Package ‘rsq’

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Description

Recorded are the numbers of male satellites, and other characteristics of 173 female horseshoe crabs.

Usage

data("hcrabs")

Format

A data frame with 173 observations on the following 5 variables.

spine   the female crab’s spine condition, coded 1: both good; 2: one worn or broken; 3: both worn or broken.
width   the female crab’s carapace width (cm).
num.satellites the number of satellite males.
weight  the female crab’s weight (kg).

Details

A nesting female horseshoe crab may have male crabs residing nearby, called satellites, besides the male crab residing in her nest. Brockmann (1996) investigated factors (including the female crab’s color, spine condition, weight, and carapace width) which may influence the presence/absence of satellite males. This data set has been discussed by Agresti (2002).

Author(s)

Dabao Zhang, Department of Statistics, Purdue University

Source

hschool

References


See Also

rsq, rsq.partial, pcor, simglm.

Examples

data(hcrabs)
summary(hcrabs)
head(hcrabs)

attach(hcrabs)
y <- ifelse(num.satellites>0,1,0)
bnfit <- glm(y~color+spine+width+weight,family=binomial)
rsq(bnfit)
rsq(bnfit,adj=TRUE)
rsq.partial(bnfit)

quasips <- glm(num.satellites~color+spine+width+weight,family=quasipoisson)
rsq(quasips)
rsq(quasips,adj=TRUE)
rsq.partial(quasips)

hschool

*Attendance Behavior of High School Juniors*

Description

Recorded are the number of days of absence, gender, and two test scores of 316 high school juniors from two urban high schools.

Usage

data("hschool")

Format

A data frame with 316 observations on the following 5 variables.

- school: school of the two, coded 1 or 2;
- male: whether the student is male, coded 1: male; 0: female;
- math: the standardized test score for math;
- langarts: the standardized test score for language arts;
- daysabs: the number of days of absence.
Details

Some school administrators studied the attendance behavior of high school juniors at two schools. Predictors of the number of days of absence include gender of the student and standardized test scores in math and language arts. The original source of this data set is unknown.

Author(s)

Dabao Zhang, Department of Statistics, Purdue University

Source

UCLA IDRE Statistical Consulting Group for data analysis.

See Also

rsq, rsq.partial, pcor, simglm.

Examples

data(hschool)
summary(hschool)
head(hschool)

require(MASS)
absfit <- glm.nb(daysabs~school+male+math+langarts,data=hschool)
summary(absfit)
rsq(absfit)
rsq(absfit,adj=TRUE)

rsq.partial(absfit)

---

lifetime

Lifetimes in Two Different Environments.

Description

There are 27 tests in each of the two environments.

Usage

data("lifetime")

Format

A data frame with 54 observations on the following 2 variables.

time  the lifetime (x10).
env   the environment of each test (kg/mm^2).
Details
This data set is discussed by Wang et al. (1992).

Author(s)
Dabao Zhang, Department of Statistics, Purdue University

Source

See Also
rsq, rsq.partial, pcor, simglm.

Examples
```r
data(lifetime)
summary(lifetime)
head(lifetime)

attach(lifetime)

igfit <- glm(time~env,family=inverse.gaussian)
rsq(igfit)
rsq(igfit,adj=TRUE)
```

---

**pcor**

*Partial Correlation for Generalized Linear Models*

Description
Calculate the partial correlation for both linear and generalized linear models.

Usage
```r
pcor(objF, objR=NULL, adj=FALSE, type=c('v', 'kl', 'sse', 'lr', 'n'))
```

Arguments
- **objF**: an object of class "lm" or "glm", a result of a call to `lm`, `glm`, or `glm.nb` to fit the full model.
- **objR**: an object of class "lm" or "glm", a result of a call to `lm`, `glm`, or `glm.nb` to fit the reduced model.
- **adj**: logical; if TRUE, calculate the adjusted partial R^2.
type: the type of R-squared used:
'v' (default) – variance-function-based (Zhang, 2016), calling rsq.v;
'kl' – KL-divergence-based (Cameron and Windmeijer, 1997), calling rsq.kl;
'sse' – SSE-based (Efron, 1978), calling rsq.sse;
'lr' – likelihood-ratio-based (Maddala, 1983; Cox and Snell, 1989; Magee, 1990), calling rsq.lr;
'n' – corrected version of 'lr' (Nagelkerke, 1991), calling rsq.n.

