Package ‘SimpleTable’

February 19, 2015

Version 0.1-2

Date 2012-6-2

Title Bayesian Inference and Sensitivity Analysis for Causal Effects from 2 x 2 and 2 x 2 x K Tables in the Presence of Unmeasured Confounding

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Depends R (>= 2.5.1), hdrcde, locfit, MCMCpack, tcltk

Description SimpleTable provides a series of methods to conduct Bayesian inference and sensitivity analysis for causal effects from 2 x 2 and 2 x 2 x K tables when unmeasured confounding is present or suspected.

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Repository CRAN

Date/Publication 2012-06-03 06:07:30

NeedsCompilation no

R topics documented:

analyze2x2 *Analyze 2 x 2 Table in the Presence of Unmeasured Confounding*

Description

analyze2x2 performs a causal Bayesian analysis of a 2 x 2 table in which it is assumed that unmeasured confounding is present. The binary treatment variable is denoted $X = 0$ (control), 1 (treatment); and the binary outcome variable is denoted $Y = 0$ (failure), 1 (success). The notation and terminology are from Quinn (2008).

Usage

```
analyze2x2(C00, C01, C10, C11, a00, a01, a10, a11,
           b00, b01, b10, b11, c00, c01, c10, c11, nsamp = 50000)
```

Arguments

- `C00` The number of observations in $(X = 0, Y = 0)$ cell of the table. In other words, the number of observations that received control and failed.
- `C01` The number of observations in $(X = 0, Y = 1)$ cell of the table. In other words, the number of observations that received control and succeeded.
- `C10` The number of observations in $(X = 1, Y = 0)$ cell of the table. In other words, the number of observations that received treatment and failed.
- `C11` The number of observations in $(X = 1, Y = 1)$ cell of the table. In other words, the number of observations that received treatment and succeeded.
- `a00` One of four parameters (with `a01`, `a10`, and `a11` governing the Dirichlet prior for θ (the joint probabilities of X and Y). This prior has the effect of adding `a00` - 1 observations to the $(X = 0, Y = 0)$ cell of the table.
- `a01` One of four parameters (with `a00`, `a10`, and `a11` governing the Dirichlet prior for θ (the joint probabilities of X and Y). This prior has the effect of adding `a01` - 1 observations to the $(X = 0, Y = 1)$ cell of the table.
- `a10` One of four parameters (with `a00`, `a01`, and `a11` governing the Dirichlet prior for θ (the joint probabilities of X and Y). This prior has the effect of adding `a10` - 1 observations to the $(X = 1, Y = 0)$ cell of the table.
- `a11` One of four parameters (with `a00`, `a01`, and `a10` governing the Dirichlet prior for θ (the joint probabilities of X and Y). This prior has the effect of adding `a11` - 1 observations to the $(X = 1, Y = 1)$ cell of the table.
- `b00` One of two parameters (with `c00`) governing the beta prior for the distribution of potential outcome types within the $(X = 0, Y = 0)$ cell of the table. This prior adds the same information as would be gained from observing `b00` - 1 Helped units in the $(X = 0, Y = 0)$ cell of the table.
- `b01` One of two parameters (with `c01`) governing the beta prior for the distribution of potential outcome types within the $(X = 0, Y = 1)$ cell of the table. This prior adds the same information as would be gained from observing `b01` - 1 Always Succeed units in the $(X = 0, Y = 1)$ cell of the table.

