian_sense_for_chi_square_goodness_of_fit(  
  StanS4class,  
  dig = 3,  
  Colour = TRUE,  
  plot.replicated.points = FALSE,  
  head.only = FALSE,  
  counter.plot.via.schatter.plot = TRUE,  
  Show.table = TRUE  
)
```

Arguments

StanS4class	An S4 object of class <code>stanfitExtended</code> which is an inherited class from the S4 class <code>stanfit</code> . This R object is a fitted model object as a return value of the function <code>fit_Bayesian_FROC()</code> . It can be passed to <code>DrawCurves()</code> , <code>ppp()</code> and ... etc
dig	A variable to be passed to the function <code>rstan::sampling()</code> of rstan in which it is named <code>...</code> ?. A positive integer representing the Significant digits, used in stan Cancellation. Default = 5,
Colour	Logical: TRUE of FALSE. whether Colour of curves is dark theme or not.
plot.replicated.points	TRUE or FALSE. If true, then plot replicated points (hits, false alarms) by the scatter plot. This process will takes a long times. So if user has no time, then FALSE will help you.
head.only	Logical: TRUE of FALSE. Whether head part or entire of the table are shown. If TRUE, only head part are shown. Default is FALSE.
counter.plot.via.schatter.plot	Logical: TRUE of FALSE. Whether counter plot via schatter plot is drawn, Default = TRUE.
Show.table	Logical: TRUE of FALSE. Whether table includes the terms used calculation of p-value are shown.

Details

Here, we briefly review how to get the chi square samples in the Bayesian paradigm.

First, Let

$$f(y|\theta)$$

be a model (likelihood) for a future data-set y and a model parameter θ . Let

$$\pi(\theta|D)$$

be the posterior for given data D . In this situation, the Hamiltonian Monte Carlo method is performed to obtain the MCMC samples of size N . Denote MCMC samples by

$$\theta_1, \theta_2, \theta_3, \dots, \theta_N$$

from posterior $p(\theta|D)$ of given data D . Alternatively, we get the sequence of models

$$f(y|\theta_1), f(y|\theta_2), f(y|\theta_3), \dots, f(y|\theta_N).$$

To get the samples

$$y_1, y_2, \dots, y_N$$

from the posterior predictive distribution, we merely draw the y_1, y_2, \dots, y_N from $f(y|\theta_1), f(y|\theta_2), f(y|\theta_3), \dots, f(y|\theta_N)$, respectively. That is for all i y_i is drawn from the distribution $f(y|\theta_i)$. In notation, it may write;

$$y_1 \sim f(\cdot|\theta_1)$$

$$y_2 \sim f(\cdot|\theta_2)$$

$$\begin{aligned}
 y_3 &\sim f(\cdot|\theta_3) \\
 &\dots \\
 y_N &\sim f(\cdot|\theta_1 N)
 \end{aligned}$$

Once, we draw samples from the posterior predictive density, we can calculate an arbitrary integral with the posterior measure by the law of large number, or it is sometimes called MonteCarlo integral and we apply it to the following integral which is the desired posterior predictive p-value.

$$pvaluefordataD := \int I(\chi(Data|\theta) > \chi(D|\theta))f(\theta|Data)\pi(\theta|D)d\theta d(Data)$$

Recall that the chi square goodness of fit statistics χ is dependent of the model parameter θ and data D . that is,

$$\chi = \chi(D|\theta).$$

Integrating $\chi(D|\theta)$ with the posterior predictive measure, we get the

$$\chi(D)$$

which depends only of the data D , that is,

So, in the return value of this function is p value.

My hand, especially right has ache, so I quit this documentation, Good Luck, 2019 may 29. I do not have confidence whether my explanation success.

In this manner we get the two sequence of samples, one is from the posterior distribution and one is the posterior predictive distribution. Using these two kind of samples, we can calculate the test statistics as the Bayesian manner. That is, in frequentist method, the test statistics are calculated by the fixed model parameters, such as the maximal likelihood estimators. However, in Bayesian context, the parameter is not deterministic and hence we should calculate test statistics with the posterior measure. To accomplish this task, this package include the function.

Value

The main return is a nonnegative real number indicating p value of the Chi square goodness of fit. And the other components to calculate p values.

See Also

`get_samples_from_Posterior_Predictive_distribution`, `chi_square_goodness_of_fit_from_input_all_param`

Examples

```
## Not run:
# First, fit the model to data. The number of sampling of the Hamiltonian Monte Carlo
# methods should be a little number, if user computer has low ability,
# since the calculation of the posterior predictive p values is heavy.
```

```
fit <- fit_Bayesian_FROC(BayesianFROC::dataList.Chakra.1 ,ite = 1111)
```

```
# Next, extract the posterior predictive p value from the fitted model object "fit",
# and to do so, we have to make a object "output".

output <- p_value_of_the_Bayesian_sense_for_chi_square_goodness_of_fit(fit)

# From the above R script, the table will appear in the R cosole.
# If the TRUE is more, then model fitting is better.
# Finally, we obtain the following p value;

p.value <- output$p.values.for.chisquare

# The significant level of p value is 0.05 in frequentist paradium, but,
# In this p value I think it should be more greater, and
# should use e.g., 0.6 instead of 0.05 for significant level.
# If significant level is 0.5, then test

p.value > 0.5

# If it is FALSE, then the fitting is bad.
# If p value is more greater than the fitting is more better.

# If user has no time, then plot.replicated.points=FALSE will help you.
# By setting FALSE, the replicated data from the posterior predictive
# distribution does not draw, and hence the running time of function become shorter.

TPs.FPs <- p_value_of_the_Bayesian_sense_for_chi_square_goodness_of_fit(fit,
                               plot.replicated.points = FALSE)

# If user want to use the scatter plots of hits and false alarms from the posterior
# predictive distribution for the submission, then the color plot is not appropriate.
# So, by setting the argument Colour = FALSE, the scatter plot become black and white.
# So, user can use this scatter plot for submission.

p_value_of_the_Bayesian_sense_for_chi_square_goodness_of_fit(fit,Colour = FALSE)

# Since p values are depend on data only, so it is better to show this dependency more
# explicitly as follows;

p_value_of_the_Bayesian_sense_for_chi_square_goodness_of_fit(
  fit_Bayesian_FROC(dataList.High))
```

```

)

# Close the graphic device
Close_all_graphic_devices()

## End(Not run)# dottest

```

```

rank_statistics_with_two_parameters
      Rank Statistics

```

Description

Rank Statistics

Usage

```

rank_statistics_with_two_parameters(
  values.of.f.at.one.MCMC.samples,
  values.of.f.at.a.sample.from.priors
)

```

Arguments

```

values.of.f.at.one.MCMC.samples
      The value of f at a vector whose components are constructed by the all parame-
      ters at one MCMC sample.
values.of.f.at.a.sample.from.priors
      The value of f at a vector of model parameters from the prior distribution.

```

Value

The value of the Rank Statistics

Examples

```

## Not run:
#===== The first example =====

rank_statistics_with_two_parameters(c(1,2,3,4,5),4)

#===== The Second Example =====

```



```

a <- Draw_a_simulated_data_set_and_Draw_posterior_samples()

rank_statistics_with_two_parameters(
  a$MCMC.samples.sended.by.fun,
  a$prior.samples.sended.by.fun
)

## End(Not run)# dottest

```

replicate_model_MRMC *Replicate Models*

Description

Replicate Models For Replicated Data From True Distributions.

Usage

```

replicate_model_MRMC(
  initial.seed = 123,
  mu.truth = BayesianFROC::mu_truth,
  v.truth = BayesianFROC::v_truth,
  z.truth = BayesianFROC::z_truth,
  NI = 200,
  NL = 142,
  ModifiedPoisson = FALSE,
  replication.number = 2,
  summary = FALSE,
  ite = 1111
)

```

Arguments

<code>initial.seed</code>	The variable <code>initial.seed</code> is used to replicate datasets. That is, if you take <code>initial.seed = 1234</code> , then the seed 1234, 1235, 1236, 1237, 1238, etc are for the first replication, the second replication, the third replication, etc. If the n -th model does not converge for some n , then such model has no mean and thus the non-convergent models are omitted to calculate the errors.
<code>mu.truth</code>	array of dimension (M,Q). Mean of the signal distribution of bi-normal assumption.
<code>v.truth</code>	array of dimension (M,Q). Standard Deviation of represents the signal distribution of bi-normal assumption.
<code>z.truth</code>	This is a parameter of the latent Gaussian assumption for the noise distribution.

NI Number of Images.

NL Number of Lesions.

ModifiedPoisson

Logical, that is TRUE or FALSE.

If ModifiedPoisson = TRUE, then Poisson rate of false alarm is calculated *per lesion*, and model is fitted so that the FROC curve is an expected curve of points consisting of the pairs of TPF per lesion and FPF *per lesion*.

Similarly,

If ModifiedPoisson = FALSE, then Poisson rate of false alarm is calculated *per image*, and model is fitted so that the FROC curve is an expected curve of points consisting of the pair of TPF per lesion and FPF *per image*.

For more details, see the author's paper in which I explained *per image* and *per lesion*. (for details of models, see [vignettes](#), now, it is omitted from this package, because the size of vignettes are large.)

If ModifiedPoisson = TRUE, then the *False Positive Fraction (FPF)* is defined as follows (F_c denotes the number of false alarms with confidence level c)

$$\frac{F_1 + F_2 + F_3 + F_4 + F_5}{N_L},$$

$$\frac{F_2 + F_3 + F_4 + F_5}{N_L},$$

$$\frac{F_3 + F_4 + F_5}{N_L},$$

$$\frac{F_4 + F_5}{N_L},$$

$$\frac{F_5}{N_L},$$

where N_L is a number of lesions (signal). To emphasize its denominator N_L , we also call it the *False Positive Fraction (FPF) per lesion*.

On the other hand,

if ModifiedPoisson = FALSE (Default), then *False Positive Fraction (FPF)* is given by

$$\frac{F_1 + F_2 + F_3 + F_4 + F_5}{N_I},$$

$$\frac{F_2 + F_3 + F_4 + F_5}{N_I},$$

$$\frac{F_3 + F_4 + F_5}{N_I},$$

$$\frac{F_4 + F_5}{N_I},$$

$$\frac{F_5}{N_I},$$

where N_I is the number of images (trial). To emphasize its denominator N_I , we also call it the *False Positive Fraction (FPF) per image*.

The model is fitted so that the estimated FROC curve can be regarded as the expected pairs of FPF per image and TPF per lesion (ModifiedPoisson = FALSE)

or as the expected pairs of FPF per image and TPF per lesion (ModifiedPoisson = TRUE)

If ModifiedPoisson = TRUE, then FROC curve means the expected pair of **FPF per lesion** and TPF.

On the other hand, if ModifiedPoisson = FALSE, then FROC curve means the expected pair of **FPF per image** and TPF.

So, data of FPF and TPF are changed thus, a fitted model is also changed whether ModifiedPoisson = TRUE or FALSE. In traditional FROC analysis, it uses only per images (trial). Since we can divide one image into two images or more images, number of trial is not important. And more important is per signal. So, the author also developed FROC theory to consider FROC analysis under per signal. One can see that the FROC curve is rigid with respect to change of a number of images, so, it does not matter whether ModifiedPoisson = TRUE or FALSE. This rigidity of curves means that the number of images is redundant parameter for the FROC trial and thus the author try to exclude it.

Revised 2019 Dec 8 Revised 2019 Nov 25 Revised 2019 August 28

replication.number

For fixed number of lesions, images, the dataset of hits and false alarms are replicated, and the number of replicated datasets are specified by this variable.

summary

Logical: TRUE or FALSE. Whether to print the verbose summary. If TRUE then verbose summary is printed in the R console. If FALSE, the output is minimal. I regret, this variable name should be verbose.

ite

A variable to be passed to the function `rstan::sampling()` of **rstan** in which it is named `iter`. A positive integer representing the number of samples synthesized by Hamiltonian Monte Carlo method, and, Default = 10000.

Value

A list, each component is an S4 object of class `stanfitExtended`.

Revised 2019 Nov 7

Examples