Details
When the fitting object of the reduced model is not specified, the partial correlation of each covariate (excluding factor covariates with more than two levels) in the model will be calculated.

Value
The partial correlation coefficient is returned.

Author(s)
Dabao Zhang, Department of Statistics, Purdue University

References


See Also
rsq, rsq.partial.
Examples

data(hcrabs)
attach(hcrabs)
y <- ifelse(num.satellites>0,1,0)
bnfit <- glm(y~color+spine+width+weight,family=binomial)
rsq.partial(bnfit)

bnfitr <- glm(y~color+weight,family=binomial)
rsq.partial(bnfit, bnfitr)

quasibn <- glm(y~color+spine+width+weight,family=quasibinomial)
rsq.partial(quasibn)

quasibnr <- glm(y~color+weight,family=binomial)
rsq.partial(quasibn, quasibnr)

rsq  

R-Squared for Generalized Linear (Mixed) Models

Description

Calculate the coefficient of determination, aka $R^2$, for both linear and generalized linear (mixed) models.

Usage

rsq(fitObj, adj=FALSE, type=c('v', 'kl', 'sse', 'lr', 'n'))

Arguments

fitObj  
an object of class "lm", "glm", "merMod", "lmerMod", or "lmf"; usually a result of a call to lm, glm, glm.nb, lmer or glmer or glmer.nb in lme4, or lme in nlme.

adj  
logical; if TRUE, calculate the adjusted $R^2$.

type  
the type of R-squared (only applicable for generalized linear models):
'v' (default) – variance-function-based (Zhang, 2017), calling rsq.v;
'kl' – KL-divergence-based (Cameron and Windmeijer, 1997), calling rsq.kl;
'sse' – SSE-based (Efron, 1978), calling rsq.sse;
'lr' – likelihood-ratio-based (Maddala, 1983; Cox and Snell, 1989; Magee, 1990), calling rsq.lr;
'n' – corrected version of 'lr' (Nagelkerke, 1991), calling rsq.n.

Details

Calculate the R-squared for (generalized) linear models. For (generalized) linear mixed models, there are three types of $R^2$ calculated on the basis of observed response values, estimates of fixed effects, and variance components, i.e., model-based $R_M^2$ (proportion of variation explained by the model in total, including both fixed-effects and random-effects factors), fixed-effects $R_F^2$ (proportion of variation explained by the fixed-effects factors), and random-effects $R_R^2$ (proportion of variation explained by the random-effects factors).
Value

The R^2 or adjusted R^2. For (generalized) linear mixed models,

\[ R_M^2 \]

proportion of variation explained by the model in total, including both fixed-effects and random-effects factors.

\[ R_F^2 \]

proportion of variation explained by the fixed-effects factors.

\[ R_R^2 \]

proportion of variation explained by the random-effects factors.

Author(s)

Dabao Zhang, Department of Statistics, Purdue University

References


See Also

rsq.partial,pcor,simglm.

Examples

data(hcrabs)
attach(hcrabs)
y <- ifelse(num.satellites>0,1,0)
bnfit <- glm(y~color+spine+width+weight,family=binomial)
rsq(bnfit)
rsq(bnfit,adj=TRUE)

quasibn <- glm(y~color+spine+width+weight,family=quasibinomial)
rsq(quasibn)
rsq(quasibn,adj=TRUE)
```r
psfit <- glm(num.satellites~color+spine+width+weight,family=poisson)
rsq(psfit)
rsq(psfit,adj=TRUE)

quasips <- glm(num.satellites~color+spine+width+weight,family=quasipoisson)
rsq(quasips)
rsq(quasips,adj=TRUE)

# Linear mixed models
require(lme4)
lmm1 <- lmer(Reaction~Days+(Days|Subject),data=sleepstudy)
rsq(lmm1)
rsq.lmm(lmm1)

# Generalized linear mixed models
data(cbpdp)
glmm1 <- glmer(cbind(incidence,size-incidence)~period+(1|herd),data=cbpp,family=binomial)
rsq(glmm1)
```

---

**rsq.glmm**  
*R-Squared for Generalized Linear Mixed Models*

**Description**

Calculate the variance-function-based R-squared for generalized linear mixed models.