b10	One of two parameters (with c10) governing the beta prior for the distribution of potential outcome types within the $(X = 1, Y = 0)$ cell of the table. This prior adds the same information as would be gained from observing b10 - 1 Hurt units in the $(X = 1, Y = 0)$ cell of the table.
b11	One of two parameters (with c11) governing the beta prior for the distribution of potential outcome types within the $(X = 1, Y = 1)$ cell of the table. This prior adds the same information as would be gained from observing b11 - 1 Always Succeed units in the $(X = 1, Y = 1)$ cell of the table.
c00	One of two parameters (with b00) governing the beta prior for the distribution of potential outcome types within the $(X = 0, Y = 0)$ cell of the table. This prior adds the same information as would be gained from observing b00 - 1 Never Succeed units in the $(X = 0, Y = 0)$ cell of the table.
c01	One of two parameters (with b01) governing the beta prior for the distribution of potential outcome types within the $(X = 0, Y = 1)$ cell of the table. This prior adds the same information as would be gained from observing c01 - 1 Hurt units in the $(X = 0, Y = 1)$ cell of the table.
c10	One of two parameters (with b10) governing the beta prior for the distribution of potential outcome types within the $(X = 1, Y = 0)$ cell of the table. This prior adds the same information as would be gained from observing c10 - 1 Never Succeed units in the $(X = 1, Y = 0)$ cell of the table.
c11	One of two parameters (with b11) governing the beta prior for the distribution of potential outcome types within the $(X = 1, Y = 1)$ cell of the table. This prior adds the same information as would be gained from observing b11 - 1 Helped units in the $(X = 1, Y = 1)$ cell of the table.
nsamp	Size of the Monte Carlo sample used to summarize the posterior.

Details

analyze2x2 performs the Bayesian analysis of a 2 x 2 table described in Quinn (2008). summary and plot methods can be used to examine the output.

Value

An object of class SimpleTable.

Author(s)

Kevin M. Quinn

References

Quinn, Kevin M. 2008. “What Can Be Learned from a Simple Table: Bayesian Inference and Sensitivity Analysis for Causal Effects from 2 x 2 and 2 x 2 x K Tables in the Presence of Unmeasured Confounding.” Working Paper.

See Also

ConfoundingPlot, analyze2x2xK, ElicitPsi, summary.SimpleTable, plot.SimpleTable

Examples

```
## Not run:
## Example from Quinn (2008)
## (original data from Oliver and Wolfinger. 1999.
##   ``Jury Aversion and Voter Registration.''
##     American Political Science Review. 93: 147-152.)
##
##        Y=0       Y=1
## X=0    19        143
## X=1    114       473
##

## uniform prior on the potential outcome distributions
S.unif <- analyze2x2(C00=19, C01=143, C10=114, C11=473,
                     a00=.25, a01=.25, a10=.25, a11=.25,
                     b00=1, c00=1, b01=1, c01=1,
                     b10=1, c10=1, b11=1, c11=1)

summary(S.unif)
plot(S.unif)


## a prior belief in an essentially negative monotonic treatment effect
S.mono <- analyze2x2(C00=19, C01=143, C10=114, C11=473,
                     a00=.25, a01=.25, a10=.25, a11=.25,
     b00=0.02, c00=10, b01=25, c01=3,
                     b10=3, c10=25, b11=10, c11=0.02)

summary(S.mono)
plot(S.mono)

## End(Not run)
```

`analyze2x2xK` *Analyze 2 x 2 x K Table in the Presence of Unmeasured Confounding*

Description

`analyze2x2xK` performs a causal Bayesian analysis of a 2 x 2 x K table in which it is assumed that unmeasured confounding is present. The binary treatment variable is denoted $X = 0$ (control), 1 (treatment); the binary outcome variable is denoted $Y = 0$ (failure), 1 (success); and the categorical measured confounder is denoted $W = 0, \dots, K - 1$. The notation and terminology are from Quinn (2008).

Usage

```
analyze2x2xK(SimpleTableList, Wpriorvector)
```

Arguments

`SimpleTableList`
: A list of K `SimpleTable` objects formed by using `analyze2x2` to analyze the K conditional (X, Y) tables given each level of the measured confounder W.

`Wpriorvector`
: K-vector giving the parameters of the Dirichlet prior for ϕ where $\phi_k \equiv \Pr(W = k)$ for $k = 0, \ldots, K-1$. The kth element of `Wpriorvector` corresponds to the kth element of W.

Details

`analyze2x2xK` performs the Bayesian analysis of a 2 x 2 x K table described in Quinn (2008). `summary` and `plot` methods can be used to examine the output.

Value

An object of class `SimpleTable`.

Author(s)

Kevin M. Quinn

References

Quinn, Kevin M. 2008. “What Can Be Learned from a Simple Table: Bayesian Inference and Sensitivity Analysis for Causal Effects from 2 x 2 and 2 x 2 x K Tables in the Presence of Unmeasured Confounding.” Working Paper.