```
## Not run:
#=====
# Plot FROC curves for a single model in the replicated models
#=====

list.of.fitted.model.objects <- replicate_model_MRMC(replication.number = 2)

DrawCurves(StanS4class = list.of.fitted.model.objects[[2]],
            modalityID = 1:list.of.fitted.model.objects[[2]]@dataList$M,
            readerID = 1:list.of.fitted.model.objects[[2]]@dataList$Q )

# Revised 2019 Sept 9

## End(Not run)
```

```
replicate_MRMC_dataList
```

MRMC: Replicates Datasets From Threshold, Mean and S.D.

Description

Make several datasets from a given model parameter.

Usage

```
replicate_MRMC_dataList(
  replication.number = 2,
  initial.seed = 123,
  mu.truth = BayesianFROC::mu_truth,
  v.truth = BayesianFROC::v_truth,
  z.truth = BayesianFROC::z_truth,
  NI = 200,
  NL = 142,
  ModifiedPoisson = TRUE,
  summary = FALSE
)
```

Arguments

replication.number

A positive integer, specifying number of replicated datasets by this function. For fixed number of lesions, images, the dataset of hits and false alarms are replicated, and the number of replicated datasets are specified by this variable.

initial.seed	The variable <code>initial.seed</code> is used to replicate datasets. That is, if you take <code>initial.seed = 1234</code> , then the seed 1234, 1235, 1236, 1237, 1238, etc are for the first replication, the second replication, the third replication, etc. If the n-th model does not converge for some n, then such model has no mean and thus the non-convergent models are omitted to calculate the errors.
mu.truth	array of dimension (M,Q). Mean of the signal distribution of bi-normal assumption.
v.truth	array of dimension (M,Q). Standard Deviation of represents the signal distribution of bi-normal assumption.
z.truth	This is a parameter of the latent Gaussian assumption for the noise distribution.
NI	Number of Images.
NL	Number of Lesions.
ModifiedPoisson	

Logical, that is TRUE or FALSE.

If `ModifiedPoisson = TRUE`, then Poisson rate of false alarm is calculated **per lesion**, and model is fitted so that the FROC curve is an expected curve of points consisting of the pairs of TPF per lesion and FPF **per lesion**.

Similarly,

If `ModifiedPoisson = TRUE`, then Poisson rate of false alarm is calculated **per image**, and model is fitted so that the FROC curve is an expected curve of points consisting of the pair of TPF per lesion and FPF **per image**.

For more details, see the author's paper in which I explained *per image* and *per lesion*. (for details of models, see [vignettes](#), now, it is omitted from this package, because the size of vignettes are large.)

If `ModifiedPoisson = TRUE`, then the *False Positive Fraction (FPF)* is defined as follows (F_c denotes the number of false alarms with confidence level c)

$$\frac{F_1 + F_2 + F_3 + F_4 + F_5}{N_L},$$

$$\frac{F_2 + F_3 + F_4 + F_5}{N_L},$$

$$\frac{F_3 + F_4 + F_5}{N_L},$$

$$\frac{F_4 + F_5}{N_L},$$

$$\frac{F_5}{N_L},$$

where N_L is a number of lesions (signal). To emphasize its denominator N_L , we also call it the *False Positive Fraction (FPF) per lesion*.

On the other hand,
if ModifiedPoisson = FALSE (Default), then *False Positive Fraction (FPF)* is given by

$$\frac{F_1 + F_2 + F_3 + F_4 + F_5}{N_I},$$

$$\frac{F_2 + F_3 + F_4 + F_5}{N_I},$$

$$\frac{F_3 + F_4 + F_5}{N_I},$$

$$\frac{F_4 + F_5}{N_I},$$

$$\frac{F_5}{N_I},$$

where N_I is the number of images (trial). To emphasize its denominator N_I , we also call it the *False Positive Fraction (FPF) per image*.

The model is fitted so that the estimated FROC curve can be regarded as the expected pairs of FPF per image and TPF per lesion (ModifiedPoisson = FALSE)

or as the expected pairs of FPF per image and TPF per lesion (ModifiedPoisson = TRUE)

If ModifiedPoisson = TRUE, then FROC curve means the expected pair of **FPF per lesion** and TPF.

On the other hand, if ModifiedPoisson = FALSE, then FROC curve means the expected pair of **FPF per image** and TPF.

So, data of FPF and TPF are changed thus, a fitted model is also changed whether ModifiedPoisson = TRUE or FALSE. In traditional FROC analysis, it uses only per images (trial). Since we can divide one image into two images or more images, number of trial is not important. And more important is per signal. So, the author also developed FROC theory to consider FROC analysis under per signal. One can see that the FROC curve is rigid with respect to change of a number of images, so, it does not matter whether ModifiedPoisson = TRUE or FALSE. This rigidity of curves means that the number of images is redundant parameter for the FROC trial and thus the author try to exclude it.

Revised 2019 Dec 8 Revised 2019 Nov 25 Revised 2019 August 28

summary

Logical: TRUE or FALSE. Whether to print the verbose summary. If TRUE then verbose summary is printed in the R console. If FALSE, the output is minimal. I regret, this variable name should be verbose.

Value

A list, each component is also a list, representing an FROC dataset.

Examples

```

#=====
#           Visualization of replicated datasets synthesized by default values
#=====

# Replicates datasets from a model with user specified parameters (now, it is default).
  a <-replicate_MRMC_dataList()

# Calculates FPF and TPF and plot it for the first replicatec dataset

  plot_FPF_and_TPF_from_a_dataset(a[[1]])

# Calculates FPF and TPF and plot it for the second replicatec dataset

  plot_FPF_and_TPF_from_a_dataset(a[[2]])

# Reviessed 2019 Oct 9

```

sbcc

SBC

Description

Priors should guarante suitable conditions such that the ...

Usage

```
sbcc(stanmodel, data, M, iter, refresh)
```

Arguments

stanmodel	see ?sbc
data	To specify priors.
M	The number of samples for rank statistics
iter	MCMC iterations
refresh	????

Value

????

Author(s)

Some Stan developer, I am not sure,...., who?

Examples

```
## Not run:

stanModel <- stan_model_of_sbc()

Simulation_Based_Calibration_single_reader_single_modality_via_rstan_sbc(
  ite = 233,
  M = 11,
  epsilon = 0.04,
  stanModel = stanModel
)

## End(Not run)# dontrun
```

seq_array_ind

Makes a Matrix from a vector of itegers

Description

To make sbc funtion

Usage

```
seq_array_ind(d, col_major = FALSE)
```

Arguments

d A vector of integers
col_major A logical, whether,.... ?

Value

A matrix, dimension is prod(d) times length(d).

Author(s)

Some Stan developer, I am not sure,...., who?

Examples

```
a <- seq_array_ind(1:3,col_major = TRUE)
#> a
#
#      [,1] [,2] [,3]
# [1,]    1    1    1
# [2,]    1    2    1
# [3,]    1    1    2
# [4,]    1    2    2
# [5,]    1    1    3
# [6,]    1    2    3
```

```
b<-seq_array_ind(1:3,col_major = FALSE)
```

showGM	<i>Show the Graphical Model for the case of a single reader and a single modality</i>
--------	---

Description

This function shows the graphical model for a single reader and a single modality FROC statistical model.

Usage

```
showGM()
```

Examples

```
## Not run:
  showGM()

## End(Not run)# dontrun
```

```
show_codes_in_my_manuscript
      Show R codes used in my manuscript
```

Description

Show R codes used in my manuscript

Usage

```
show_codes_in_my_manuscript()
```

Value

NULL

Examples

```
#####
#           R codes in my manuscript
#####

show_codes_in_my_manuscript()
```

```
Simulation_Based_Calibration_histogram
      Draw a histogram of the rank statistics
```

Description

To validate that the MCMC procedure is correct or not, we show the histogram of rank statistics. If the resulting histogram is uniformly distributed, then we can conclude that the MCMC sampling is correct. If the histogram is far from uniformity, then the MCMC sampling or specification of priors is not correct or not appropriate.

Usage

```
Simulation_Based_Calibration_histogram(
  N = 3,
  sd = 5,
  C = 5,
  initial.seed.for.drawing.a.rank.statistics = 1234567,
  fun = stats::var,
  NI = 259,
  NL = 259,
```

```

    initial.seed.for.drawing.a.data = 1234,
    ModifiedPoisson = FALSE,
    ite = 1111,
    DrawCurve = FALSE
)

```

Arguments

N samples size of the rank statistics.

sd Standard Deviation of priors

C No. of Confidence levels

initial.seed.for.drawing.a.rank.statistics
seed

fun An one dimensional real valued function defined on the parameter space. This is used in the definition of the rank statistics. Generally speaking, the element of the parameter space is a vector, so the function should be defined on vectors. In my model parameter is mean, standard deviation, C thresholds of the latent Gaussian, so this function should be defined on the C+2 dimensional Euclidean space.

NI No. of images

NL No. of Lesions

initial.seed.for.drawing.a.data
seed

ModifiedPoisson
Logical, that is TRUE or FALSE.
If ModifiedPoisson = TRUE, then Poisson rate of false alarm is calculated *per lesion*, and model is fitted so that the FROC curve is an expected curve of points consisting of the pairs of TPF per lesion and FPF *per lesion*.
Similarly,
If ModifiedPoisson = TRUE, then Poisson rate of false alarm is calculated *per image*, and model is fitted so that the FROC curve is an expected curve of points consisting of the pair of TPF per lesion and FPF *per image*.
For more details, see the author's paper in which I explained *per image* and *per lesion*. (for details of models, see [vignettes](#), now, it is omitted from this package, because the size of vignettes are large.)
If ModifiedPoisson = TRUE, then the *False Positive Fraction (FPF)* is defined as follows (F_c denotes the number of false alarms with confidence level c)

$$\frac{F_1 + F_2 + F_3 + F_4 + F_5}{N_L},$$

$$\frac{F_2 + F_3 + F_4 + F_5}{N_L},$$

$$\frac{F_3 + F_4 + F_5}{N_L},$$

$$\frac{F_4 + F_5}{N_L},$$

$$\frac{F_5}{N_L},$$

where N_L is a number of lesions (signal). To emphasize its denominator N_L , we also call it the *False Positive Fraction (FPF) per lesion*.

On the other hand,

if ModifiedPoisson = FALSE (Default), then *False Positive Fraction (FPF)* is given by

$$\frac{F_1 + F_2 + F_3 + F_4 + F_5}{N_I},$$

$$\frac{F_2 + F_3 + F_4 + F_5}{N_I},$$

$$\frac{F_3 + F_4 + F_5}{N_I},$$

$$\frac{F_4 + F_5}{N_I},$$

$$\frac{F_5}{N_I},$$

where N_I is the number of images (trial). To emphasize its denominator N_I , we also call it the *False Positive Fraction (FPF) per image*.

The model is fitted so that the estimated FROC curve can be ragraded as the expected pairs of FPF per image and TPF per lesion (ModifiedPoisson = FALSE)

or as the expected pairs of FPF per image and TPF per lesion (ModifiedPoisson = TRUE)

If ModifiedPoisson = TRUE, then FROC curve means the expected pair of FPF **per lesion** and TPF.

On the other hand, if ModifiedPoisson = FALSE, then FROC curve means the expected pair of **FPF per image** and TPF.

So,data of FPF and TPF are changed thus, a fitted model is also changed whether ModifiedPoisson = TRUE or FALSE. In traditional FROC analysis, it uses only per images (trial). Since we can divide one image into two images or more images, number of trial is not important. And more important is per signal. So, the author also developed FROC theory to consider FROC analysis under per signal. One can see that the FROC curve is rigid with respect to change of a number of images, so, it does not matter whether ModifiedPoisson = TRUE or FALSE. This rigidity of curves means that the number of images is redundant parameter for the FROC trial and thus the author try to exclude it.

Revised 2019 Dec 8 Revised 2019 Nov 25 Revised 2019 August 28

ite	A variable to be passed to the function <code>rstan::sampling()</code> of rstan in which it is named <code>iter</code> . A positive integer representing the number of samples synthesized by Hamiltonian Monte Carlo method, and, Default = 10000.
DrawCurve	Logical: TRUE or FALSE. Whether the curve is to be drawn. TRUE or FALSE. If you want to draw the FROC and AFROC curves, then you set <code>DrawCurve = TRUE</code> , if not then <code>DrawCurve = FALSE</code> . The reason why the author make this variable <code>DrawCurve</code> is that it takes long time in MRMC case to draw curves, and thus Default value is FALSE in the case of MRMC data.

Value

samples of rank statistics

Examples