**Usage**

```r
rsq.glmm(fitObj,adj=FALSE)
```

**Arguments**

- `fitObj`: an object of class "glmerMod", usually, a result of a call to `glmer` or `glmer.nb` in `lme4`.
- `adj`: logical; if TRUE, calculate the adjusted R^2.

**Details**

There are three types of R^2 calculated on the basis of observed response values, estimates of fixed effects, and variance components, i.e., model-based R_M^2 (proportion of variation explained by the model in total, including both fixed-effects and random-effects factors), fixed-effects R_F^2 (proportion of variation explained by the fixed-effects factors), and random-effects R_R^2 (proportion of variation explained by the random-effects factors).
Value

- $R_M^2$: proportion of variation explained by the model in total, including both fixed-effects and random-effects factors.
- $R_F^2$: proportion of variation explained by the fixed-effects factors.
- $R_R^2$: proportion of variation explained by the random-effects factors.

Author(s)

Dabao Zhang, Department of Statistics, Purdue University

References


See Also

`vresidual`, `rsq`, `rsq.v`.

Examples

```r
require(lme4)
data(cbpp)
glmm1 <- glmer(cbind(incidence,size-incidence)~period+(1|herd),data=cbpp,family=binomial)
rsq(glmm1)
```
Value

The R^2 or adjusted R^2.

Author(s)

Dabao Zhang, Department of Statistics, Purdue University

References


See Also

rsq, rsq.partial, pcor.

Examples

data(hcrabs)
attach(hcrabs)
y <- ifelse(num.satellites>0,1,0)
bnfit <- glm(y~color+spine+width+weight,family=binomial)
rsq.kl(bnfit)
rsq.kl(bnfit,adj=TRUE)

psfit <- glm(num.satellites~color+spine+width+weight,family=poisson)
rsq.kl(psfit)
rsq.kl(psfit,adj=TRUE)

# Effectiveness of Bycycle Safety Helmets in Thompson et al. (1989)
y <- matrix(c(17,218,233,758),2,2)
x <- factor(c("yes","no"))
tbn <- glm(y~x,family=binomial)
rsq.kl(tbn)
rsq.kl(tbn,adj=TRUE)

rsq.lmm  

*R-Squared for Linear Mixed Models*

**Description**

Calculate the R-squared for linear mixed models.

**Usage**

rsq.lmm(fitObj,adj=FALSE)
Arguments

- `fitObj`: an object of class "merMod" or "lmerMod" or "lme", usually, a result of a call to `lmer` in lme4, or `lme` in nlme.
- `adj`: logical; if TRUE, calculate the adjusted R^2.

Details

There are three types of R^2 calculated on the basis of observed response values, estimates of fixed effects, and variance components, i.e., model-based R_M^2 (proportion of variation explained by the model in total, including both fixed-effects and random-effects factors), fixed-effects R_F^2 (proportion of variation explained by the fixed-effects factors), and random-effects R_R^2 (proportion of variation explained by the random-effects factors).

Value

- `R_M^2`: proportion of variation explained by the model in total, including both fixed-effects and random-effects factors.
- `R_F^2`: proportion of variation explained by the fixed-effects factors.
- `R_R^2`: proportion of variation explained by the random-effects factors.

Author(s)

Dabao Zhang, Department of Statistics, Purdue University

References


See Also

- `rsq`, `rsq.v`.

Examples

```r
# lmer in lme4
require(lme4)
lmm1 <- lmer(Reaction~Days+(Days|Subject), data=sleepstudy)
rsq(lmm1)
rsq.lmm(lmm1)

# lme in nlme
require(nlme)
lmm2 <- lme(Reaction~Days, data=sleepstudy, random=~Days|Subject)
rsq(lmm2)
rsq.lmm(lmm2)
```
Description

Calculate the likelihood-ratio-based \( R^2 \) for generalized linear models.