See Also

`ConfoundingPlot`, `analyze2x2`, `ElicitPsi`, `summary.SimpleTable`, `plot.SimpleTable`

Examples

```
## Not run:
## Example from Quinn (2008)
## (original data from Oliver and Wolfinger. 1999.
##   ``Jury Aversion and Voter Registration.''
##     American Political Science Review. 93: 147-152.)
##
##
##             W=0
##          Y=0   Y=1
##  X=0      1     21
##  X=1     10     93
##
##
##             W=1
##          Y=0   Y=1
##  X=0      5     32
##  X=1     27     92
##
```

```
##
##             W=2
##          Y=0   Y=1
##  X=0      4     44
##  X=1     52    186
##
##
##             W=3
##          Y=0   Y=1
##  X=0      7     20
##  X=1     19     47
##
##
##             W=4
##          Y=0   Y=1
##  X=0      2     26
##  X=1      6     55
##


## a prior belief in an essentially negative monotonic treatment effect
## with the largest effects among those for whom W <= 2

S.mono.0 <- analyze2x2(C00=1, C01=21, C10=10, C11=93,
                       a00=.25, a01=.25, a10=.25, a11=.25,
                       b00=0.02, c00=10, b01=25, c01=3,
                       b10=3, c10=25, b11=10, c11=0.02)

S.mono.1 <- analyze2x2(C00=5, C01=32, C10=27, C11=92,
                       a00=.25, a01=.25, a10=.25, a11=.25,
                       b00=0.02, c00=10, b01=25, c01=3,
                       b10=3, c10=25, b11=10, c11=0.02)

S.mono.2 <- analyze2x2(C00=4, C01=44, C10=52, C11=186,
                       a00=.25, a01=.25, a10=.25, a11=.25,
                       b00=0.02, c00=10, b01=25, c01=3,
                       b10=3, c10=25, b11=10, c11=0.02)

S.mono.3 <- analyze2x2(C00=7, C01=20, C10=19, C11=47,
                       a00=.25, a01=.25, a10=.25, a11=.25,
                       b00=0.02, c00=10, b01=15, c01=1,
                       b10=1, c10=15, b11=10, c11=0.02)

S.mono.4 <- analyze2x2(C00=2, C01=26, C10=6, C11=55,
                       a00=.25, a01=.25, a10=.25, a11=.25,
                       b00=0.02, c00=10, b01=15, c01=1,
                       b10=1, c10=15, b11=10, c11=0.02)

S.mono.all <- analyze2x2xK(list(S.mono.0, S.mono.1, S.mono.2,
                        S.mono.3, S.mono.4),
                           c(0.2, 0.2, 0.2, 0.2, 0.2))

summary(S.mono.all)
```

```
plot(S.mono.all)

## End(Not run)
```

ConfoundingPlot *Confounding Plot of Quinn (2008)*

Description

ConfoundingPlot implements the "confounding plot" discussed in Quinn (2008). This plot displays, in the context of binary treatment ($X = 0$: control, 1: treatment) and binary outcome ($Y = 0$: failure, 1: success), all types of unmeasured confounding that would keep a true causal effect of interest within some user-defined tolerance of the estimated causal effect.

Usage

```
ConfoundingPlot(theta00, theta01, theta10, theta11,
                conditioning = c("None", "Treated", "Control"),
                PrY1.setX0 = NULL, PrY1.setX1 = NULL,
                PrY1.setX0.withinTreated = NULL,
                PrY1.setX1.withinControl = NULL,
                epsilon = 0.025, color = "black", legend = FALSE)
```

Arguments

theta00 The *observed* joint probability that X is control and Y is failure ($\Pr(X = 0, Y = 0)$). In a 2 x 2 table in which C_{00} is the number of observations in the ($X = 0$, $Y = 0$) cell and in which there are C total observations one can consistently estimate theta00 with C_{00}/C.

theta01 The *observed* joint probability that X is control and Y is success ($\Pr(X = 0, Y = 1)$). In a 2 x 2 table in which C_{01} is the number of observations in the ($X = 0$, $Y = 1$) cell and in which there are C total observations one can consistently estimate theta01 with C_{01}/C.