```
## Not run:
g <- Simulation_Based_Calibration_histogram(N=2,ite = 2222)

graphics::hist(g$rank.statistics)

g <- Simulation_Based_Calibration_histogram(
  NI=1111111,
  NL=1111111,
  # N =100 would be better more than N =10
  # But this is only example, we take very small N
  N=10,
  ite=3333,
  sd=1,
  initial.seed.for.drawing.a.rank.statistics = 123456789,
  DrawCurve = TRUE
)

g <- Simulation_Based_Calibration_histogram(
  NI=1111111,
  NL=1111111,
  # N =100 would be better more than N =10
  # But this is only example, we take very small N
  N=10,
  ite=3333,
  sd=1,initial.seed.for.drawing.a.rank.statistics = 123456789,
  DrawCurve = TRUE,
  C=11)
#===== The Second Example: =====

# If you want to see the replicated data, then the following code is available.
# In the following, I extract the dataset which is very small rank statistics, e.g.
# less than 10. And draw the CFP and CTP for observation of dataset.
```

```

gggg <- Simulation_Based_Calibration_histogram(
NI=11111111,
NL=11111111,
N=22,
ite=2222)

a <- gggg$rank.statistics<10

aa <- the_row_number_of_logical_vector(a)

draw.CFP.CTP.from.dataList(gggg$fit.list[[ aa[1] ] ]@dataList)

## End(Not run)#\dontrun

```

Simulation_Based_Calibration_single_reader_single_modality_via_rstan_sbc
*Simulation Based Calibration (SBC) for a single reader and a single
modality case*

Description

Implements the SBC algorithm for a single reader and a single modality case.

Prior _____ **Under Construction**_____

I do not use the following prior, but instead the precise prior is defined in the file: sbcVer2.stan. I am tired and not want to write this.

For sufficiently small ϵ ,

$$\epsilon < \tilde{p}_c(\theta) < 1 - \epsilon,$$

$$q_c(\theta) > c\epsilon,$$

namely

$$\epsilon < \log \frac{\Phi(\theta_{c+1})}{\Phi(\theta_c)},$$

$$\epsilon < \Phi\left(\frac{\theta_{c+1} - \mu}{\sigma}\right) - \Phi\left(\frac{\theta_c - \mu}{\sigma}\right) < 1 - \epsilon$$

We have to consider this equation.

To satisfy the condition $q_c(\theta) > c\epsilon$, we propose the following priors.

$$\begin{aligned}
\theta_1 &\sim \text{Unif}(-111, \Phi^{-1}(\exp^{-5\epsilon})), \\
\theta_2 &\sim \text{Unif}(\Phi^{-1}(\Phi(\theta_1) \exp^\epsilon), \Phi^{-1}(\exp^{-4\epsilon})), \\
\theta_3 &\sim \text{Unif}(\Phi^{-1}(\Phi(\theta_2) \exp^\epsilon), \Phi^{-1}(\exp^{-3\epsilon})), \\
\theta_4 &\sim \text{Unif}(\Phi^{-1}(\Phi(\theta_3) \exp^\epsilon), \Phi^{-1}(\exp^{-2\epsilon})), \\
\theta_5 &\sim \text{Unif}(\Phi^{-1}(\Phi(\theta_4) \exp^\epsilon), \Phi^{-1}(\exp^{-1\epsilon})).
\end{aligned}$$

To satisfy the condition $\epsilon < p_c(\theta) < 1 - \epsilon$, we propose the following priors for more general condition $f < p_c(\theta) < g$, where f and g are function of ϵ, c , e.g., $f = \epsilon, g = 1 - \epsilon$.

$$\begin{aligned}
\theta_1 &\sim \text{Unif}(\phi^{-1}(1 - g), \phi^{-1}(1 - f)), \\
\theta_2 &\sim \text{Unif}(\phi^{-1}\left(\frac{\phi(\theta_1)}{1 - f}\right), \phi^{-1}\left(\frac{1 - g}{(1 - f)^1}\right)), \\
\theta_3 &\sim \text{Unif}(\phi^{-1}\left(\frac{\phi(\theta_2)}{1 - f}\right), \phi^{-1}\left(\frac{1 - g}{(1 - f)^1}\right)), \\
\theta_4 &\sim \text{Unif}(\phi^{-1}\left(\frac{\phi(\theta_3)}{1 - f}\right), \phi^{-1}\left(\frac{1 - g}{(1 - f)^1}\right)), \\
\theta_5 &\sim \text{Unif}(\phi^{-1}\left(\frac{\phi(\theta_4)}{1 - f}\right), \phi^{-1}\left(\frac{1 - g}{(1 - f)^1}\right)),
\end{aligned}$$

where $\phi(\theta) := \Phi\left(\frac{\theta - \mu}{\sigma}\right)$ and $\phi^{-1}(\tau) := \mu + \sigma\Phi^{-1}(\tau)$.

To show that the above equations are well-defined, we have to show

- (1) the support of the above uniform distribution is not empty
- (2) the condition $q_c(\theta) > c\epsilon$ holds.

To show (1), we have to verify

$$\Phi^{-1}(\exp^{-c\epsilon}) - \Phi^{-1}(\Phi(\theta_c) \exp^\epsilon)$$

Suppose that we obtain $\theta_1, \theta_2, \dots, \theta_c$ distributed by the above.

$$\begin{aligned}
&\exp^{-(C+1-c)\epsilon} - \Phi(\theta_c) \exp^\epsilon \\
&> \exp^{-(C+1-c-1)\epsilon} - \exp^{(C+1-c)\epsilon} \exp^\epsilon \\
&> 0
\end{aligned}$$

Recall that the number of false alarms is distributed by Poisson with rate

$$q_c(\theta) = \log \frac{\Phi(\theta_{c+1})}{\Phi(\theta_c)}$$

Because $q_c(\theta)$ cannot be zero, but if we use non-informative priors for the model parameter θ , then some synthesized parameter gives $q_c(\theta) = 0$ which causes undesired results in SBC.

Thus, for sufficiently small fixed ϵ , we should assume that

$$q_c(\theta) > c\epsilon,$$

namely,

$$\epsilon < \log \frac{\Phi(\theta_{c+1})}{\Phi(\theta_c)},$$

from which

$$\Phi^{-1}(\Phi(\theta_c) \exp^\epsilon) < \theta_{c+1},$$

where we assume $\Phi(\theta_c) \exp^\epsilon < 1$, namely, $\theta_c < \Phi^{-1}(\exp^{-\epsilon})$.

$$\begin{aligned} \theta_1 &\sim \text{Unif}(-111, \Phi^{-1}(\exp^{-\epsilon})), \\ \theta_2 &\sim \text{Unif}(-\Phi^{-1}(\Phi(\theta_1) \exp^\epsilon), \Phi^{-1}(\exp^{-\epsilon})), \\ \theta_3 &\sim \text{Unif}(-\Phi^{-1}(\Phi(\theta_2) \exp^\epsilon), \Phi^{-1}(\exp^{-\epsilon})), \\ \theta_4 &\sim \text{Unif}(-\Phi^{-1}(\Phi(\theta_3) \exp^\epsilon), \Phi^{-1}(\exp^{-\epsilon})), \\ \theta_5 &\sim \text{Unif}(-\Phi^{-1}(\Phi(\theta_4) \exp^\epsilon), \Phi^{-1}(\exp^{-\epsilon})). \end{aligned}$$

These assumptions are necessary restriction for the equation $q_c(\theta) > \epsilon$.

Furthermore, we should consider the Bernoulli success rate for the number of hits. Next, recall that the number of hits is distributed by the binomial distribution of rate $p_c(\theta)$ which should be in between zero and one. However, non-informative prior cannot holds this condition. Thus, we should investigate the prior such that it restricts the hit rate to be in the interval $[0,1]$.

Recall that

$$p_c(\theta) = \Phi\left(\frac{\theta_{c+1} - \mu}{\sigma}\right) - \Phi\left(\frac{\theta_c - \mu}{\sigma}\right).$$

We have to assume

$$\epsilon < p_c(\theta) < 1 - \epsilon,$$

from which, we obtain

$$\begin{aligned} \epsilon &< \Phi\left(\frac{\theta_{c+1} - \mu}{\sigma}\right) - \Phi\left(\frac{\theta_c - \mu}{\sigma}\right) < 1 - \epsilon \\ \epsilon + \Phi\left(\frac{\theta_c - \mu}{\sigma}\right) &< \Phi\left(\frac{\theta_{c+1} - \mu}{\sigma}\right) < 1 - \epsilon + \Phi\left(\frac{\theta_c - \mu}{\sigma}\right) \end{aligned}$$

To go further step, we assume that

$$\Phi\left(\frac{\theta_c - \mu}{\sigma}\right) < \epsilon,$$

from which, we can apply Φ^{-1} to $1 - \epsilon + \Phi(\frac{\theta_c - \mu}{\sigma})$. So,

$$\frac{\theta_c - \mu}{\sigma} < \Phi^{-1}(\epsilon),$$

and thus

$$\theta_c < \mu + \sigma\Phi^{-1}(\epsilon).$$

$$\begin{aligned} \Phi^{-1}(\epsilon + \Phi(\frac{\theta_c - \mu}{\sigma})) &< \frac{\theta_{c+1} - \mu}{\sigma} < \Phi^{-1}(1 - \epsilon + \Phi(\frac{\theta_c - \mu}{\sigma})) \\ \mu + \sigma\Phi^{-1}(\epsilon + \Phi(\frac{\theta_c - \mu}{\sigma})) &< \theta_{c+1} < \mu + \sigma\Phi^{-1}(1 - \epsilon + \Phi(\frac{\theta_c - \mu}{\sigma})) \end{aligned}$$

To accomplish the above, we should assume that

$$\theta_{c+1} \sim \text{Uniform}(\mu + \sigma\Phi^{-1}(\epsilon + \Phi(\frac{\theta_c - \mu}{\sigma})), \mu + \sigma\Phi^{-1}(1 - \epsilon + \Phi(\frac{\theta_c - \mu}{\sigma}))),$$

namely,

$$\theta_1 \sim \text{Unif}(-111, 111),$$

$$\theta_2 \sim \text{Uniform}(\mu + \sigma\Phi^{-1}(\epsilon + \Phi(\frac{\theta_1 - \mu}{\sigma})), \mu + \sigma\Phi^{-1}(1 - \epsilon + \Phi(\frac{\theta_1 - \mu}{\sigma}))),$$

$$\theta_3 \sim \text{Uniform}(\mu + \sigma\Phi^{-1}(\epsilon + \Phi(\frac{\theta_2 - \mu}{\sigma})), \mu + \sigma\Phi^{-1}(1 - \epsilon + \Phi(\frac{\theta_2 - \mu}{\sigma}))),$$

$$\theta_4 \sim \text{Uniform}(\mu + \sigma\Phi^{-1}(\epsilon + \Phi(\frac{\theta_3 - \mu}{\sigma})), \mu + \sigma\Phi^{-1}(1 - \epsilon + \Phi(\frac{\theta_3 - \mu}{\sigma}))),$$

$$\theta_5 \sim \text{Uniform}(\mu + \sigma\Phi^{-1}(\epsilon + \Phi(\frac{\theta_4 - \mu}{\sigma})), \mu + \sigma\Phi^{-1}(1 - \epsilon + \Phi(\frac{\theta_4 - \mu}{\sigma}))),$$

Combining the necessary conditions of hit rates and false alarm rates,

we should assume their intersections.

Set

$$X_c := \Phi^{-1}(\Phi(\theta_c) \exp^\epsilon),$$

$$Y_c := \mu + \sigma\Phi^{-1}(\epsilon + \Phi(\frac{\theta_c - \mu}{\sigma}))$$

$$Z_c := \mu + \sigma\Phi^{-1}(1 - \epsilon + \Phi(\frac{\theta_c - \mu}{\sigma})),$$

then,

$$\theta_1 \sim \text{Unif}(-111, 111),$$

$$\theta_2 \sim \text{Unif}(\max(X_1, Y_1), Z_1),$$

$$\theta_3 \sim \text{Unif}(\max(X_2, Y_2), Z_2),$$

$$\theta_4 \sim \text{Unif}(\max(X_3, Y_3), Z_3),$$

$$\theta_5 \sim \text{Unif}(\max(X_4, Y_4), Z_4).$$

To justify these priors, we have to implement the SBC algorithm.

In the above uniform distribution, the support of them should not be empty. However it is not satisfied without any restriction. So, we should require the inequality that

$$\Phi^{-1}(\Phi(\theta_c) \exp^\epsilon) < \mu + \sigma \Phi^{-1}(1 - \epsilon + \Phi(\frac{\theta_c - \mu}{\sigma})),$$

which is satisfied in sufficiently small θ_c and the continuity of this equation implies that the set of solutions of θ_c satisfying the inequality is not empty. Thus we have to find the minimum of parameter θ_c^* such that it satisfies the inequality.

#'

Usage