Usage

\[
\text{rsq.lr}(\text{fitObj}, \text{adj}=\text{FALSE})
\]

Arguments

- `fitObj`: an object of class "lm" or "glm", usually, a result of a call to \texttt{lm}, \texttt{glm}, or \texttt{glm.nb}.
- `adj`: logical; if TRUE, calculate the adjusted \( R^2 \).

Details

Proposed by Maddala (1983), Cox and Snell (1989), and Magee (1990), this version of \( R^2 \) is defined with the likelihood ratio statistics, so it is not defined for quasi models. It reduces to the classical \( R^2 \) when the variance function is constant or linear.

Value

The \( R^2 \) or adjusted \( R^2 \).

Author(s)

Dabao Zhang, Department of Statistics, Purdue University

References


Maddala, G. S. (1983) \textit{Limited-Dependent and Qualitative Variables in Econometrics}. Cambridge University.


See Also

\texttt{rsq, rsq.partial, pcor, rsq.n}. 
Examples

```r
data(hcrabs)
attach(hcrabs)
y <- ifelse(num.satellites>0,1,0)
bnfit <- glm(y~color+spine+width+weight,family=binomial)
rsq.lr(bnfit)
rsq.lr(bnfit,adj=TRUE)

psfit <- glm(num.satellites~color+spine+width+weight,family=poisson)
rsq.lr(psfit)
rsq.lr(psfit,adj=TRUE)

# Effectiveness of Bycycle Safety Helmets in Thompson et al. (1989)
y <- matrix(c(17,218,233,758),2,2)
x <- factor(c("yes","no"))
tbn <- glm(y~x,family=binomial)
rsq.lr(tbn)
rsq.lr(tbn,adj=TRUE)
```

---

### rsq.n

**Corrected Likelihood-Ratio-Based R-Squared**

**Description**

Corrected likelihood-ratio-based $R^2$ for generalized linear models.

**Usage**

```r
rsq.n(fitObj,adj=FALSE)
```

**Arguments**

- `fitObj`: an object of class "lm" or "glm", usually, a result of a call to `lm`, `glm`, or `glm.nb`.
- `adj`: logical; if TRUE, calculate the adjusted $R^2$.

**Details**

Nagelkerke (1991) proposed this version of $R^2$ to correct the likelihood-ratio-statistic-based one which was proposed by Maddala (1983), Cox and Snell (1989), and Magee (1990). This corrected generalization of $R^2$ cannot reduce to the classical $R^2$ in case of linear models. It is not defined for quasi models.

**Value**

The $R^2$ or adjusted $R^2$.

**Author(s)**

Dabao Zhang, Department of Statistics, Purdue University
**References**


**See Also**

rsq, rsq.partial, pcor, rsq.lr

**Examples**

```r
data(hcrabs)
attach(hcrabs)
y <- ifelse(num.satellites>0,1,0)
bnfit <- glm(y~color+spine+width+weight,family=binomial)
rsq.n(bnfit)
rsq.n(bnfit,adj=TRUE)

psfit <- glm(num.satellites~color+spine+width+weight,family=poisson)
rsq.n(psfit)
rsq.n(psfit,adj=TRUE)

# Effectiveness of Bycycle Safety Helmets in Thompson et al. (1989)
y <- matrix(c(17,218,233,758),2,2)
x <- factor(c("yes","no"))
tbn <- glm(y~x,family=binomial)
rsq.n(tbn)
rsq.n(tbn,adj=TRUE)
```

**rsq.partial**

Partial R-Squared for Generalized Linear Models

**Description**

Calculate the coefficient of partial determination, aka partial R^2, for both linear and generalized linear models.