theta10 The *observed* joint probability that X is treatment and Y is failure ($\Pr(X = 1, Y = 0)$). In a 2 x 2 table in which C_{10} is the number of observations in the ($X = 1$, $Y = 0$) cell and in which there are C total observations one can consistently estimate theta10 with C_{10}/C.

theta11 The *observed* joint probability that X is treatment and Y is success ($\Pr(X = 1, Y = 1)$). In a 2 x 2 table in which C_{11} is the number of observations in the ($X = 1$, $Y = 1$) cell and in which there are C total observations one can consistently estimate theta11 with C_{11}/C.

conditioning A string detailing whether the post-intervention distribution, and hence the estimand of interest, is restricted to a particular subgroup. Possible values are: None, Treated, and Control. If conditioning = None then the post-intervention distribution is for all units. This is consistent with the causal estimand being the average treatment effect (ATE). If `conditioning = Treated` then the post-intervention is calculated only for just the treated units. This is consistent with the causal estimand being the average treatment effect within the treated (ATT). Finally, if `conditioning = Control` then the post-intervention distribution is calculated for just the control units. this is consistent with the causal estimand being the average treatment effect within the controls (ATC). Default is `None`.

`PrY1.setX0` Optional value giving the *assumed* probability that a randomly chosen unit will have $Y = 1$ (success) if its X value is set to 0 (control) by outside intervention. If `PrY1.setX0 = NULL` (the default) then `PrY1.setX0` is set to the *observed* conditional probability that Y is 1 given that X is 0. In the terms of Quinn (2008), the reference distribution is the prima facie post-intervention distribution. Setting `PrY1.setX0` to some non-`NULL` value allows one to use reference distributions other than the prima facie post-intervention distribution. This is useful if one wants to start with a particular value for ATE (that is not the prima facie ATE) and see how unmeasured confounding might affect that inference. Only applicable if `conditioning = None`.

`PrY1.setX1` Optional value giving the *assumed* probability that a randomly chosen unit will have $Y = 1$ (success) if its X value is set to 1 (treatment) by outside intervention. If `PrY1.setX1 = NULL` (the default) then `PrY1.setX1` is set to the *observed* conditional probability that Y is 1 given that X is 1. In the terms of Quinn (2008), the reference distribution is the prima facie post-intervention distribution. Setting `PrY1.setX1` to some non-`NULL` value allows one to use reference distributions other than the prima facie post-intervention distribution. This is useful if one wants to start with a particular value for ATE (that is not the prima facie ATE) and see how unmeasured confounding might affect that inference. Only applicable if `conditioning = None`.

`PrY1.setX0.withinTreated`

Optional value giving the *assumed* probability that a randomly chosen unit which received treatment would have $Y = 1$ (success) if its X value were set to 0 (control) by outside intervention. If `PrY1.setX0.withinTreated = NULL` (the default) then `PrY1.setX0.withinTreated` is set to the *observed* conditional probability that Y is 1 given that X is 0. In the terms of Quinn (2008), the reference distribution is the prima facie post-intervention distribution. Setting `PrY1.setX0.withinTreated` to some non-`NULL` value allows one to use reference distributions other than the prima facie post-intervention distribution. This is useful if one wants to start with a particular value for ATT (that is not the prima facie ATT) and see how unmeasured confounding might affect that inference. Only applicable if `conditioning = Treated`.

`PrY1.setX1.withinControl`

Optional value giving the *assumed* probability that a randomly chosen unit which received control would have $Y = 1$ (success) if its X value were set to 1 (treatment) by outside intervention. If `PrY1.setX1.withinControl = NULL` (the default) then `PrY1.setX1.withinControl` is set to the *observed* conditional probability that Y is 1 given that X is 1. In the terms of Quinn (2008), the reference distribution is the prima facie post-intervention distribution. Setting `PrY1.setX1.withinControl` to some non-`NULL` value allows one to use reference distributions other than the prima facie post-intervention distribution. This is useful if one wants to start with a particular value for ATC (that is not the prima facie ATC) and see how unmeasured confounding might affect that inference. Only applicable if `conditioning = Control`.

`epsilon` A scalar or array of tolerance values between 0 and 1. The plot depicts all regions of the space of confounders for which the absolute difference between the true post-intervention distribution and the assumed post-intervention distribution is less than `epsilon`. See Quinn (2008) for details. If `epsilon` is an array then `color` (see below) must also be an array and the various tolerance regions will be overlaid in color.

