## Package 'asypow'

June 26, 2015

Title Calculate Power Utilizing Asymptotic Likelihood Ratio Methods

Version 2015.6.25

Date 2015-06-25

Author S original by Barry W. Brown, James Lovato and Kathy Russel. R port by Kjetil B Halvorsen <kjetil1001@gmail.com>

Description A set of routines written in the S language that calculate power and related quantities utilizing asymptotic likelihood ratio methods.

Maintainer Kjetil B Halvorsen <kjetil1001@gmail.com>

**Depends** R  $(>= 2.2.0)$ , stats

LazyLoad TRUE

License ACM | file LICENSE

NeedsCompilation no

License\_restricts\_use yes

Repository CRAN

Date/Publication 2015-06-26 10:55:16

## R topics documented:



#### <span id="page-1-0"></span>2 asypow.n



<span id="page-1-1"></span>asypow.n *Asymptotic Sample Size*

## Description

Calculates the sample size required to obtain the desired power for a test via likelihood ratio methods.

## Usage

asypow.n(asypow.obj, power, significance)

#### **Arguments**



## Value

Returns the sample size needed to achieve specified power at the specified significance level.

## References

Cox, D.R. and Hinkley, D.V. (1974). *Theoretical Statistics* Chapman and Hall, London.

## See Also

[asypow.noncent](#page-2-1), [asypow.sig](#page-4-1), [asypow.power](#page-3-1)

```
# Three Sample Poisson Example :
# Three independent Poisson processes produce events at
# mean rates of 1, 2 and 3 per day. For how many days
# must the processes be observed to have an 80% chance
# of detecting that the means are different at an
# overall significance level of 0.05?
# Step 1 : Find the information matrix
pois.mean \leq c(1,2,3)info.pois <- info.poisson.kgroup(pois.mean, group.size=3)
# Step 2: Create the constraints matrix
constraints \leq matrix(c(2,1,2,2,2,3), ncol=3, byrow=TRUE)
# Step 3: Find the noncentrality parameter and
```
## <span id="page-2-0"></span>asypow.noncent 3

```
# degrees of freedom for the test
poisson.object <- asypow.noncent(pois.mean, info.pois, constraints)
# Step 4: Compute sample size needed for
# 0.8 power with significance level 0.05
n.pois <- asypow.n(poisson.object, 0.8, 0.05)
# Step 5: Divide the sample size by 3 (the number of processes)
# to get the number of days required.
n.days <- n.pois/3
print(n.days)
```
<span id="page-2-1"></span>asypow.noncent *Asymptotic Noncentrality Parameter*

## Description

Given an information matrix, alternative hypothesis parameter values, and constraints that create the null hypothesis from the alternative, calculates noncentrality parameter, degrees of freedom and parameter value estimates under the null hypothesis.

#### Usage

asypow.noncent(theta.ha, info.mat, constraints, nobs.ell=1, get.ho=TRUE)

## Arguments



## Value

Returns a list including



## <span id="page-3-0"></span>References

Cox, D.R. and Hinkley, D.V. (1974). *Theoretical Statistics* Chapman and Hall, London.

## See Also

[asypow.n](#page-1-1), [asypow.sig](#page-4-1), [asypow.power](#page-3-1)

## Examples

```
# Three Sample Poisson Example :
# Three independent Poisson processes produce events at
# mean rates of 1, 2 and 3 per day.
# Find the information matrix
pois.mean \leq c(1,2,3)info.pois <- info.poisson.kgroup(pois.mean,group.size=3)
# Create the constraints matrix
constraints \leq matrix(c(2,1,2,2,2,3),ncol=3,byrow=TRUE)
# Calculate noncentrality parameter, degrees of freedom and parameter
# value estimates under the null hypothesis for the test.
poisson.object <- asypow.noncent(pois.mean,info.pois,constraints)
```
<span id="page-3-1"></span>asypow.power *Asymptotic Power*

#### Description

Calculates the power of a test via likelihood ratio methods.

#### Usage

```
asypow.power(asypow.obj, sample.size, significance)
```
#### Arguments



#### Value

Returns the power of the test.