```
Simulation-Based-Calibration_single_reader_single_modality_via_rstan_sbc(
  epsilon = 0.01,
  ite = 3333,
  NL = 259,
  NI = 57,
  C = 3,
  M = 500,
  BBB = 0.3,
  AAA = 3e-04,
  vvv = 0.3,
  vvvv = 11,
  mmm = 0,
  mmmm = 1,
  stanModel,
  sbc_from_rstan = TRUE
)
```

Arguments

epsilon	lower bound of Poisson for false positives.
ite	A variable to be passed to the function <code>rstan::sampling()</code> of rstan in which it is named <code>iter</code> . A positive integer representing the number of samples synthesized by Hamiltonian Monte Carlo method, and, Default = 10000.
NL	number of lesions
NI	number of images
C	number of confidence levels
M	To be passed to the function <code>rstan::sbc()</code> in rstan .
BBB	a real
AAA	a real
vvv	a real

vvvv a real
 mmm a real
 mmmm a real
 stanModel An object of the class stanfit of sbc. This is for the package developer.
 sbc_from_rstan A logical, wheter rstan::sbc() is used

Details

The implementation is done using the `rstan::sbc`. The stan file is `SBC.stan` The implementation is done using the function `rstan::sbc`. The stan file is `SBC.stan` The variable in this function is a collection of parameters of priors

If we use non-informative prior, then from the prior the odd model parameter are synthesized. For example, If two thresholds $z[c]$ and $z[c+1]$ agree for some c , then the false alarm rate becomes zero with the following error from `rstan::sbc`:

```

failed to create the sampler; sampling not done
Error in new_CppObject_xp(fields$.module, fields$.pointer, ...) :
Exception: poisson_rng: Rate parameter is 0, but must be > 0!

```

Thus, we have to use very strong prior to avoid to synthesize such odd parameters of model.

SBC is a validation algorithm for models with respect to its prior.

I cannot fined the prior in which we can fit a model to various datasets.

What is SBC?

Aim of SBC is to evaluate *how* the computed posteriors are incorrect. To do so, SBC algorithm makes a histogram whose uniformity indicates MCMC samples contains bias.

For example,

If histogram is concave, namely there are spikes at the boundaries of histogram, then it indicates that MCMC samples is correlated. If a histogram is convex (\cap -shaped), then it indicates that over-dispersed posteriors relative to the **true** posterior.

if histogram is concave, namely there are spikes at the boundaries of histogram, then it indicates that MCMC samples is correlated.

If a histogram is convex (\cap -shaped), then it indicates that over-dispersed posteriors relative to the **true** posterior.

If a histogram is weighted to right or left, then posterior moves opposite direction, namely left or right respectively.

We may say that SBC is a statistical test of the null hypothesis H_0 :

$$H_0 : \text{MCMC sampling is correct.}$$

If the histogram is far from uniformity, then we reject H_0 and say that MCMC sampling contains bias.

Parameters of our model

w The first threshold

- dz The difference of thresholds, that is, $dz[c] := z[c+1] - z[c]$
- m Mean of signal Gaussian
- v Standard deviation (Do not confuse it with Variance) of signal Gaussian

Value

A list of S3 class "sbc", which is an output of the function `rstan::sbc()` in **rstan**.

References

Talts, S., Betancourt, M., Simpson, D., Vehtari, A., and Gelman, A. (2018). Validating Bayesian Inference Algorithms with Simulation-Based Calibration. arXiv preprint arXiv:1804.06788. <https://arxiv.org/abs/1804.06788>

data Format:

A single reader and a single modality case

NI=63, NL=124 In R console ->	confidence level c	No. of false alarms f	No. of hits h
<i>definitely</i> present	$c[1] = 5$	$f[1] = F_5 = 1$	$h[1] = H_5 = 41$
<i>probably</i> present	$c[2] = 4$	$f[2] = F_4 = 2$	$h[2] = H_4 = 22$
equivocal	$c[3] = 3$	$f[3] = F_3 = 5$	$h[3] = H_3 = 14$
subtle	$c[4] = 2$	$f[4] = F_2 = 11$	$h[4] = H_2 = 8$
<i>very</i> subtle	$c[5] = 1$	$f[5] = F_1 = 13$	$h[5] = H_1 = 1$

Recall our model for the above data format;

$$H_5 \sim \text{Binomial}(p_5, N_L)$$

$$H_4 \sim \text{Binomial}(p_4, N_L)$$

$$H_3 \sim \text{Binomial}(p_3, N_L)$$

$$H_2 \sim \text{Binomial}(p_2, N_L)$$

$$H_1 \sim \text{Poisson}(p_1, N_L)$$

$$F_5 \sim \text{Poisson}(q_5)$$

$$F_4 \sim \text{Poisson}(q_4)$$

$$F_3 \sim \text{Poisson}(q_3)$$

$$F_2 \sim \text{Poisson}(q_2)$$

$$F_1 \sim \text{Poisson}(q_1)$$

where

$$p_5 = p_5(z_1, \dots, z_C; \mu, \sigma) = \int_{z_5}^{\infty} \text{Gaussian}(z | \mu, \sigma) dz$$

$$p_4 = p_4(z_1, \dots, z_C; \mu, \sigma) = \int_{z_4}^{z_5} \text{Gaussian}(z|\mu, \sigma) dz$$

$$p_3 = p_3(z_1, \dots, z_C; \mu, \sigma) = \int_{z_3}^{z_4} \text{Gaussian}(z|\mu, \sigma) dz$$

$$p_2 = p_2(z_1, \dots, z_C; \mu, \sigma) = \int_{z_2}^{z_3} \text{Gaussian}(z|\mu, \sigma) dz$$

$$p_1 = p_1(z_1, \dots, z_C; \mu, \sigma) = \int_{z_1}^{z_2} \text{Gaussian}(z|\mu, \sigma) dz$$

$$q_5 = q_5(z_1, \dots, z_C) = \int_{z_5}^{\infty} d \log \Phi(z)$$

$$q_4 = q_4(z_1, \dots, z_C) = \int_{z_4}^{z_5} d \log \Phi(z)$$

$$q_3 = q_3(z_1, \dots, z_C) = \int_{z_3}^{z_4} d \log \Phi(z)$$

$$q_2 = q_2(z_1, \dots, z_C) = \int_{z_2}^{z_3} d \log \Phi(z)$$

$$q_1 = q_1(z_1, \dots, z_C) = \int_{z_1}^{z_2} d \log \Phi(z)$$

Priors

$$z[c] \sim ?$$

$$m \sim ?$$

$$v \sim ?$$

In SBC, we have to specify proper priors, thus, we use the above priors. So, what reader should do is to specify the above parameters, that is, ww, www, zz, zzz, mm, mmm, vv, vvv and further a number of imagesNL and a number of lesion NI and a number of confidence levels should be specified. In the above example data format, the number of confidence level is the number of rows, and now it is 5, that is C=5.

Revised 2019 August 4

I am not statistician nor researcher nor human. My leg is gotten by death who is prurigo nodularis. Death is soon. I cannot understand, I hate statistics. I do not want to waste my time to this FROC analysis. My program is volunteer, I am no money no supported. Completely my own support or my parents. Completely my own. I am tired for this no end point running. I have not money to research or place or circumstance. No healthy condition. This program is made with my blood and pain, great pain. I no longer want to live. I hate all. Honesty.

Simulation_Based_Calibration_via_rstan_sbc_MRMC

Simulation Based Calibration (SBC) for a single reader and a single modality case

Description

Implements the SBC algorithm for the a single reader and a single modality case.

Usage