**Usage**

```r
rsq.partial(objF, objR=NULL, adj=FALSE, type=c("v", "kl", "sse", "lr", "n"))
```
Arguments

objF  an object of class "lm" or "glm", a result of a call to \texttt{lm}, \texttt{glm}, or \texttt{glm.nb} to fit the full model.

objR  an object of class "lm" or "glm", a result of a call to \texttt{lm}, \texttt{glm}, or \texttt{glm.nb} to fit the reduced model.

adj  logical; if TRUE, calculate the adjusted partial $R^2$.

type  the type of R-squared:

\texttt{'v'} (default) – variance-function-based (Zhang, 2016), calling \texttt{rsq.v};

\texttt{'kl'} – KL-divergence-based (Cameron and Windmeijer, 1997), calling \texttt{rsq.kl};

\texttt{'sse'} – SSE-based (Efron, 1978), calling \texttt{rsq.sse};

\texttt{'lr'} – likelihood-ratio-based (Maddala, 1983; Cox and Snell, 1989; Magee, 1990), calling \texttt{rsq.lr};

\texttt{'n'} – corrected version of \texttt{'lr'} (Nagelkerke, 1991), calling \texttt{rsq.n}.

Details

When the fitting object of the reduced model is not specified, the partial $R^2$ of each term in the model will be calculated.

Value

Returned values include adjustment and partial.rsq. When objR is not NULL, variable.full and variable.reduced are returned; otherwise variable is returned.

adjustment  logical; if TRUE, calculate the adjusted partial $R^2$.

variable.full  all covariates in the full model.

variable.reduced  all covariates in the reduced model.

variable  all covariates in the full model.

partial.rsq  partial $R^2$ or the adjusted partial $R^2$.

Author(s)

Dabao Zhang, Department of Statistics, Purdue University

References


Maddala, G. S. (1983) \textit{Limited-Dependent and Qualitative Variables in Econometrics}. Cambridge University.
rsq.sse


See Also

rsq, pcor.

Examples

data(hcrabs)
attach(hcrabs)
y <- ifelse(num.satellites>0,1,0)
bfit <- glm(y~color+spine+width+weight,family=binomial)
rsq.partial(bfit)

bnfitr <- glm(y~color+weight,family=binomial)
rsq.partial(bfit, bnfitr)

quasibn <- glm(y~color+spine+width+weight,family=quasibinomial)
rsq.partial(quasibn)

quasibnr <- glm(y~color+weight,family=binomial)
rsq.partial(quasibn, quasibnr)

---

### rsq.sse

**SSE-Based R-Squared**

#### Description

The sum-of-squared-errors-based \( R^2 \) for generalized linear models.

#### Usage

```r
rsq.sse(fitObj, adj=FALSE)
```

#### Arguments

- **fitObj**: an object of class "lm" or "glm", usually, a result of a call to `lm`, `glm`, or `glm.nb`.
- **adj**: logical; if TRUE, calculate the adjusted \( R^2 \).

#### Details

This version of \( R^2 \) was proposed by Efron (1978). It is calculated on the basis of the formula of the classical \( R^2 \).
Value

The R^2 or adjusted R^2.

Author(s)

Dabao Zhang, Department of Statistics, Purdue University

References


See Also

`rsq, rsq.partial, pcor`.

Examples

data(hcrabs)
attach(hcrabs)
y <- ifelse(num.satellites>0,1,0)
bnfit <- glm(y~color+spine+width+weight,family=binomial)
rsq.sse(bnfit)
rsq.sse(bnfit,adj=TRUE)

psfit <- glm(num.satellites~color+spine+width+weight,family=poisson)
rsq.sse(psfit)
rsq.sse(psfit,adj=TRUE)

# Effectiveness of Bycycle Safety Helmets in Thompson et al. (1989)
y <- matrix(c(17,218,233,758),2,2)
X <- factor(c("yes","no"))
tbn <- glm(y~X,family=binomial)
rsq.sse(tbn)
rsq.sse(tbn,adj=TRUE)

rsq.v

Variance-Function-Based R-Squared

Description

Calculate the variance-function-based R-squared for generalized linear (mixed) models.

Usage

`rsq.v(fitObj,adj=FALSE)"
Arguments

fitObj an object of class "lm", "glm", "lme", or "glmerMod", usually, a result of a call to lm, glm, glm.nb, glmer, or glmer.nb.
adj logical; if TRUE, calculate the adjusted $R^2$.