## References

Cox, D.R. and Hinkley, D.V. (1974). *Theoretical Statistics* Chapman and Hall, London.

## <span id="page-4-0"></span>asypow.sig 5

## See Also

[asypow.noncent](#page-2-1), [asypow.n](#page-1-1), [asypow.sig](#page-4-1)

#### Examples

```
# Single Group Binomial Example:
# Consider testing the null hypothesis that the binomial
# probability is p = .2 with a sample size of 47 and
# signficance level of 0.05. What is the power of the
# test if p is actually .4?
# Step 1: Find the information matrix
info.binom <- info.binomial.kgroup(.4)
# Step 2: Create the constraints matrix
constraints \leq c(1, 1, .2)# Step 3: Find the noncentrality parameter and
# degrees of freedom for the test
binom.object <- asypow.noncent(.4, info.binom, constraints)
# Step 4: Compute the power of a test with
# sample size of 47 and a significance level 0.05
power.binom <- asypow.power(binom.object, 47, 0.05)
print(power.binom)
```
<span id="page-4-1"></span>asypow.sig *Asymptotic Significance*

#### Description

Calculates the significance level of a test via likelihood ratio methods.

#### Usage

```
asypow.sig(asypow.obj, sample.size, power)
```
## Arguments



## Value

Returns the significance level of the test.

## References

Cox, D.R. and Hinkley, D.V. (1974). *Theoretical Statistics* Chapman and Hall, London.

## See Also

[asypow.noncent](#page-2-1), [asypow.n](#page-1-1), [asypow.power](#page-3-1)

#### Examples

```
# Single Group Binomial Example:
# Consider testing the null hypothesis that the binomial
# probability is p = .2 when the actual probability is .4.
# What significance level corresponding to a sample
# size of 47 and power of .8?
# Step 1: Find the information matrix
info.binom <- info.binomial.kgroup(.4)
# Step 2: Create the constraints matrix
constraints \leq c(1, 1, .2)# Step 3: Find the noncentrality parameter and
# degrees of freedom for the test
binom.object <- asypow.noncent(.4, info.binom, constraints)
# Step 4: Compute the power of a test with
# sample size of 47 and a significance level 0.05
sig.binom <- asypow.sig(binom.object, 47, 0.8)
print(sig.binom)
```
<span id="page-5-1"></span>info.binomial.design *Expected Information Matrix for a Binomial Design*

## **Description**

Calculates the expected information matrix for a binomial design where the parameter  $p$ , probability of an event, depends on a covariate, x, through a logistic,  $p = \exp(u)/(1 + \exp(u))$  p =  $exp(u)/(1+exp(u))$ , or complementary  $log, p = 1-exp(-exp(u))$   $p = 1-exp(-exp(u))$ , model. The variable u is either a linear,  $u = a + bx$ , or quadratic,  $u = a + bx + cx^2$ , function of the covariate x.

#### Usage

```
info.binomial.design(model="linear", link="logistic", theta,
                  xpoints, natx=1, group.size=1)
```
## Arguments



<span id="page-5-0"></span>

<span id="page-6-0"></span>

## Value

The information matrix for one observation for this design.

If model = "linear" and there are k groups, the information matrix is a square  $(2k) \times (2k)$  matrix which is indexed by the parameters  $(a,b)$  for group 1, then  $(a,b)$  for group 2, etc.

If model = "quadratic", the information matrix is a square  $(3k) \times (3k)$  matrix which is indexed by the parameter  $(a,b,c)$  for group 1, then  $(a,b,c)$  for group 2, etc.

## References

Cox, D.R. and Hinkley, D.V. (1974). *Theoretical Statistics* Chapman and Hall, London.

## See Also

[info.poisson.design](#page-16-1), [info.ordinal.design](#page-13-1), [info.expsurv.design](#page-8-1)

## Examples

```
# Find the information matrix for a 2 group
# logistic binomial Design with a quadratic
# combination of covariate x and different
# sample sizes at each point
abc \le rbind(c(1.2, .9, .3),c(0.33, .21, .05))
covar \leq c(1, 2, 3, 4, 5)sample.size <- rbind(c(10,11,12,10,9), c(8,7,10,8,9))
info.binom <- info.binomial.design(model="quadratic", link="logistic",
                                theta = abc, xpoints = covar,
                                natx=sample.size)
```
print(info.binom)

<span id="page-7-1"></span><span id="page-7-0"></span>info.binomial.kgroup *Expected Information Matrix for Single or Multiple Group Binomial*

## Description

Calculates expected information matrix for a single observation for single or multiple group binomial distribution.