```
Simulation_Based_Calibration_via_rstan_sbc_MRMC(
  ww = -0.81,
  www = 0.001,
  mm = 0.65,
  mmm = 0.001,
  vv = 5.31,
  vvv = 0.001,
  zz = 1.55,
  zzz = 0.001,
  A_mean = 0.6,
  A_variance = 0.1,
  vv_hyper_v = 0.05,
  vvv_hyper_v = 0.01,
  NL = 259,
  NI = 57,
  C = 3,
  M = 5,
  Q = 4
)
```

Arguments

ww	A real number representing parameter of prior, indicating mean of prior for the first threshold
www	A real number representing parameter of prior, variance of prior for the first threshold
mm	A real number representing parameter of prior, mean of prior for the mean of signal distribution
mmm	A real number representing parameter of prior, variance of prior for the variance of signal distribution
vv	A real number representing parameter of prior, mean of prior for the mean of signal distribution
vvv	A real number representing parameter of prior, variance of prior for the variance of signal distribution

zz	A real number representing parameter of prior, mean of prior for the differences of thresholds
zzz	A real number representing parameter of prior, variance of prior for the differences of thresholds
A_mean	A real number representing parameter of prior, indicating mean of prior for the A
A_variance	A real number representing parameter of prior, indicating mean of prior for the A
vv_hyper_v	A real number representing parameter of prior, indicating mean of prior for the hyper_v
vvv_hyper_v	A real number representing parameter of prior, indicating variance of prior for the hyper_v
NL	number of lesions
NI	number of images
C	number of confidence levels
M	number of modalities
Q	number of readers

Details

The implementation is done using the `rstan::sbc`. The stan file is `SBC.stan`

Value

A list of S3 class "sbc", which is an outputs of the `sbc` function in `rstan`.

References

Talts, S., Betancourt, M., Simpson, D., Vehtari, A., and Gelman, A. (2018). Validating Bayesian Inference Algorithms with Simulation-Based Calibration. arXiv preprint arXiv:1804.06788

See Also

`rstan::sbc`, which implements *SBC*.

Stan file: `SBC_MRMC.stan`

size_of_return_value *Size of R object*

Description

This return value can add each other or any number by the manner: return + number of R object

Usage

```
size_of_return_value(
  object,
  summary = TRUE,
  is_return_value = TRUE,
  base_size = 0,
  col = FALSE
)
```

Arguments

object	Any R object, whose size is measured.
summary	A logical, whether the result is printed.
is_return_value	A logical, printed word is used as " return value " if it is TRUE.
base_size	This value is added to the return value, namely, object size + base_size is the return value. This is for the package developer.
col	A logical, wheter print is colored.

Value

return value of `utils::object.size()`

small_margin *Margin*

Description

If each variable is smaller, then the margin of it is smaller, so plot region become larger. But title and x axis title will be vanished.

Usage

```
small_margin(  
  Down.oma = 1,  
  Left.oma = 1,  
  Top.oma = 1,  
  Right.oma = 1,  
  Down.mar = 1,  
  Left.mar = 1,  
  Top.mar = 1,  
  Right.mar = 1  
)
```

Arguments

Down.oma	smaller gives larger plot region
Left.oma	smaller gives larger plot region
Top.oma	smaller gives larger plot region
Right.oma	smaller gives larger plot region
Down.mar	smaller gives larger plot region
Left.mar	smaller gives larger plot region
Top.mar	smaller gives larger plot region
Right.mar	smaller gives larger plot region

Details

To show FROC curve or signal and noise distributions in Shiny Graphical devices, the author write down this function `small_margin`. By taking margin too small, we gives more larger plot regions in Shiny Graphical devices. 2019 August 6

Value

NONE

See Also

[draw_latent_signal_distribution\(\)](#)
[draw_latent_noise_distribution\(\)](#)
[DrawCurves\(\)](#)
[DrawCurves_srsc\(\)](#)

Examples

```
small_margin()  
graphics::plot(1:3,1:3)
```

```
small_margin(2,2,2,2)
graphics::plot(1:3,1:3)

small_margin(2,2,2,2,4,4,4,4)
graphics::plot(1:3,1:3)
colors()
graphics::rect(
  par()$usr[1],
  par()$usr[2],
  par()$usr[3],
  par()$usr[4],

  col = "steelblue3",
  border = NA)

small_margin(0.1,0.1)
graphics::plot(1:2,1:2, type="n")
```

snippet_for_BayesianFROC

Edit Snippet

Description

Snippet for the package BayesianFROC. Copy and paste to the snippet edition tools in your R studio for the conforable usage of the package BayesianFROC. This is under construction. To edit snippet, you should open the editor located in Tools > Global options > Code > Edit snippets.

Usage

```
snippet_for_BayesianFROC()
```

Details

if \$ are included such as

```
foo$b
```

then in message it should be

```
message("foo$a")
```

2020 JULy2

Value

nothing

Examples

```
snippet_for_BayesianFROC()
```

```
sortAUC
```

```
Prints a Ranking for AUCs for MRMC Data
```

Description

prints a modality ranking according to their AUCs.

Usage

```
sortAUC(StanS4class, digits = 3, simple = FALSE)
```

Arguments

StanS4class	An S4 object of class <code>stanfitExtended</code> which is an inherited class from the S4 class <code>stanfit</code> . This R object is a fitted model object as a return value of the function <code>fit_Bayesian_FROC()</code> . It can be passed to <code>DrawCurves()</code> , <code>ppp()</code> and ... etc
digits	To be passed to <code>round()</code> for AUC, to determine the significant digits of AUCs.
simple	Logical, TRUE or FALSE. If TRUE, then it is simple. <code>@export</code>

Details

This is a ranking. Sort a data-frame involving AUC and corresponding modality IDs.

Value

A data-frame, representing sorted ranking of modality ID and its AUC. Revised 2019 Sept 9

Examples

```
## Not run:
#=====
#          1)      Fit a model to an MRMC data-set named dd
#=====

fit <- fit_Bayesian_FROC(
  ite = 1111,
  summary = FALSE,
  cha = 1,
  dataList = dd
)
```

```

#=====
#           2)           Sort the AUC and make a ranking table
#=====

                                sortAUC(fit)

# Then, a ranking table will appear.

# Revised 2019 Sept 9

## End(Not run)

```

```

stanfitExtended           stanfitExtended, an S4 class inherited from the S4 class stanfit

```

Description

Inherits from the class `stanfit` which is an S4 class defined in the package **rstan** :

Details

Revised in 2019.Jun 5 Revised in 2019 Oct 19 Revised in 2019 Nov 25

—— To read the table of R object of class `stanfit` in case of MRMC —————

* The AUC denoted by `AA[modalityID , readerID]` are shown.

For example, `AA[2, 3]` means the AUC of the 2 nd modality and the 3 rd reader.

* The column of 2.5% and 97.5% means the lower and upper bounds of the 95

Slots

`plotdataMRMC` Plot data for MRMC case.

`plotdata` This is a data frame with four components which is used to draw curves such as FROC curves and AFROC curves. So, this slot includes the component:

```

fit@plotdata$x.AFROC,
fit@plotdata$y.AFROC,
fit@plotdata$x.FROC,
fit@plotdata$y.AFROC

```

where `fit` is an object of class `stanfitExtended`.

For example, we can use this slot such as `plot(fit@plotdata$x.AFROC, fit@plotdata$y.AFROC)`
) The author think this slot is not good because it increases the object size.

`dataList` An FROC dataset. Using the dataset, the fitting has done.

`studyDesign` A character, e.g., "srsc.per.image", "srsc.per.lesion", according to False Positive Fraction (FPF) is per image or per lesion.

`metadata` An additional data calculated from `dataList`, such as cumulative hits and false alarms,....etc.

`WAIC` A WAIC calculated by the function `waic` .

`convergence` A logical R object TRUE or FALSE. If TRUE, then it means your model is good in the R hat criterion.

`PreciseLogLikelihood` This is TRUE or FALSE. If TRUE, then target formulation is used in the stan file. However, non-target formulation has warning for non-linear Jacobian issue. So, the author use target formulations for all .stan files, and thus this slot is now, redundant.

`chisquare` This is a chi square calculated with Expected A Posterior estimates, i.e., the posterior mean estimates. Chi square statistic is $\chi^2(Data|\theta)$, there are three simple ways to get it.

$$(1) \int \chi^2(Data|\theta)\pi(\theta|Data)d\theta$$

$$(2) \chi^2(Data|\int \theta\pi(\theta|Data)d\theta)$$

$$(3) \int \chi^2(Data|\theta)f(Data|\theta)\pi(\theta|Data)d\theta$$

where, $f(Data|\theta)$ denotes a likelihood and $\pi(\theta|Data)$ is a posterior. This slot retains the (2)

See also `ppp()`

`index` This is for programming phase.

`Divergences` This is the number of the divergence transitions in the MCMC simulation.

`MCMC.Iterations` A MCMC iterations which does not count the burn-in period.

`Divergence.rate` A divergence rate, that is the number of the divergence iterations over total MCMC iterations. Burn-in period is not included.

`model_name` A slot of the `stanfit` which is an S4 class defined in the *rstan* package.

`model_pars` A slot of the `stanfit` which is an S4 class in the package *rstan*.

`par_dims` A slot of the `stanfit` which is an S4 class in the package *rstan*.

`mode` A slot of the `stanfit` which is an S4 class in the package *rstan*.

`sim` A slot of the `stanfit` which is an S4 class in the package *rstan*.

`inits` A slot of the `stanfit` which is an S4 class in the package *rstan*.

`stan_args` A slot of the `stanfit` which is an S4 class in the package *rstan*.

`stanmodel` A slot of the `stanfit` which is an S4 class in the package *rstan*.

`date` A slot of the `stanfit` which is an S4 class in the package *rstan*.

`.MISC` A slot of the `stanfit` which is an S4 class in the package *rstan*.

Stan_code_validation *stan code*

Description

Title

Usage

```
Stan_code_validation(
  z = BayesianFROC::z,
  mu = BayesianFROC::mu,
  v = BayesianFROC::v,
  T.or.F = T
)
```

Arguments

z	thresholds
mu	mean
v	standard deviation
T.or.F	logical, if true hten a logical is return hit rate <1 and if false hit rate is returned.

Examples

```
Stan_code_validation(z=c(4.7,5,6),mu+555,v/1000000000)
```

```
Stan_code_validation(z=c(4.7,5,6),mu+5,v/10,T.or.F = FALSE)
```

```
#ppp[1,3,4]/denoo[1,3,4]
```

stan_model_of_sbc *Creates an object of class stanfit of SBC*

Description

Creates an object of class stanfit of SBC

Usage

```
stan_model_of_sbc()
```

Value

An object of class stanfit for SBC

Examples

```
## Not run:
stan_model_of_sbc()

## End(Not run)
```

StatisticForANOVA	<i>Statistic for ANOVA</i>
-------------------	----------------------------

Description

Provides a statistic to test the null hypothesis that all modalities are same.

Usage

```
StatisticForANOVA()
```

Value

None

summarize_MRMC	<i>Summarize the estimates for MRMC case</i>
----------------	--

Description

Summarize the estimates for MRMC case

Usage

```
summarize_MRMC(StanS4class, dig = 3)
```

Arguments

StanS4class	An S4 object of class <code>stanfitExtended</code> which is an inherited class from the S4 class <code>stanfit</code> . This R object is a fitted model object as a return value of the function <code>fit_Bayesian_FROC()</code> . It can be passed to <code>DrawCurves()</code> , <code>ppp()</code> and ... etc
dig	A variable to be passed to the function <code>rstan::sampling()</code> of rstan in which it is named <code>...??</code> . A positive integer representing the Significant digits, used in stan Cancellation. Default = 5,

Value

Nothing

Examples

```
## Not run:
fit <- fit_Bayesian_FROC(
  dataList.Chakra.Web.orderd,
  ite = 1111,
  summary =FALSE
)

summarize_MRMC(fit)

## End(Not run)# dottest
```

```
summary_AUC_comparison_MRMC
```

Print summary for AUC comparisons for MRMC

Description

It prints the results of AUC comparison for MRMC data.

Usage