Details

The $R^2$ relies on the variance function, and is well-defined for quasi models. It reduces to the classical $R^2$ when the variance function is constant or linear. For (generalized) linear mixed models, there are three types of $R^2$ calculated on the basis of observed response values, estimates of fixed effects, and variance components, i.e., model-based $R_M^2$ (proportion of variation explained by the model in total, including both fixed-effects and random-effects factors), fixed-effects $R_F^2$ (proportion of variation explained by the fixed-effects factors), and random-effects $R_R^2$ (proportion of variation explained by the random-effects factors).

Value

The $R^2$ or adjusted $R^2$. For (generalized) linear mixed models,

- $R_M^2$ proportion of variation explained by the model in total, including both fixed-effects and random-effects factors.
- $R_F^2$ proportion of variation explained by the fixed-effects factors.
- $R_R^2$ proportion of variation explained by the random-effects factors.

Author(s)

Dabao Zhang, Department of Statistics, Purdue University

References


See Also

vresidual, rsq, rsq.glmm, rsq.partial, pcor.

Examples

data(hcrabs)
attach(hcrabs)
y <- ifelse(num.satellites>0,1,0)
bnfit <- glm(y~color+spine+width+weight,family=binomial)
rsq.v(bnfit)
rsq.v(bnfit,adj=TRUE)

quasibn <- glm(y~color+spine+width+weight,family=quasibinomial)
rsq.v(quasibn)
# Generalized linear mixed models

```r
require(lme4)
data(cbpp)
glmm1 <- glmer(cbind(incidence, size-incidence)~period+(1|herd), data=cbpp, family=binomial)
rsq.v(glmm1)
```

---

**simglm**  
*Simulate Data from Generalized Linear Models*

**Description**

Simulate data from linear and generalized linear models. Only the first covariate truely affects the response variable with coefficient equal to $\lambda$.

**Usage**

```r
simglm(family=c("binomial", "gaussian", "poisson" ,"Gamma"), lambda=3, n=50, p=3)
```

**Arguments**

- `family`: the family of the distribution.
- `lambda`: size of the coefficient of the first covariate.
- `n`: the sample size.
- `p`: the number of covarites.

**Details**

The first covariate takes 1 in half of the observations, and 0 or -1 in the other half. When $\lambda$ gets larger, it is supposed to easier to predict the response variable.

**Value**

Returned values include $yx$ and $\beta$.

- `$yx$`: a data frame including the response $y$ and covariates $x.1$, $x.2$, and so on.
- `$\beta$`: true values of the regression coefficients.

**Author(s)**

Dabao Zhang, Department of Statistics, Purdue University

**References**

See Also

rsq, rsq.partial, pcor.

Examples

# Poisson Models
sdata <- simglm(family="poisson",lambda=4)
fitf <- glm(y~x.1+x.2+x.3,family=poisson,data=sdata$yx)
rsq(fitf)  # type='v'

fitr <- glm(y~x.2+x.3,family=poisson,data=sdata$yx)
rsq(fitr)  # type='v'
rsq(fitr,type='kl')
rsq(fitr,type='lr')
rsq(fitr,type='n')

pcor(fitr)  # type='v'
pcor(fitr,type='kl')
pcor(fitr,type='lr')
pcor(fitr,type='n')

# Gamma models with shape=100
n <- 50
sdata <- simglm(family="Gamma",lambda=4,n=n)
fitf <- glm(y~x.1+x.2+x.3,family=Gamma,data=sdata$yx)
rsq(fitf)  # type='v'
rsq.partial(fitf)  # type='v'

fitr <- glm(y~x.2,family=Gamma,data=sdata$yx)
rsq(fitr)  # type='v'
rsq(fitr,type='kl')
rsq(fitr,type='lr')
rsq(fitr,type='n')

# Likelihood-ratio-based R-squared
y <- sdata$yx$y
yhatr <- fitr$fitted.values
fit0 <- update(fitr,.~1)
yhat0 <- fit0$fitted.values
llr <- sum(log(dgamma(y,shape=100,scale=yhatr/100)))
ll0 <- sum(log(dgamma(y,shape=100,scale=yhat0/100)))

# Likelihood-ratio-based R-squared
1-exp(-2*(llr-ll0)/n)

# Corrected likelihood-ratio-based R-squared
(1-exp(-2*(llr-ll0)/n))/(1-exp(2*ll0/n))
Description

Simulate data from linear and generalized linear mixed models. The coefficients of the two covariate are specified by beta.