The natural null hypothesis for a single group is that that the probability is some specified value. For multiple groups, the natural null hypothesis is that the group probabilities are the same.

## Usage

info.binomial.kgroup(p, group.size=1)

#### **Arguments**



#### Value

Expected information matrix for a single observation. The matrix is square with each dimension the number of groups.

#### References

Cox, D.R. and Hinkley, D.V. (1974). *Theoretical Statistics* Chapman and Hall, London.

## See Also

[info.poisson.kgroup](#page-17-1), [info.ordinal.kgroup](#page-15-1), [info.expsurv.kgroup](#page-9-1)

```
# Find the information matrix for a 2 sample binomial with
# probability of events .2 and .4 and sample sizes 10 and 11
info.binom \leftarrow info.binomial.kgroup(c(.2,.4), c(10,11))print(info.binom)
```
<span id="page-8-1"></span><span id="page-8-0"></span>info.expsurv.design *Expected Information Matrix for a Clinical Trial with Exponential Survival Design*

## Description

Calculates expected information matrix for a clinical trial with exponential survival.

The clinical trial will accrue subjects over a time period  $L$ . Each subject will enter the study at a random time between 0 and  $L$ , so the subject's follow up time,  $U$ , will be uniformly distributed between 0 and L. A subject with follow up time  $U$ , can die at a time t between 0 and  $U$ , or the subject can be withdrawn alive at time  $U$ . The density of time to death is exponential distribution with hazard, w.

The parameter  $w$  depends on a covariate,  $x$ , via the exponentiation of a linear or quadratic function of  $x, w = \exp(a + bx)$  or  $w = \exp(a + bx + cx^2)$ .

This model is both the proportional hazards model and the accelerated failure model for exponential survival.

#### Usage

```
info.expsurv.design(model="linear", theta, L, xpoints,
                 natx=1, group.size=1)
```
## Arguments



## <span id="page-9-0"></span>Value

The information matrix for one observation for this design.

If model = "linear" and there are k groups, the information matrix is a square  $(2k) \times (2k)$  matrix which is indexed by the parameters  $(a,b)$  for group 1, then  $(a,b)$  for group 2, etc.

If model = "quadratic", the information matrix is a square  $(3k) \times (3k)$  matrix which is indexed by the parameter  $(a,b,c)$  for group 1, then  $(a,b,c)$  for group 2, etc.

### References

Cox, D.R. and Hinkley, D.V. (1974). *Theoretical Statistics* Chapman and Hall, London.

## See Also

[info.binomial.design](#page-5-1), [info.poisson.design](#page-16-1), [info.ordinal.design](#page-13-1)

#### Examples

# Find the information matrix for a clinical trial # with hazard w(x) =  $-0.848 + 0.7*x$  which lasts # three years and has 10 x values equally spaced # between -3 and 3 with equal sample sizes.  $ab \leftarrow c(-.848, .7)$ covar  $\leq$  seq(-3, 3, length=10)  $LL < -3$ info.expsurv  $\le$  info.expsurv.design(theta = ab, L = LL, xpoints = covar) print(info.expsurv)

<span id="page-9-1"></span>info.expsurv.kgroup *Expected Information Matrix for a Single or Multiple Group Clinical Trial with Exponential Survival*

#### Description

Calculates expected information matrix for a single observation for a single or multiple group clinical trial with exponential survival.

The clinical trial will accrue subjects over a time period L. Each subject will enter the study at a random time between 0 and  $L$ , so the subject's follow up time,  $U$ , will be uniformly distributed between 0 and L. A subject with follow up time  $U$ , can die at a time t between 0 and  $U$ , or the subject can be withdrawn alive at time  $U$ . The density of time to death is exponential distribution with hazard, w.