```
summary_AUC_comparison_MRMC(StanS4class, significantLevel = 0.8, dig = 3)
```

Arguments

StanS4class	An S4 object of class <code>stanfitExtended</code> which is an inherited class from the S4 class <code>stanfit</code> . This R object is a fitted model object as a return value of the function <code>fit_Bayesian_FROC()</code> . It can be passed to <code>DrawCurves()</code> , <code>ppp()</code> and ... etc
significantLevel	This is a number between 0 and 1. The results are shown if posterior probabilities are greater than this quantity.
dig	A variable to be passed to the function <code>rstan::sampling()</code> of rstan in which it is named <code>...??</code> . A positive integer representing the Significant digits, used in stan Cancellation. Default = 5,

```
summary_AUC_comparison_MRMC_without_crayon
  Print summary for AUC comparisons for MRMC without color
```

Description

It prints the results of AUC comparison for MRMC data.

Usage

```
summary_AUC_comparison_MRMC_without_crayon(
  StanS4class,
  significantLevel = 0.8,
  dig = 3
)
```

Arguments

StanS4class	An S4 object of class <code>stanfitExtended</code> which is an inherited class from the S4 class <code>stanfit</code> . This R object is a fitted model object as a return value of the function <code>fit_Bayesian_FROC()</code> . It can be passed to <code>DrawCurves()</code> , <code>ppp()</code> and ... etc
significantLevel	This is a number between 0 and 1. The results are shown if posterior probabilities are greater than this quantity.
dig	A variable to be passed to the function <code>rstan::sampling()</code> of rstan in which it is named <code>...</code> ?. A positive integer representing the Significant digits, used in stan Cancellation. Default = 5,

```
summary_AUC_comparison_MRMC_with_crayon
  Print summary for AUC comparisons for MRMC hier with color
```

Description

It prints the results of AUC comparison for MRMC data.

Usage

```
summary_AUC_comparison_MRMC_with_crayon(
  StanS4class,
  significantLevel = 0.8,
  dig = 3
)
```

Arguments

StanS4class	An S4 object of class <code>stanfitExtended</code> which is an inherited class from the S4 class <code>stanfit</code> . This R object is a fitted model object as a return value of the function <code>fit_Bayesian_FROC()</code> . It can be passed to <code>DrawCurves()</code> , <code>ppp()</code> and ... etc
significantLevel	This is a number between 0 and 1. The results are shown if posterior probabilities are greater than this quantity.
dig	A variable to be passed to the function <code>rstan::sampling()</code> of rstan in which it is named <code>...</code> ?. A positive integer representing the Significant digits, used in stan Cancellation. Default = 5,

summary_EAP_CI_srsc *Summary*

Description

EAP and CI

Usage

```
summary_EAP_CI_srsc(StanS4class, dig = 5, summary = TRUE)
```

Arguments

StanS4class	An S4 object of class <code>stanfitExtended</code> which is an inherited class from the S4 class <code>stanfit</code> . This R object is a fitted model object as a return value of the function <code>fit_Bayesian_FROC()</code> . It can be passed to <code>DrawCurves()</code> , <code>ppp()</code> and ... etc
dig	digits of estimates.
summary	Logical: TRUE of FALSE. Whether to print the verbose summary. If TRUE then verbose summary is printed in the R console. If FALSE, the output is minimal. I regret, this variable name should be verbose.

Value

The estimates

Examples

```
## Not run:
#####The first example#####

#1) Build the data for singler reader and single modality case.
```

```

dat <- list(c=c(3,2,1),      #Confidence level
           h=c(97,32,31),  #Number of hits for each confidence level
           f=c(1,14,74),   #Number of false alarms for each confidence level

           NL=259,         #Number of lesions
           NI=57,         #Number of images
           C=3)           #Number of confidence level

# where, c denotes Confidence level,
#       h denotes number of Hits for each confidence level,
#       f denotes number of False alarms for each confidence level,
#       NL denotes Number of Lesions,
#       NI denotes Number of Images,

# 2) Fit the FROC model to the above data

fit <- BayesianFROC::fit_Bayesian_FROC(dat)

# 3) Extract estimates, that is posterior means and 95% credible intervals

estimates <- summary_EAP_CI_srsc( fit )

## End(Not run)# dottest

```

Test_Null_Hypothesis_that_all_modalities_are_same

Test the Null hypothesis that all modalities are same

Description

Test null hypothesis that all modalities have same observer performance ability, using Bayes factor.

Usage

```

Test_Null_Hypothesis_that_all_modalities_are_same(
  dataList,
  ite = 1111,
  cha = 1,
  summary = FALSE
)

```

Arguments

<code>dataList</code>	MRMC is the only case in which the function is available for this function.
<code>ite</code>	A variable to be passed to the function <code>rstan::sampling()</code> of rstan in which it is named <code>iter</code> . A positive integer representing the number of samples synthesized by Hamiltonian Monte Carlo method, and, Default = 10000.
<code>cha</code>	A variable to be passed to the function <code>rstan::sampling()</code> of rstan in which it is named <code>chains</code> . A positive integer representing the number of chains generated by Hamiltonian Monte Carlo method, and, Default = 1.
<code>summary</code>	Logical: TRUE or FALSE. Whether to print the verbose summary. If TRUE then verbose summary is printed in the R console. If FALSE, the output is minimal. I regret, this variable name should be verbose.

Details

From input data (variable: `dataList`), the two objects of class `stanfit` are created. one is fitted to the null hypothesis model and the another one representing alternative hypothesis. These two `stanfit`. objects are compared by the Bayes factor.

Value

none

`the_row_number_of_logical_vector`

Extract the row number from a logical vector

Description

Extract the row number from a logical vector

Usage

```
the_row_number_of_logical_vector(vector.logical)
```

Arguments

`vector.logical` vector with logical component

Value

the row number of logical component

Author(s)

Issei Tsunoda

Examples

```
a <-c(TRUE,FALSE,FALSE,TRUE,TRUE)

b <- the_row_number_of_logical_vector(a)

# Then, return value object, b is a vector of

#> b
# 1, 4, 5

# From this, we can count the TRUE, as following manner:

Number.of.TRUE <- length(b)

# Of course, it is:
#> Number.of.TRUE
# 3

length(b) == sum(a)
```

TRUE.Counter.in.vector

Count TRUE in a Vector whose components are all Logical R objects

Description

For the posterior predictive p value.

Usage

```
TRUE.Counter.in.vector(vector.logical)
```

Arguments

`vector.logical` vector with logical component

Value

A positive integer.

Examples

```

=====
#
#                               Revised 2019 oct. This is same as sum(), I did not know this
#                               =====
a <-c(TRUE,FALSE,FALSE,TRUE,TRUE)

TRUE.Counter.in.vector(a)

# Of course, it is:
#> Number.of.TRUE
# 3

sum(a) == TRUE.Counter.in.vector(a)

# I did not know this equality,... no longer this function is needed

```

v

*Standard Deviation: parameter of an MRMC model***Description**

A posterior mean of the model parameter for data [ddd](#) as an example of truth parameter.

Author(s)

Issei Tsunoda <tsunoda.issei1111@gmail.com >

See Also

make_true_parameter_MRMC

validation.dataset_srsc

*Error of estimates with respect to truth***Description**

Let us denote a model parameter by θ_0 N_I by a number of images and number of lesions by N_L which are specified by user as the variables of the function.

(I) Replicates models for datasets $D_1, D_2, \dots, D_k, \dots, D_K$.

Draw a dataset D_k from a likelihood (model), namely $D_k \sim \text{likelihood}(|\theta_0)$.

Draw a MCMC samples $\{\theta_i(D_k)\}$ **from a posterior, namely** $\theta_i \sim \pi(|D_k)$.

Calculate a posterior mean, namely $\bar{\theta}(D_k) := \sum_i \theta_i(D_k)$.

Calculates error for D_k $\epsilon_k := \text{Truth} - \text{posterior mean estimates of } D_k = |\theta_0 - \bar{\theta}(D_k)|$ (or $= \theta_0 - \bar{\theta}(D_k)$, accordingly by the user specified absolute.errors).

(II) Calculates mean of errors mean of errors $\bar{\epsilon}(\theta_0, N_I, N_L) = \frac{1}{K} \sum \epsilon_k$

Running this function, we can see that the error $\bar{\epsilon}(\theta_0, N_I, N_L)$ decreases monotonically as a given number of images N_I or a given number of lesions N_L increases.

Also, the scale of error also will be found. Thus this function can show how our estimates are correct. Scale of error differs for each component of model parameters.

Revised 2019 August 28

Usage

```
validation.dataset_srsc(
  replicate.datset = 3,
  ModifiedPoisson = FALSE,
  mean.truth = 0.6,
  sd.truth = 5.3,
  z.truth = c(-0.8, 0.7, 2.38),
  NL = 259,
  NI = 57,
  ite = 1111,
  cha = 1,
  summary = TRUE,
  serial.number = 1,
  base_size = 0,
  absolute.errors = TRUE
)
```

Arguments

replicate.datset

A Number indicate that how many you replicate dataset from user's specified dataset.

ModifiedPoisson

Logical, that is TRUE or FALSE.

If ModifiedPoisson = TRUE, then Poisson rate of false alarm is calculated **per lesion**, and model is fitted so that the FROC curve is an expected curve of points consisting of the pairs of TPF per lesion and FPF **per lesion**.

Similarly,

If ModifiedPoisson = TRUE, then Poisson rate of false alarm is calculated **per image**, and model is fitted so that the FROC curve is an expected curve of points consisting of the pair of TPF per lesion and FPF **per image**.

For more details, see the author's paper in which I explained *per image* and *per lesion*. (for details of models, see [vignettes](#), now, it is omitted from this package, because the size of vignettes are large.)

If ModifiedPoisson = TRUE, then the *False Positive Fraction (FPF)* is defined as follows (F_c denotes the number of false alarms with confidence level c)

$$\frac{F_1 + F_2 + F_3 + F_4 + F_5}{N_L},$$

$$\frac{F_2 + F_3 + F_4 + F_5}{N_L},$$

$$\frac{F_3 + F_4 + F_5}{N_L},$$

$$\frac{F_4 + F_5}{N_L},$$

$$\frac{F_5}{N_L},$$

where N_L is a number of lesions (signal). To emphasize its denominator N_L , we also call it the *False Positive Fraction (FPF) per lesion*.

On the other hand,

if ModifiedPoisson = FALSE (Default), then *False Positive Fraction (FPF)* is given by

$$\frac{F_1 + F_2 + F_3 + F_4 + F_5}{N_I},$$

$$\frac{F_2 + F_3 + F_4 + F_5}{N_I},$$

$$\frac{F_3 + F_4 + F_5}{N_I},$$

$$\frac{F_4 + F_5}{N_I},$$

$$\frac{F_5}{N_I},$$

where N_I is the number of images (trial). To emphasize its denominator N_I , we also call it the *False Positive Fraction (FPF) per image*.

The model is fitted so that the estimated FROC curve can be regarded as the expected pairs of FPF per image and TPF per lesion (ModifiedPoisson = FALSE)

or as the expected pairs of FPF per image and TPF per lesion (ModifiedPoisson = TRUE)

If ModifiedPoisson = TRUE, then FROC curve means the expected pair of **FPF per lesion** and TPF.

On the other hand, if ModifiedPoisson = FALSE, then FROC curve means the expected pair of **FPF per image** and TPF.

So, data of FPF and TPF are changed thus, a fitted model is also changed whether ModifiedPoisson = TRUE or FALSE. In traditional FROC analysis, it uses only per images (trial). Since we can divide one image into two images or more images, number of trial is not important. And more important is per signal. So, the author also developed FROC theory to consider FROC analysis under per signal. One can see that the FROC curve is rigid with respect to change of a number of images, so, it does not matter whether ModifiedPoisson = TRUE or FALSE. This rigidity of curves means that the number of images is redundant parameter for the FROC trial and thus the author try to exclude it.

Revised 2019 Dec 8 Revised 2019 Nov 25 Revised 2019 August 28

mean.truth	This is a parameter of the latent Gaussian assumption for the noise distribution.
sd.truth	This is a parameter of the latent Gaussian assumption for the noise distribution.
z.truth	This is a parameter of the latent Gaussian assumption for the noise distribution.
NL	Number of Lesions.
NI	Number of Images.
ite	A variable to be passed to the function <code>rstan::sampling()</code> of rstan in which it is named <code>iter</code> . A positive integer representing the number of samples synthesized by Hamiltonian Monte Carlo method, and, Default = 10000.
cha	A variable to be passed to the function <code>rstan::sampling()</code> of rstan in which it is named <code>chains</code> . A positive integer representing the number of chains generated by Hamiltonian Monte Carlo method, and, Default = 1.
summary	Logical: TRUE or FALSE. Whether to print the verbose summary. If TRUE then verbose summary is printed in the R console. If FALSE, the output is minimal. I regret, this variable name should be verbose.
serial.number	An positive integer or Character. This is for programming perspective. The author use this to print the serial number of validation. This will be used in the validation function.
base_size	An numeric for size of object, this is for the package developer.
absolute.errors	A logical specifying whether mean of errors is defined by TRUE $\bar{\epsilon}(\theta_0, N_I, N_L) = \frac{1}{K} \sum \epsilon_k $ FALSE $\bar{\epsilon}(\theta_0, N_I, N_L) = \frac{1}{K} \sum \epsilon_k$

Value

Return values is,

Stanfit objects for each Replicated datasets

Errors EAPs minus true values, in the above notations, it is $\bar{\epsilon}(\theta_0, N_I, N_L)$

Variances of estimators. This calculates the vaiance of posterior means over all replicated datasets

Examples