`color` An array of colors for the plotting regions. `color` must have length equal to the length of `epsilon` (see above).

`legend` Logical value indicating whether a legend should be printed.

Details

For full details see Quinn (2008).

Author(s)

Kevin M. Quinn

References

Quinn, Kevin M. 2008. "What Can Be Learned from a Simple Table: Bayesian Inference and Sensitivity Analysis for Causal Effects from 2 x 2 and 2 x 2 x K Tables in the Presence of Unmeasured Confounding." Working Paper.

See Also

analyze2x2, analyze2x2xK, ElicitPsi,

Examples

```
## Example from Quinn (2008)
## (original data from Oliver and Wolfinger. 1999.
##   ``Jury Aversion and Voter Registration.''
##     American Political Science Review. 93: 147-152.)
##
##        Y=0       Y=1
## X=0    19        143
## X=1    114       473
##

C <- 19 + 143 + 114 + 473
theta00 <- 19/C
theta01 <- 143/C
theta10 <- 114/C
theta11 <- 473/C

## may have to adjust size of graphics device to make labels readable
ConfoundingPlot(theta00=theta00, theta01=theta01,
```

```
        theta10=theta10, theta11=theta11, legend=TRUE)


## same data but with various epsilons and a legend
## may have to adjust size of graphics device to make labels readable
ConfoundingPlot(theta00=theta00, theta01=theta01,
        theta10=theta10, theta11=theta11,
epsilon=c(.01, .025, .05, .1),
color=c("black", "darkblue", "blue", "cyan"),
legend=TRUE)



## same data but reference distribution is now just within the treated
## may have to adjust size of graphics device to make labels readable
ConfoundingPlot(theta00=theta00, theta01=theta01,
        theta10=theta10, theta11=theta11,
conditioning="Treated", legend=TRUE)



## set PrY1.setX0 and PrY1.setX1 in order to get a reference
## post-intervention distribution that is consistent with
## ATE = -0.2 (note there are many ways to do this)
## may have to adjust size of graphics device to make labels readable
ConfoundingPlot(theta00=theta00, theta01=theta01,
        theta10=theta10, theta11=theta11,
PrY1.setX0=.9, PrY1.setX1=.7,
legend=TRUE)


## another way to get ATE = -0.2
## may have to adjust size of graphics device to make labels readable
ConfoundingPlot(theta00=theta00, theta01=theta01,
        theta10=theta10, theta11=theta11,
PrY1.setX0=.85, PrY1.setX1=.65,
legend=TRUE)


## a way to get ATE = -0.2 that is impossible given the observed data
##  (note the complete lack of any shaded regions in the left panel of plot)
## may have to adjust size of graphics device to make labels readable
ConfoundingPlot(theta00=theta00, theta01=theta01,
        theta10=theta10, theta11=theta11,
PrY1.setX0=.5, PrY1.setX1=.3,
legend=TRUE)
```

`ElicitPsi` *Prior Elicitation for Analysis of 2 x 2 in Presence of Unmeasured Confounding*

Description

`ElicitPsi` provides a Tcl/Tk graphical user interface that allows users to vary the parameters of the beta prior distributions over the ψ parameters (the potential outcome distributions within cells of the (X, Y) table) used by `analyze2x2`. See Quinn (2008).

Usage

```
ElicitPsi(C00, C01, C10, C11, maxvalue = 100,
          a00 = 0.25, a01 = 0.25, a10 = 0.25, a11 = 0.25,
          nsamp = 50000, output.object = "output.SimpleTable")
```