#### Usage

```
info.expsurv.kgroup(w, L, group.size=1)
```
## <span id="page-10-0"></span>info.mvlogistic 11

#### **Arguments**



## Value

Expected information matrix for a single observation. The matrix is square with dimension equal to the number of groups.

#### References

Cox, D.R. and Hinkley, D.V. (1974). *Theoretical Statistics* Chapman and Hall, London.

## See Also

[info.binomial.kgroup](#page-7-1), [info.poisson.kgroup](#page-17-1), [info.ordinal.kgroup](#page-15-1)

#### Examples

```
# Find the information matrix for a clinical trial of
# length 3 with hazard 1
info.expsurv <- info.expsurv.kgroup(1, 3)
print(info.expsurv)
```
<span id="page-10-1"></span>info.mvlogistic *Expected Information Matrix for a Multivariate Logistic Model*

## Description

Calculates the expected information matrix for a multivariate logistic model where the parameter p, probability of an event, depends on the covariates,  $x = c(x[1], x[2], \ldots, x[n]$ , through a logistic,  $p = \exp(u)/(1 + \exp(u))$ , model. The variable u is a linear combination of the covariates via a set of coefficients,  $\text{coef} = c(\text{coef}[1], \dots, \text{coef}[n]), u = \sum_{i=1}^{n} \text{coef}[i]x[i].$ 

The usual use of this routine is for tabulated data in which case the x's will all be 0 or 1 valued indicator variables.

## <span id="page-11-0"></span>Usage

info.mvlogistic(coef, design, rss=1)

## Arguments



#### Value

The information matrix for one observation for this design.

## References

Cox, D.R. and Hinkley, D.V. (1974). *Theoretical Statistics* Chapman and Hall, London.

## See Also

[info.mvloglin](#page-12-1)

```
# Find the information matrix for a multivariate
# logistic design with variables x, y and z
# Define coefficient matrix so that
# u = 1 + .5*x + .7*y + .9*zcoef \leftarrow c(1, .5, .7, .9)# Define the design matrix so that there are 10 design points
intercept \leq rep(1, 10)
x \le rnorm(10)
y \le - rnorm(10)z \le- rnorm(10)
design <- cbind(intercept, x, y, z)
# Use info.mvlogistic to find the information matrix for
# this design
info.xyz <- info.mvlogistic(coef, design)
print(info.xyz)
```
#### <span id="page-12-1"></span><span id="page-12-0"></span>Description

Calculates the expected information matrix for a multivariate log-linear model where the parameter p, probability of an event, depends on the covariates,  $x = c(x[1], \ldots, x[n])$ , through an exponential,  $p = \exp(u)$ . The variable u is a log-linear combination of the covariates via a set of coefficients,  $\text{coef} = c(\text{coef}[1], \dots, \text{coef}[n], u = \sum_{i=1}^{n} \log(\text{coef}[i]x[i]).$ 

The usual use of this routine is for tabulated data in which case the x's will all be 0 or 1 valued indicator variables.

#### Usage

info.mvloglin(coef, design, rss=1)

#### Arguments



## Value

The information matrix for one observation for this design.

#### References

Cox, D.R. and Hinkley, D.V. (1974). *Theoretical Statistics* Chapman and Hall, London.

## See Also

#### [info.mvlogistic](#page-10-1)

```
# Find the information matrix for a multivariate
# log-linear design with variables x, y and z
# Define coefficient matrix so that
# u = .1 + .2*x + .3*y + .3*z\cot f \leq c(.1, .2, .3, .4)# Define the design matrix so that there are 10 design points
```

```
intercept < - rep(1, 10)x \leq -\text{seq}(0.1, 0.2, \text{length}=10)y <- seq(.25, .3, length=10)
z \leq - seq(.2, .3, length=10)
design <- cbind(intercept, x, y, z)
# Use info.mvloglin to find the information matrix for
# this design
info.xyz <- info.mvloglin(coef, design)
print(info.xyz)
```
<span id="page-13-1"></span>info.ordinal.design *Expected Information Matrix for an Ordinal Design*

#### **Description**

Calculates the expected information matrix for an ordinal design where the parameters  $p_i$ , probability of an event in category j or less, depend on a covariate, x, through a logistic,  $p_i = \exp(u_i)/(1+\epsilon)$  $\exp(u_i)$ , or complementary log,  $p_j = 1 - \exp(-\exp(u_i))$ , model. The variable  $u_j$  is a linear,  $u_j = a_j + bx$ , or quadratic,  $u_j = a_j + bx + cx^2$ , function of the covariate x.