```

## Not run:
#===== The first example =====

# It is sufficient to run the function with default variable

datasets <- validation.dataset_srsc()

#===== The second example =====

# If user do not familiar with the values of thresholds, then
# it would be better to use the actual estimated values
# as an example of true parameters. In the following,
# I explain this.

# First, to get estimates, we run the following:

fit <- fit_Bayesian_FROC(dataList.Chakra.1,ite = 1111,summary =FALSE,cha=3)

# Secondly, extract the expected a posterior estimators (EAPs) from the object fit

z <- rstan::get_posterior_mean(fit,par=c("z"))[, "mean-all chains"]

# Thirdly we use this z as a true values.

datasets <- validation.dataset_srsc(z.truth = z)

#=====
#          1)          extract replicated fitted model object
#=====

# Replicates models

a <- validation.dataset_srsc(replicate.datset = 3,ite = 111)

```

```
# Check convergence, in the above MCMC iterations = 111 which is too small to get
# a convergence MCMC chain, and thus the following example will the example
# of a non-convergent model in the r hat criteria.
```

```
ConfirmConvergence( a$fit[[3]])
```

```
# Check trace plot to confirm whether MCMC chain do converge or not.
```

```
stan_trace( a$fit[[3]],pars = "A")
```

```
# Check p value
ppp( a$fit[[3]])
```

```
# In the above example, the posterior predictive p value is enough large,
# but the model did not converge in R that criteria, which will cause
# that the model does not fit to data. However p value is said
# we can not reject the null hypothesis that the model does fit.
# The author think this contradiction cause that the
# number of MCMC iterations are too small which leads us to incorrect
# Monte Carlo integral for p value. Thu p value is not correct.
# Calculation of p value relies on the law of large number and thus
# to obtain reliable posterior predictive p value, we need enough large
# MCMC samples. 2019 August 29
```

```
# Revised in 2019 August 29
```

```
#####
#          1)          Histogram of error of postrior means for replicated datasets
#          #####
#'
```

```
a<- validation.dataset_srsc(replicate.datset = 100)
hist(a$error.of.AUC,breaks = 111)
hist(a$error.of.AUC,breaks = 30)
```

```

#=====
#                               absolute.errors = FALSE generates negative biases
#=====

validation.dataset_srsc(absolute.errors = FALSE)

#=====
#                               absolute.errors = TRUE dose not generate negative biases
#=====

validation.dataset_srsc(absolute.errors = TRUE)

## End(Not run)# dontrun

```

validation.draw_srsc *Draw Curves for validation dataset*

Description

drawing curves.

Red curve indicates an FROC curve of truth parameter.

Other curves are drawn using replicated estimates.

Usage

```

validation.draw_srsc(
  validation.data,
  mesh.for.drawing.curve = 11111,
  upper_y = 1,
  DrawFROCcurve = TRUE
)

```

Arguments

validation.data

This is a return value of the function validation.dataset_srsc.

mesh.for.drawing.curve

A positive large integer, indicating number of dots drawing the curves, Default =10000.

upper_y

This is a upper bound for the axis of the vertical coordinate of FROC curve.

DrawFROCcurve

Logical: TRUE of FALSE. Whether or not FROC curves are shown.

Value

NULL

Examples

```
## Not run:
#-----
#                               1)      Draw the curve for each replicated dataset
#-----

  datasets <- validation.dataset_srsc()

  validation.draw_srsc(datasets)

#-----
#                               1)      Draw the curve for each replicated dataset
#-----

  datasets <- validation.dataset_srsc(replicate.datset = 5)

  validation.draw_srsc(datasets)

## End(Not run)# dottest
```

viewdata	<i>Build a table of FROC data</i>
----------	-----------------------------------

Description

Create a tabular representation of FROC data from FROC data object.

Usage

```
viewdata(dataList, summary = TRUE, head.only = FALSE)
```

Arguments

dataList	_____
	A Single reader and A single modality (SRSC) case.

In a single reader and a single modality case, it should include f, h, NL, NI, C .
For example data, see the datasets endowed with this package.

data Format:

A single reader and a single modality case

NI=63, NL=124 In R console ->	confidence level c	No. of false alarms f	No. of hits h
<i>definitely</i> present	$c[1] = 5$	$f[1] = F_5 = 1$	$h[1] = H_5 = 41$
<i>probably</i> present	$c[2] = 4$	$f[2] = F_4 = 2$	$h[2] = H_4 = 22$
equivocal	$c[3] = 3$	$f[3] = F_3 = 5$	$h[3] = H_3 = 14$
subtle	$c[4] = 2$	$f[4] = F_2 = 11$	$h[4] = H_2 = 8$
<i>very</i> subtle	$c[5] = 1$	$f[5] = F_1 = 13$	$h[5] = H_1 = 1$

Multiple readers and multiple modalities case, i.e., MRMC case

In multiple readers and multiple modalities case, i.e., MRMC case, it should include $m, q, c, h, f, NL, C, M, Q$ which means the followings:

C means the highest number of confidence level, this is a scalar.

M means the number of modalities

Q means the number of readers.

c means the confidence level vector. This vector must be made by $\text{rep}(\text{rep}(C:1), M*Q)$.

m means the modality ID vector.

q means the reader ID vector.

h means the number of hits vector.

f means the number of false alarm vector.

NL means the Total number of lesions for all images, this is a scalar.

The detail of these dataset, please see the endowed datasets. Note that the maximal number of confidence level, denoted by C , are included, however, its each confidence level vector also created in the program by C . So, to confirm your false positives and hits are correctly correspond to confidence levels, you should confirm the orders by the function `viewdata_MRMC`.

<code>summary</code>	Logical: TRUE or FALSE. If true then results are printed, if FALSE this function do nothing.
<code>head.only</code>	Logical: TRUE or FALSE. Whether it prints data of head part only (TRUE) or entire (FALSE). If TRUE, only head part are shown. Default is FALSE

Value

Nothing

In order to confirm your data, please view table before fitting. Confidence level vector are created in my program regardless of user's confidence level vectors.

Author(s)

Issei Tsunoda

Examples

```
## Not run:  
  
# The first example, we prepare the data in this package.  
  
    dat <- get(data("dataList.Chakra.1"))  
  
    viewdata(dat)  
  
# The second example, we consider a dataset of multiple readers and multiple modalities  
  
    dat <- get(data("dataList.Chakra.Web"))  
  
    viewdata(dat)  
  
## End(Not run)# doctest
```

viewdata_MRMC

View MRMC data

Description

Build a table for data dataList.

Usage

```
viewdata_MRMC(dataList, summary = TRUE, head.only = FALSE)
```

Arguments

dataList	<p>it should include m, q, c, h, f, NL, C, M, Q which means from the right</p> <p>m means the modality ID vector</p> <p>q means the reader ID vector</p> <p>c means the confidence level</p> <p>h means the number of hits</p> <p>f means the number of false alarm</p> <p>NL means the Total number of lesions for all images</p> <p>C means the highest number of confidence level</p> <p>M means the number of modalities</p> <p>Q means the number of readers.</p> <p>The detail of these dataset, please see the endowed datasets. Note that the maximal number of confidence level, denoted by C, are included, however, its each confidence level should not included your data. So, to confirm your false positives and hits are correctly correspondence to confidence levels, you should confirm the orders by the function viewdata_MRMC.</p>
summary	TRUE or FALSE, if true then results are printed, if FALSE this function do nothing.
head.only	Logical: TRUE or FALSE. Whether head part or entire. If TRUE, only head part are shown. Default is FALSE

viewdata_srsc	<i>Build a table of data in the case of A Single reader and A Single modality (srsc)</i>
---------------	--

Description

In order to confirm that your dataset is correctly formulated, please view the data via table. my program makes new column of confidence levels which are used in my program. So, it is possible that your order of confidence level and Program's order of confidence level are inverse. This function's result table are the one which are used in program.

Usage

```
viewdata_srsc(dataList, summary = TRUE)
```

Arguments

dataList	<p>it should include f, h, NL, NI, C. The detail of these dataset, please see the endowed datasets. Note that the maximal number of confidence level, denoted by C, are included, however, its each confidence level should not included your data. So, to confirm your false positives and hits are correctly correspondence to confidence levels, user should confirm the orders by the function.</p>
summary	TRUE or FALSE, if true then results are printed, if FALSE this function do nothing.

Examples

```
## Not run:
# First, we prepare an example FROC data "dataList.Chakra.1" in this package.
# Note that this data should be formed as a single reader and a single modality.
# If data are multiple readers and multiple modalities, i.e.,MRMC-data,
# then another function named viewdataMRMC is available for MRMC-data.

dat <- get(data("dataList.Chakra.1"))

# Show data named "dat";

viewdata_srsc(dat)

#The Reason why the author made this \code{viewdata_srsc} is
#the code does not refer your confidence level.
#More precisely, my program made the column vector of confidence levels
#from the its highest number,
#so, it may be occur the interpretaion of code for hits and false alarm
#are inverse order compared with your data.