Arguments

`C00`	The number of observations in $(X = 0, Y = 0)$ cell of the table. In other words, the number of observations that received control and failed.
`C01`	The number of observations in $(X = 0, Y = 1)$ cell of the table. In other words, the number of observations that received control and succeeded.
`C10`	The number of observations in $(X = 1, Y = 0)$ cell of the table. In other words, the number of observations that received treatment and failed.
`C11`	The number of observations in $(X = 1, Y = 1)$ cell of the table. In other words, the number of observations that received treatment and succeeded.
`maxvalue`	The largest possible value for the parameters of the beta priors that are being elicited. This value is used to set the slider bars appropriately.
`a00`	One of four parameters (with `a01`, `a10`, and `a11` governing the Dirichlet prior for θ (the joint probabilities of X and Y). This prior has the effect of adding `a00` - 1 observations to the $(X = 0, Y = 0)$ cell of the table.
`a01`	One of four parameters (with `a00`, `a10`, and `a11` governing the Dirichlet prior for θ (the joint probabilities of X and Y). This prior has the effect of adding `a01` - 1 observations to the $(X = 0, Y = 1)$ cell of the table.
`a10`	One of four parameters (with `a00`, `a01`, and `a11` governing the Dirichlet prior for θ (the joint probabilities of X and Y). This prior has the effect of adding `a10` - 1 observations to the $(X = 1, Y = 0)$ cell of the table.
`a11`	One of four parameters (with `a00`, `a01`, and `a10` governing the Dirichlet prior for θ (the joint probabilities of X and Y). This prior has the effect of adding `a11` - 1 observations to the $(X = 1, Y = 1)$ cell of the table.
`nsamp`	Size of the Monte Carlo sample used to summarize the posterior.
`output.object`	String giving the name of the output object the result are sent to. Default is `output.SimpleTable`.

Details

See `analyze2x2` and Quinn (2008) for details regarding the model and prior specification used.

Value

While `ElicitPsi` does not formally have a return value, it does put a number of objects in the global environment. These objects are:

`b00` One of two parameters (with `c00`) governing the beta prior for the distribution of potential outcome types within the $(X = 0, Y = 0)$ cell of the table. This prior adds the same information as would be gained from observing `b00` - 1 Helped units in the $(X = 0, Y = 0)$ cell of the table.

`b01` One of two parameters (with `c01`) governing the beta prior for the distribution of potential outcome types within the $(X = 0, Y = 1)$ cell of the table. This prior adds the same information as would be gained from observing `b01` - 1 Always Succeed units in the $(X = 0, Y = 1)$ cell of the table.

`b10` One of two parameters (with `c10`) governing the beta prior for the distribution of potential outcome types within the $(X = 1, Y = 0)$ cell of the table. This prior adds the same information as would be gained from observing `b10` - 1 Hurt units in the $(X = 1, Y = 0)$ cell of the table.

`b11` One of two parameters (with `c11`) governing the beta prior for the distribution of potential outcome types within the $(X = 1, Y = 1)$ cell of the table. This prior adds the same information as would be gained from observing `b11` - 1 Always Succeed units in the $(X = 1, Y = 1)$ cell of the table.

`c00` One of two parameters (with `b00`) governing the beta prior for the distribution of potential outcome types within the $(X = 0, Y = 0)$ cell of the table. This prior adds the same information as would be gained from observing `b00` - 1 Never Succeed units in the $(X = 0, Y = 0)$ cell of the table.

`c01` One of two parameters (with `b01`) governing the beta prior for the distribution of potential outcome types within the $(X = 0, Y = 1)$ cell of the table. This prior adds the same information as would be gained from observing `c01` - 1 Hurt units in the $(X = 0, Y = 1)$ cell of the table.

`c10` One of two parameters (with `b10`) governing the beta prior for the distribution of potential outcome types within the $(X = 1, Y = 0)$ cell of the table. This prior adds the same information as would be gained from observing `c10` - 1 Never Succeed units in the $(X = 1, Y = 0)$ cell of the table.

`c11` One of two parameters (with `b11`) governing the beta prior for the distribution of potential outcome types within the $(X = 1, Y = 1)$ cell of the table. This prior adds the same information as would be gained from observing `b11` - 1 Helped units in the $(X = 1, Y = 1)$ cell of the table.

In addition, if the user presses the `Calculate Effects` button, `analyze2x2` is called with the current values of prior parameters. The output from `analyze2x2` is written to an object in the global environment with the name given by the `output.object` argument (see argument list above).

Author(s)

Kevin M. Quinn

References

Quinn, Kevin M. 2008. "What Can Be Learned from a Simple Table: Bayesian Inference and Sensitivity Analysis for Causal Effects from 2 x 2 and 2 x 2 x K Tables in the Presence of Unmeasured Confounding." Working Paper.