#### Usage

```
info.ordinal.design(model="linear", link="logistic", theta,
                 xpoints, natx=1, group.size=1)
```
#### Arguments

theta Matrix of parameters for the linear combination of the covariate x. Each row represents a group so if model = "linear"

 $\theta[i,] = c(a[1], a[2], a[3], \ldots, a[r-1], b)$ 

where  $r$  is the number of categories. If model = "quadratic"

 $\theta[i,] = c(a[1], a[2], \ldots, a[r-1], b, c)$ 

theta[i,] = c(a[1],a[2],a[3],...,a[r-1],b,c)

xpoints Matrix of covariate values for each group. If there is only 1 group or all groups have the same covariate value, xpoints should be a vector; otherwise, the number of rows in xpoints must equal the number of rows in theta.

model One of {"linear", "quadratic"}. Specifies the function of the covariate x that will be used. Linear indicates,  $u_j = a_j + bx$ , and quadratic indicates,  $u_j =$  $a_j + bx + cx^2$ ,  $j = 1, ..., r - 1$ . Only enough to ensure a unique match need be supplied.

link One of {"logistic", "complementary log"}. Specifies the link between the linear or quadratic combination of the covariate x and the parameters of the ordinal model,  $p_j$ . Logistic indicates  $p_j = \exp(u_j)/(1 + \exp(u_j))$ , and complementary log indicates,  $p_j = 1 - \exp(-\exp(u_j))$ ,  $j = 1, \ldots, r - 1$ . Only enough to ensure a unique match need be supplied.

<span id="page-13-0"></span>

<span id="page-14-0"></span>

## Value

The information matrix for one observation for this design.

If model = "linear" and there are r categories and  $k$  groups, the information matrix is a square  $(rk) \times (rk)$  matrix which is indexed by the parameters  $a[1], a[2], \ldots, a[r-1], b$  for group 1, then  $(a[1], a[2], \ldots, a[r-1], b)$  for group 2, etc.

If model = "quadratic", the information matrix is a square  $((r + 1)k) \times ((r + 1)k)$  matrix which is indexed by the parameters  $(a[1], a[2], \ldots, a[r-1], b, c)$  for group 1, then  $(a[1], a[2], \ldots, a[r-1], b, c)$  $1, b, c$  for group 2, etc.

## References

Cox, D.R. and Hinkley, D.V. (1974). *Theoretical Statistics* Chapman and Hall, London.

#### See Also

[info.binomial.design](#page-5-1), [info.poisson.design](#page-16-1), [info.expsurv.design](#page-8-1)

```
# Find the information matrix for an ordinal design
# with one group and equal sample sizes.
# Assume 4 categories and use a logistic
# line and quadratic model. Let
# u[1] = 1 + 2.5*x# u[2] = 2 + 2.5*x# u[3] = 3 + 2.5*x# Use values x = -3, 0, 3theta <-c(1, 2, 3, 2.5)covar < -c(-3, 0, 3)info.ord <- info.ordinal.design(theta = theta, xpoints = covar)
print(info.ord)
```
<span id="page-15-1"></span><span id="page-15-0"></span>

## Description

Calculates expected information matrix for a single observation for ordered outcomes in a single or multiple groups.

The natural null hypothesis for a single group is that the probabilities of the outcomes is some specified set of values. For multiple groups, the natural null hypothesis is that the probabilities are the same.

#### Usage

info.ordinal.kgroup(p, group.size=1)

## Arguments



## Value

Expected information matrix for a single observation. The matrix is dimensioned  $(k(n - 1)) \times$  $(k(n - 1))$  ( k\*(n-1) ) X ( k\*(n-1) ).