Usage

simglmm(family=c("binomial","gaussian","poisson","negative.binomial"),
beta=c(2,0),tau=1,n=200,m=10,balance=TRUE)

Arguments

- family: the family of the distribution.
- beta: regression coefficients (excluding the intercept which is set as zero).
- tau: the variance of the random intercept.
- n: the sample size.
- m: the number of groups.
- balance: simulate balanced data if TRUE, unbalanced data otherwise.

Details

The first covariate takes 1 in half of the observations, and 0 or -1 in the other half. When beta gets larger, it is supposed to easier to predict the response variable.

Value

Returned values include yx, beta, and u.

- yx: a data frame including the response y and covariates x1, x2, and so on.
- beta: true values of the regression coefficients.
- u: the random intercepts.

Author(s)

Dabao Zhang, Department of Statistics, Purdue University

References


See Also

rsq, rsq.lmm, rsq.glmm, simglm.
Examples

```r
require(lme4)

# Linear mixed models
gdata <- simglmm(family="gaussian")
lmm1 <- lmer(y~x1+x2+(1|subject),data=gdata$yx)
rsq(lmm1)

# Generalized linear mixed models
bdata <- simglmm(family="binomial",n=400,m=20)
glmm1 <- glmer(y~x1+x2+(1|subject),family="binomial",data=bdata$yx)
rsq(glmm1)
```

---

toxo  
*Toxoplasmosis Test in El Salvador*

Description

Recorded are the numbers of subjects testing positive for toxoplasmosis in 34 cities of El Salvador.

Usage

```r
data("toxo")
```

Format

A data frame with the test results in 34 cities of El Salvador, including the following 4 variables.

- `city`: index of each city.
- `positive`: the number of subjects testing positive for toxoplasmosis.
- `nsubs`: the total number of subjects tested.
- `rainfall`: annual rainfall (mm) in home city of subject.

Details

All subjects are between 11 and 15 year old. The data set was abstracted from a larger data set in Rmington et al. (1970).

Author(s)

Dabao Zhang, Department of Statistics, Purdue University

Source

References


See Also

rsq, rsq.partial, pcor, simglm.

Examples

data(toxo)
summary(toxo)
attach(toxo)

toxofit<-glm(cbind(positive,nsubs-positive)~rainfall+I(rainfall^2)+I(rainfall^3),family=binomial)
rsq(toxofit)
rsq(toxofit,adj=TRUE)
rsq.partial(toxofit)
detach(toxo)

vresidual

Variance-Function-Based Residuals

Description

Calculate the variance-function-based residuals for generalized linear models, which are used to calculate the variance-function-based R-squared.

Usage

vresidual(y,yfit,family=binomial(),variance=NULL)

Arguments

y a vector of observed values.
yfit a vector of fitted values.
family family of the distribution.
variance variance function (specified by family by default).

Details

The calculated residual relies on the variance function, and is well-defined for quasi models. It reduces to the classical residual when the variance function is constant or linear. Note that only the variance function is required to specify, via either "family" or "variance".
Value

Variance-function-based residuals.

Author(s)

Dabao Zhang, Department of Statistics, Purdue University

References


See Also

`rsq.v`, `rsq`.

Examples

data(hcrabs)
attach(hcrabs)
y <- ifelse(num.satellites>0,1,0)
bfit <- glm(y~color+spine+width+weight,family="binomial")
vresidual(y,bfit$fitted.values,family="binomial")

# Effectiveness of Bycycle Safety Helmets in Thompson et al. (1989)
y <- matrix(c(17,218,233,758),2,2)
x <- factor(c("yes","no"))
tbn <- glm(y~x,family="binomial")
yfit <- cbind(tbn$fitted.values, 1-tbn$fitted.values)
vr0 <- vresidual(matrix(0,2,1),yfit[,1],family="binomial")
vr1 <- vresidual(matrix(1,2,1),yfit[,2],family="binomial")
y[,1]*vr0+y[,2]*vr1
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