See Also

ConfoundingPlot, analyze2x2xK, analyze2x2xK, summary.SimpleTable, plot.SimpleTable

Examples

```
## Not run:
## Example from Quinn (2008)
## (original data from Oliver and Wolfinger. 1999.
##   ``Jury Aversion and Voter Registration.''
##     American Political Science Review. 93: 147-152.)
##
##        Y=0       Y=1
## X=0    19        143
## X=1    114       473
##

ElicitPsi(C00=19, C01=143, C10=114, C11=473, output.object="output.2x2")


## End(Not run)
```

---

is.SimpleTable *Is object of class SimpleTable?*

Description

Checks to see if object is of class `SimpleTable`.

Usage

```
is.SimpleTable(S)
```

Arguments

S An object to be checked.

Value

A logical value equal to `TRUE` if `S` is of class `SimpleTable` and `FALSE` otherwise.

Author(s)

Kevin M. Quinn

References

Quinn, Kevin M. 2008. "What Can Be Learned from a Simple Table: Bayesian Inference and Sensitivity Analysis for Causal Effects from 2 x 2 and 2 x 2 x K Tables in the Presence of Unmeasured Confounding." Working Paper.

See Also

`ConfoundingPlot`, `analyze2x2xK`, `ElicitPsi`, `summary.SimpleTable`, `plot.SimpleTable`

`plot.SimpleTable` *Summary plots of SimpleTable objects.*

Description

`plot.SimpleTable` summarizes a `SimpleTable` object by plotting the psterior density of the prima facie and sensitivity analysis causal effects.

Usage

```
## S3 method for class 'SimpleTable'
plot(x, estimand = c("ATE", "ATT", "ATC", "RR", "RRT", "RRC",
                                 "logRR", "logRRT", "logRRC"),
                 percent = 95, plot.bounds = TRUE, plot.pf = TRUE,
                 plot.sens = TRUE, plot.prior = FALSE,
                 color.bounds = "cyan",
                 color1.pf = "lawngreen", color2.pf = "green",
                 color1.sens = "magenta3", color2.sens = "purple4",
                 color.prior = "lightgray", ymax = NULL, ...)
```

Arguments

`x`	An object of class `SimpleTable` produced by `analyze2x2` or `analyze2x2xK` that is to be graphically summarized.
`estimand`	The causal estimand of interest. Options include: `ATE` (average treatment effect), `ATT` (average treatment effect on the treated), `ATC` (average treatment effect on the controls), `RR` (relative risk), `RRT` (relative risk on the treated), `RRC` (relative risk on the controls), `logRR` (log relative risk), `logRRT` (log relative risk on the treated), and `logRRC` (log relative risk on the controls).
`percent`	A number between 0 and 100 (exclusive) giving the size of the highest posterior density regions to be calculated and plotted. Default value is 95.
`plot.bounds`	Logical value indicating whether the large-sample nonparametric bounds should be plotted. Default value is `TRUE`.
`plot.pf`	Logical value indicating whether the posterior density of the prima facie causal effect should be plotted. Default value is `TRUE`.
`plot.sens`	Logical value indicating whether the posterior density of the sensitivity analysis causal effect should be plotted. Default value is `TRUE`.

`plot.prior`	Logical value indicating whether the prior density of the causal effect of interest should be plotted. Default value is `FALSE`.
`color.bounds`	The color of the line segment depicting the large-sample nonparametric bounds. Default value is `cyan`.
`color1.pf`	The color of the prima facie posterior density in regions outside the `percent`% highest posterior density region. Default value is `lawngreen`.
`color2.pf`	The color of the prima facie posterior density in regions inside the `percent`% highest posterior density region. Default value is `green`.
`color1.sens`	The color of the sensitivity analysis posterior density in regions outside the `percent`% highest posterior density region. Default value is `magenta3`.
`color2.sens`	The color of the sensitivity analysis posterior density in regions inside the `percent`% highest posterior density region. Default value is `purple4`.
`color.prior`	The color of the prior density of the causal effect of interest. Default value is `lightgray`.
`ymax`	The maximum height of the y-axis. If `NULL` (the default) then `ymax` is taken to be the maximum ordinate of the prima facie posterior density, the sensitivity analysis posterior density, and the prior density.
`...`	Other arguments to be passed.