## References

Cox, D.R. and Hinkley, D.V. (1974). *Theoretical Statistics* Chapman and Hall, London.

## See Also

[info.binomial.kgroup](#page-7-1), [info.poisson.kgroup](#page-17-1), [info.expsurv.kgroup](#page-9-1)

## <span id="page-16-0"></span>info.poisson.design 17

## Examples

```
# Find the information matrix for a 2 group ordinal
# model with 4 categories.
p1 \leftarrow c(.1, .2, .3) # Probabilities for group 1
p2 \leq -c(.2, .5, .7) # Probabilities for group 2
p \leftarrow \text{rbind}(p1, p2)ngrps \leq c(.4, .6) # Percentage of data in each group
info.ord <- info.ordinal.kgroup(p, ngrps)
print(info.ord)
```
<span id="page-16-1"></span>info.poisson.design *Expected Information Matrix for a Poisson Design*

## Description

Calculates the expected information matrix for a Poisson design where the parameter  $\lambda$ , the mean of the distribution, depends on a covariate,  $x$ , via the exponentiation of a linear or quadratic function of  $x, \lambda = \exp(a + bx)$  or  $\lambda = \exp(a + bx + cx^2)$ .

## Usage

```
info.poisson.design(model="linear", theta, xpoints,
                      natx=1, group.size=1)
```
## Arguments



## <span id="page-17-0"></span>Value

The information matrix for one observation for this design.

If model = "linear" and there are k groups, the information matrix is a square  $(2k) \times (2k)$  matrix which is indexed by the parameters  $(a,b)$  for group 1, then  $(a,b)$  for group 2, etc.

If model = "quadratic", the information matrix is a square  $(3k) \times (3k)$  matrix which is indexed by the parameter  $(a,b,c)$  for group 1, then  $(a,b,c)$  for group 2, etc.

#### References

Cox, D.R. and Hinkley, D.V. (1974). *Theoretical Statistics* Chapman and Hall, London.

#### See Also

[info.binomial.design](#page-5-1), [info.ordinal.design](#page-13-1), [info.expsurv.design](#page-8-1)

## Examples

```
# Find the information matrix for a 2 group
# logistic Poisson design with a quadratic
# combination of covariate x and different
# sample sizes at each point
abc <- rbind(c(1.2,.9,.3), c(0.33,.21,.05))
covar \leq c(1, 2, 3, 4, 5)sample.size <- rbind(c(10,11,12,10,9), c(8,7,10,8,9))
info.poiss <- info.poisson.design(model="quadratic",
                                theta = abc, xpoints = covar,
                                natx=sample.size)
print(info.poiss)
```
<span id="page-17-1"></span>info.poisson.kgroup *Expected Information Matrix for Single or Multiple Group Poisson*

#### Description

Calculates expected information matrix for a single observation for single or multiple group Poisson distribution.

The natural null hypothesis for a single group is that that the mean is some specified value. For multiple groups, the natural null hypothesis is that the group means are the same.

#### Usage

info.poisson.kgroup(lambda, group.size=1)

## <span id="page-18-0"></span>info.reparam 19

## Arguments



## Value

Expected information matrix for a single observation. The matrix is square with dimension equal to the number of groups.

## References

Cox, D.R. and Hinkley, D.V. (1974). *Theoretical Statistics* Chapman and Hall, London.

## See Also

[info.binomial.kgroup](#page-7-1), [info.ordinal.kgroup](#page-15-1), [info.expsurv.kgroup](#page-9-1)

## Examples

```
# Find the information matrix for a 3 sample Poisson with
# means 1, 2 and 3 and equal sample sizes
info.pois <- info.poisson.kgroup(c(1,2,3))
print(info.pois)
```
info.reparam *Reparameterize Expected Information Matrix*

## Description

Calculates the expected information matrix after reparameterization of a model using the method of propagation of error.

## Usage

info.reparam(theta, info.mat, dg)

## Arguments



## Value

Returns the expected information matrix under the new parameterization.