## End(Not run)# dottest
```

v_truth

Standard Deviation: parameter of an MRMC model

Description

A posterior mean of the model parameter for data `ddd` as an example of truth parameter.

Details

Standard Deviation Rate data of some MRMC data to use as a default value of the function `hits_creator_from_rate`. This is an array obtained from estimates of some data contained in this package. To simulate a replication of dataset, the default values should be used from an actual values. Thus the author prepare this data.

Author(s)

Issei Tsunoda <tsunoda.issei1111@gmail.com >

See Also

hits_creator_from_rate

v_truth_creator_for_many_readers_MRMC_data
v of MRMC model paramter

Description

v of MRMC model paramter

Usage

```
v_truth_creator_for_many_readers_MRMC_data(M, Q)
```

Arguments

M	An integer, indicating a number of modalities
Q	An integer, indicating a number of readers

Value

An array, representing v of MRMC model paramter

Examples

```
v <- v_truth_creator_for_many_readers_MRMC_data(M=4,Q=50)
```

waic

WAIC Calculator

Description

Calculates the WAIC of the fitted object of class stanfit whose stan file is described with target +=

.

Usage

```
waic(StanS4classwithTargetFormulation, dig = 4, summary = TRUE)
```

Arguments

<code>StanS4classwithTargetFormulation</code>	This is a fitted model object built by <code>rstan::sampling()</code> whose model block is described by <i>target formulation</i> in the rstan package. This object is available for both S4 classes: <code>stanfit</code> and <code>stanfitExtended</code> . In this package, the author made a new S4 class named <code>stanfitExtended</code> which is an inherited S4 class of rstan 's S4 class called <i>stanfit</i> . This function is also available for a such <code>stanfit</code> S4 object.
<code>dig</code>	The number of significant digits of WAIC.
<code>summary</code>	Logical: TRUE or FALSE. Whether to print the verbose summary. If TRUE then verbose summary is printed in the R console. If FALSE, the output is minimal. I regret, this variable name should be verbose.

Details

WAIC is an abbreviation for Widely Applicable Information Criterion (Watanabe-Akaike Information Criterion)

Value

A real number, representing the value of WAIC of the fitted model object `StanS4classwithTargetFormulation`.
Revised 2020 Jan

Examples

```
## Not run:
#####
#           Model selection based on WAIC
#####

# First, we prepare the data endowed with this package:

dat <- get(data("dataList.Chakra.1"))

# Second, create a fitted model object;

fit1 <- fit_Bayesian_FROC(dat,
                          ModifiedPoisson = FALSE)

# Using the fitted model object "fit", we can calculate the WAIC of it
```

```
      waic(fit1)

# Furthermore,
# the Author provides an another model for a single reader and a single modality case.
# One is false alarm rates means "per lesion" and the other means "per image".
# The above "fit" is "per image".
# Now we shall consider to compare WAIC of these two models
# To do so, next we shall fit the "per lesion" model to the data as follows:

      fit2 <- fit_Bayesian_FROC(dat,
                               ModifiedPoisson = TRUE)

      waic(fit2)

# By compare two model's WAIC we can say which model is better.
# Note that the smaller WAIC is better.

      waic(fit1)    # per lesion model
      waic(fit2)    # per image model

# For the dataset,
# We should select one of the above two models
# by the criteria that the smaller waic is better.
# Namely, if the following inequality

      waic(fit2) > waic(fit1)

# is TRUE, then we should use fit1.
# Similary, if the following inequality

      waic(fit2) < waic(fit1)

# is TRUE, then we should use fit2.
# 2019.05.21 Revised.
# 2020 Feb Revised.

## End(Not run)# dottest
```

z

*Threshold: parameter of an MRMC model***Description**

A posterior mean of the model parameter for data `ddd` as an example of truth parameter.

Author(s)

Issei Tsunoda <tsunoda.issei1111@gmail.com >

See Also

`make_true_parameter_MRMC`

z_from_dz

*Thresholds from its difference***Description**

Thresholds are created from its difference

$$z[1] = w$$

$$z[2] = z[1] + (z[2] - z[1])$$

$$z[3] = z[1] + (z[2] - z[1]) + (z[3] - z[2])$$

$$z[4] = z[1] + (z[2] - z[1]) + (z[3] - z[2]) + (z[4] - z[3])$$

Usage

`z_from_dz(w, dz)`

Arguments

`w` a real number, indicating the first threshold
`dz` a vector of real numbers, indicating the difference of thresholds

Value

A vector of real numbers

Examples

```
z_from_dz(1,c(2,3))  
z_from_dz(1,c(0.2,0.03))  
z_from_dz(1,c(0.2,0.03,0.004))
```

```
dz <-runif(3, # sample size  
          0.01, # lower bound  
          1 # upper bound  
          )
```

```
w <- rnorm(1,  
          0,  
          1  
          )
```

```
z_from_dz(w,dz )
```

z_truth

Threshold : parameter of an MRMC model

Description

A posterior mean of the model parameter for data [ddd](#) as an example of truth parameter.

Details

Threshold Rate data of some MRMC data to use as a default value of the function `hits_creator_from_rate`. This is an array obtained from estimates of some data contained in this package. To simulate a replication of dataset, the default values should be used from an actual values. Thus the author prepare this data.

Author(s)

Issei Tsunoda <tsunoda.issei1111@gmail.com >

See Also

`hits_creator_from_rate`

%>>%

*Fit a model***Description**

Fitting is done with single

Usage

```
dataList %>>% ite
```

Arguments

`dataList` A list, specifying an FROC data to be fitted a model. It consists of data of numbers of TPs, FPs, lesions, images. .In addition, if in case of mutiple readers or mutiple modalities, then modaity ID and reader ID are included also. The `dataList` will be passed to the function `rstan::sampling()` of **rstan**. This is a variable in the function `rstan::sampling()` in which it is named `data`. For the single reader and a single modality data, the `dataList` is made by the following manner:

```
dataList.Example <-list(
h = c(41,22,14,8,1),# number of hits for each confidence level
f = c(1,2,5,11,13),# number of false alarms for each confidence level

NL = 124,# number of lesions (signals)
NI = 63,# number of images (trials)
C = 5) # number of confidence,.. the author thinks it can be calculated
as the length of h or f ...? ha,why I included this. ha .. should be omitted.
```

Using this object `dataList.Example`, we can apply `fit_Bayesian_FROC()` such as `fit_Bayesian_FROC(dataList.Example)`.

To make this R object `dataList` representing FROC data, this package provides three functions:

```
convertFromJafroc() If data is a JAFROC xlsx formulation.
dataset_creator_new_version() Enter TP and FP data by table .
create_dataset() Enter TP and FP data by interactive manner.
```

Before fitting a model, we can confirm our dataset is correctly formulated by using the function `viewdata()`.

A Single reader and a single modality (SRSC) case.

In a single reader and a single modality case (`srsc`), `dataList` is a list consisting of `f,h,NL,NI,C` where `f,h` are numeric vectors and `NL,NI,C` are positive integers.

- f Non-negative integer vector specifying number of false alarms associated with each confidence level. The first component corresponding to the highest confidence level.
- h Non-negative integer vector specifying number of Hits associated with each confidence level. The first component corresponding to the highest confidence level.
- NL A positive integer, representing Number of Lesions.
- NI A positive integer, representing Number of Images.
- C A positive integer, representing Number of Confidence level.

The detail of these dataset, see the datasets endowed with this package. Note that the maximal number of confidence level, denoted by C, are included, however, Note that confidence level vector `c` should not be specified. If specified, will be ignored, since it is created by `c <- c(rep(C:1))` in the program and do not refer from user input data, where C is the highest number of confidence levels. So, you should write down your hits and false alarms vector so that it is compatible with this automatically created `c` vector.

data Format:

A single reader and a single modality case

NI=63, NL=124 In R console ->	confidence level c	No. of false alarms f	No. of hits h
definitely present	<code>c[1] = 5</code>	<code>f[1] = F₅ = 1</code>	<code>h[1] = H₅ = 41</code>
probably present	<code>c[2] = 4</code>	<code>f[2] = F₄ = 2</code>	<code>h[2] = H₄ = 22</code>
equivocal	<code>c[3] = 3</code>	<code>f[3] = F₃ = 5</code>	<code>h[3] = H₃ = 14</code>
subtle	<code>c[4] = 2</code>	<code>f[4] = F₂ = 11</code>	<code>h[4] = H₂ = 8</code>
very subtle	<code>c[5] = 1</code>	<code>f[5] = F₁ = 13</code>	<code>h[5] = H₁ = 1</code>

* *false alarms* = False Positives = FP

* *hits* = True Positives = TP

Note that in FROC data, all confidence level means *present (diseased, lesion)* case only, no confidence level indicating absent. Since each reader marks his suspicious location only if he thinks lesions are *present*, and marked positions generates the hits or false alarms, *thus* each confidence level represents that lesion is *present*. In the absent case, reader dose not mark any locations and hence, the absent confidence level does not relate this dataset. So, if reader think it is no lesion, then in such case confidence level is not needed.

Note that the first column of confidence level vector `c` should not be specified. If specified, will be ignored, since it is created by `c <- c(rep(C:1))` automatically in the program and do not refer from user input data even if it is specified explicitly, where C is the highest number of confidence levels. So you

should check the compatibility of your data and the confidence level vector `c` `<-c(rep(C:1))` via a table which can be displayed by the function `viewdata()`.

Multiple readers and multiple modalities case, i.e., MRMC case

In case of multiple readers and multiple modalities, i.e., MRMC case, in order to apply the function `fit_Bayesian_FROC()`, dataset represented by an R list object representing FROC data must contain components `m`, `q`, `c`, `h`, `f`, `NL`, `C`, `M`, `Q`.

- `C` A positive integer, representing the **highest** number of confidence level, this is a scalar.
- `M` A positive integer vector, representing the number of **modalities**.
- `Q` A positive integer, representing the number of **readers**.
- `m` A vector of positive integers, representing the **modality ID** vector.
- `q` A vector of positive integers, representing the **reader ID** vector.
- `c` A vector of positive integers, representing the **confidence level**. This vector must be made by `rep(rep(C:1), M*Q)`
- `h` A vector of non-negative integers, representing the number of **hits**.
- `f` A vector of non-negative integers, representing the number of **false alarms**.
- `NL` A positive integer, representing the Total number of **lesions** for all images, this is a scalar.

Note that the maximal number of confidence level (denoted by `C`) are included in the above R object. However, each confidence level vector is not included in the data, because it is created automatically from `C`. To confirm false positives and hits are correctly ordered with respect to the automatically generated confidence vector,

the function `viewdata()` shows the table. Revised 2019 Nov 27 Revised 2019 Dec 5

Example data.

Multiple readers and multiple modalities (i.e., MRMC)

Modality ID	Reader ID	Confidence levels	No. of false alarms	No. of hits.
<code>m</code>	<code>q</code>	<code>c</code>	<code>f</code>	<code>h</code>
1	1	3	20	111
1	1	2	29	55
1	1	1	21	22
1	2	3	6	100
1	2	2	15	44
1	2	1	22	11
2	1	3	6	66
2	1	2	24	55
2	1	1	23	1
2	2	3	5	66
2	2	2	30	55

2 2 1 40 44

—
* *false alarms* = False Positives = FP

* *hits* = True Positives = TP

ite A variable to be passed to the function `rstan::sampling()` of **rstan** in which it is named *iter*. A positive integer representing the number of samples synthesized by Hamiltonian Monte Carlo method, and, Default = 10000.

Value

A fitted model object of class `stanfitExtended`

Examples

```
## Not run:
```

```
#####  
#     In the following, d is a data-set and 1111 is a number of MCMC iterations  
#####
```

```
d %>>% 1111
```

```
## End(Not run)
```

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