Details

See Quinn (2008) for the a description of these plots along with the associated terminology and notation.

Author(s)

Kevin M. Quinn

References

Quinn, Kevin M. 2008. "What Can Be Learned from a Simple Table: Bayesian Inference and Sensitivity Analysis for Causal Effects from 2 x 2 and 2 x 2 x K Tables in the Presence of Unmeasured Confounding." Working Paper.

See Also

`ConfoundingPlot`, `analyze2x2`, `analyze2x2xK`, `ElicitPsi`, `summary.SimpleTable`

Examples

```
## Not run:
## Example from Quinn (2008)
## (original data from Oliver and Wolfinger. 1999.
##   ``Jury Aversion and Voter Registration.''
##     American Political Science Review. 93: 147-152.)
##
##        Y=0       Y=1
## X=0    19        143
```

```
## X=1    114       473
##

## a prior belief in an essentially negative monotonic treatment effect
S.mono <- analyze2x2(C00=19, C01=143, C10=114, C11=473,
                     a00=.25, a01=.25, a10=.25, a11=.25,
     b00=0.02, c00=10, b01=25, c01=3,
                     b10=3, c10=25, b11=10, c11=0.02)

## ATE (the default)
plot(S.mono)

## ATC instead of ATE
plot(S.mono, estimand="ATC")

## different colors
plot(S.mono, estimand="ATC", color1.pf="red", color2.pf="blue",
     color1.sens="gray", color2.sens="orange")


## End(Not run)
```

---

summary.SimpleTable *Summary of SimpleTable objects*

Description

summary.SimpleTable summarizes a SimpleTable object by printing the mode, mean, standard deviation, and percent% highest density region of the prima facie and sensitivity analysis posterior densities. Large-sample nonparametric bounds for the estimand of interest are also reported. Summaries of the prior distribution are also reported in situations where these summaries are numerically stable.

Usage

```
## S3 method for class 'SimpleTable'
summary(object, estimand = c("ATE", "ATT", "ATC",
                                             "RR", "RRT", "RRC",
                                             "logRR", "logRRT", "logRRC"),
                      percent = 95, ...)
```

Arguments

object — An object of class SimpleTable produced by analyze2x2 or analyze2x2xK that is to be summarized.

estimand — The causal estimand of interest. Options include: ATE (average treatment effect), ATT (average treatment effect on the treated), ATC (average treatment effect on the controls), RR (relative risk), RRT (relative risk on the treated), RRC (relative risk on the controls), logRR (log relative risk), logRRT (log relative risk on the treated), and logRRC (log relative risk on the controls).

`percent`	A number between 0 and 100 (exclusive) giving the size of the highest posterior density regions to be calculated and printed. Default value is 95.
`...`	Other arguments to be passed.

Details

See Quinn (2008) for the a description of these plots along with the associated terminology and notation.

Author(s)

Kevin M. Quinn

References

Quinn, Kevin M. 2008. "What Can Be Learned from a Simple Table: Bayesian Inference and Sensitivity Analysis for Causal Effects from 2 x 2 and 2 x 2 x K Tables in the Presence of Unmeasured Confounding." Working Paper.

See Also

ConfoundingPlot, analyze2x2, analyze2x2xK, ElicitPsi, plot.SimpleTable

Examples

```
## Not run:
## Example from Quinn (2008)
## (original data from Oliver and Wolfinger. 1999.
##   ``Jury Aversion and Voter Registration.''
##     American Political Science Review. 93: 147-152.)
##
##        Y=0       Y=1
## X=0    19        143
## X=1    114       473
##

## a prior belief in an essentially negative monotonic treatment effect
S.mono <- analyze2x2(C00=19, C01=143, C10=114, C11=473,
                     a00=.25, a01=.25, a10=.25, a11=.25,
     b00=0.02, c00=10, b01=25, c01=3,
                     b10=3, c10=25, b11=10, c11=0.02)

## ATE (the default)
summary(S.mono)

## ATC instead of ATE
summary(S.mono, estimand="ATC")


## End(Not run)
```

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