## References

Bishop, Y.M., Fienberg, S.E., and Holland, P.W. (1975) *Discrete Multivariate analysis: Theory and Practice* MIT Press, Cambridge, Mass. Cox, D.R. and Hinkley, D.V. (1974). *Theoretical Statistics* Chapman and Hall, London. Tong, Y.L. (1990). *The Multivariate Normal Distribution* Springer-Verlag, New York.

```
# A logistic model posits that the probability of response
# is a logtistic function of a + b*x.
# Consider the value of x that produces 50%
# response, x = -a/b. Since -a/b is not one of the parameters
# of the model, we must reparameterize to
# roe[1] = -a/b
# roe[2] = b
dg <- function(theta) {
# theta is a vector of length 2 containing c(a,b)# dg <- [d{roe[1]}/d{a} d{roe[1]}/d{b}
# d{roe[2]}/d{a} d{roe[2]}/d{b}]
  a \leftarrow \text{theta}[1]b \leftarrow \text{theta}[2]return(matrix(c(-1/b,a/b^2,0,1), nrow=2, ncol=2, byrow=TRUE))
}
# Let a = -0.9 and b = .7theta <-c(-.9, .7)# assign a set of covariate values
covar \leq c(0.3, .9, 1.3, 2.5)# Use info.binomial.design to calculate the information
# matrix under the original parameterization
info.orig <- info.binomial.design(model="linear", link="logistic",
                                   theta=theta, xpoints=covar)
# Get the information matrix of the reparameterized model
info.new <- info.reparam(theta, info.orig, dg)
print(info.new)
```
# <span id="page-20-0"></span>Index

∗Topic htest asypow.n, [2](#page-1-0) asypow.noncent, [3](#page-2-0) asypow.power, [4](#page-3-0) asypow.sig, [5](#page-4-0) info.binomial.design, [6](#page-5-0) info.binomial.kgroup, [8](#page-7-0) info.expsurv.design, [9](#page-8-0) info.expsurv.kgroup, [10](#page-9-0) info.mvlogistic, [11](#page-10-0) info.mvloglin, [13](#page-12-0) info.ordinal.design, [14](#page-13-0) info.ordinal.kgroup, [16](#page-15-0) info.poisson.design, [17](#page-16-0) info.poisson.kgroup, [18](#page-17-0) info.reparam, [19](#page-18-0) asypow.n, [2,](#page-1-0) *[4](#page-3-0)[–6](#page-5-0)* asypow.noncent, *[2](#page-1-0)*, [3,](#page-2-0) *[5,](#page-4-0) [6](#page-5-0)* asypow.power, *[2](#page-1-0)*, *[4](#page-3-0)*, [4,](#page-3-0) *[6](#page-5-0)* asypow.sig, *[2](#page-1-0)*, *[4,](#page-3-0) [5](#page-4-0)*, [5](#page-4-0) info.binomial.design, [6,](#page-5-0) *[10](#page-9-0)*, *[15](#page-14-0)*, *[18](#page-17-0)* info.binomial.kgroup, [8,](#page-7-0) *[11](#page-10-0)*, *[16](#page-15-0)*, *[19](#page-18-0)* info.expsurv.design, *[7](#page-6-0)*, [9,](#page-8-0) *[15](#page-14-0)*, *[18](#page-17-0)* info.expsurv.kgroup, *[8](#page-7-0)*, [10,](#page-9-0) *[16](#page-15-0)*, *[19](#page-18-0)* info.mvlogistic, [11,](#page-10-0) *[13](#page-12-0)* info.mvloglin, *[12](#page-11-0)*, [13](#page-12-0) info.ordinal.design, *[7](#page-6-0)*, *[10](#page-9-0)*, [14,](#page-13-0) *[18](#page-17-0)* info.ordinal.kgroup, *[8](#page-7-0)*, *[11](#page-10-0)*, [16,](#page-15-0) *[19](#page-18-0)* info.poisson.design, *[7](#page-6-0)*, *[10](#page-9-0)*, *[15](#page-14-0)*, [17](#page-16-0) info.poisson.kgroup, *[8](#page-7-0)*, *[11](#page-10-0)*, *[16](#page-15-0)*, [18](#page-17-0) info.reparam, [19](#page-18-0)