

Package ‘glmtoolbox’

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Type Package

Title Set of Tools to Data Analysis using Generalized Linear Models

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Description Set of tools for the statistical analysis of data using: (1) normal linear models; (2) generalized linear models; (3) negative binomial regression models as alternative to the Poisson regression models under the presence of overdispersion; (4) beta-binomial and random-clumped binomial regression models as alternative to the binomial regression models under the presence of overdispersion; (5) Zero-inflated and zero-altered regression models to deal with zero-excess in count data; (6) generalized nonlinear models; (7) generalized estimating equations for cluster correlated data.

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Author Luis Hernando Vanegas [aut, cre],
Luz Marina Rondón [aut],
Gilberto A. Paula [aut]

Maintainer Luis Hernando Vanegas <lhvanegasp@una1.edu.co>

URL <https://mlgs.netlify.app/>

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adjR2	<i>Adjusted R-squared</i>
-------	---------------------------

Description

Computes the adjusted R-squared

Usage

```
adjR2(..., digits, verbose)
```

Arguments

...	one of several model fit objects.
digits	an (optional) integer value indicating the number of decimal places to be used.
verbose	an (optional) logical indicating if should the report of results be printed.

Value

A matrix with the values of the adjusted R-squared for all model fit objects.

adjR2.glm

*Adjusted R-squared in Generalized Linear Models***Description**

Computes the adjusted deviance-based R-squared in generalized linear models.

Usage

```
## S3 method for class 'glm'
adjR2(..., digits = max(3, getOption("digits") - 2), verbose = TRUE)
```

Arguments

... one or several objects of the class *glm*, which are obtained from the fit of generalized linear models.

digits an (optional) integer value indicating the number of decimal places to be used. As default, digits is set to $\max(3, \text{getOption}(\text{"digits"}) - 2)$.

verbose an (optional) logical indicating if should the report of results be printed. As default, verbose is set to TRUE.

Details

The deviance-based R-squared is computed as $R^2 = 1 - \text{Deviance}/\text{Null.Deviance}$. Then, the adjusted deviance-based R-squared is computed as $1 - \frac{n-1}{n-p}(1 - R^2)$, where p is the number of parameters in the linear predictor and n is the sample size.

Value

a matrix with the following columns

Deviance	value of the residual deviance,
R-squared	value of the deviance-based R-squared,
df	number of parameters in the linear predictor,
adj.R-squared	value of the adjusted deviance-based R-squared,

Examples

```
##### Example 1: Fuel efficiency of cars
Auto <- ISLR::Auto
fit1 <- glm(mpg ~ horsepower*weight, family=Gamma(inverse), data=Auto)
fit2 <- update(fit1, formula=mpg ~ horsepower*weight*cylinders)
fit3 <- update(fit1, family=Gamma(log))
```

```

fit4 <- update(fit2, family=Gamma(log))
fit5 <- update(fit1, family=inverse.gaussian(log))
fit6 <- update(fit2, family=inverse.gaussian(log))

AIC(fit1,fit2,fit3,fit4,fit5,fit6)
BIC(fit1,fit2,fit3,fit4,fit5,fit6)
adjR2(fit1,fit2,fit3,fit4,fit5,fit6)

```

adjR2.gnm

Adjusted R-squared in Generalized Nonlinear Models

Description

Computes the adjusted deviance-based R-squared in generalized nonlinear models.

Usage

```

## S3 method for class 'gnm'
adjR2(..., digits = max(3, getOption("digits") - 2), verbose = TRUE)

```

Arguments

...	one or several objects of the class <i>gnm</i> , which are obtained from the fit of generalized nonlinear models.
digits	an (optional) integer value indicating the number of decimal places to be used. As default, digits is set to $\max(3, \text{getOption}(\text{"digits"}) - 2)$.
verbose	an (optional) logical indicating if should the report of results be printed. As default, verbose is set to TRUE.

Details

The deviance-based R-squared is computed as $R^2 = 1 - \text{Deviance}/\text{Null.Deviance}$. Then, the adjusted deviance-based R-squared is computed as $1 - \frac{n-1}{n-p}(1 - R^2)$, where p is the number of parameters in the "linear" predictor and n is the sample size.

Value

a matrix with the following columns

Deviance	value of the residual deviance,
R-squared	value of the deviance-based R-squared,
df	number of parameters in the "linear" predictor,
adj.R-squared	value of the adjusted deviance-based R-squared,

Examples

```
##### Example 1: The effects of fertilizers on coastal Bermuda grass
data(Grass)
fit1 <- gnm(Yield ~ b0 + b1/(Nitrogen + a1) + b2/(Phosphorus + a2) + b3/(Potassium + a3),
            family=gaussian(inverse), start=c(b0=0.1,b1=13,b2=1,b3=1,a1=45,a2=15,a3=30), data=Grass)
fit2 <- update(fit1, family=Gamma(inverse))
adjR2(fit1,fit2)

##### Example 2: Developmental rate of Drosophila melanogaster
data(Drosophila)
fit1 <- gnm(Duration ~ b0 + b1*Temp + b2/(Temp-a), family=Gamma(log),
            start=c(b0=3,b1=-0.25,b2=-210,a=55), weights=Size, data=Drosophila)
fit2 <- update(fit1, family=inverse.gaussian(log))
adjR2(fit1,fit2)

##### Example 3: Radioimmunological Assay of Cortisol
data(Cortisol)
fit1 <- gnm(Y ~ b0 + (b1-b0)/(1 + exp(b2+ b3*1Dose))^b4, family=Gamma(identity),
            start=c(b0=130,b1=2800,b2=3,b3=3,b4=0.5), data=Cortisol)
fit2 <- update(fit1, family=gaussian(identity))
adjR2(fit1,fit2)

##### Example 4: Age and Eye Lens Weight of Rabbits in Australia
data(rabbits)
fit1 <- gnm(wlens ~ b1 - b2/(age + b3), family=Gamma(log),
            start=c(b1=5.5,b2=130,b3=35), data=rabbits)
fit2 <- update(fit1, family=gaussian(log))
adjR2(fit1,fit2)
```

adjR2.lm

*Adjusted R-squared in Normal Linear Models***Description**

Extracts the adjusted R-squared in normal linear models.

Usage

```
## S3 method for class 'lm'
adjR2(..., digits = max(3, getOption("digits") - 2), verbose = TRUE)
```

Arguments

...	one or several objects of the class <i>lm</i> , which are obtained from the fit of normal linear models.
digits	an (optional) integer value indicating the number of decimal places to be used. As default, digits is set to <code>max(3, getOption("digits") - 2)</code> .
verbose	an (optional) logical indicating if should the report of results be printed. As default, verbose is set to TRUE.

Details

The R-squared is computed as $R^2 = 1 - RSS/Null.RSS$. Then, the adjusted R-squared is computed as $1 - \frac{n-1}{n-p}(1 - R^2)$, where p is the number of parameters in the linear predictor and n is the sample size.

Value

a matrix with the following columns

RSS	value of the residual sum of squares,
R-squared	value of the R-squared,
df	number of parameters in the linear predictor,
adj.R-squared	value of the adjusted R-squared,

Examples

```
##### Example 1: Fuel efficiency of cars
fit1 <- lm(mpg ~ log(hp) + log(wt) + qsec, data=mtcars)
fit2 <- lm(mpg ~ log(hp) + log(wt) + qsec + log(hp)*log(wt), data=mtcars)
fit3 <- lm(mpg ~ log(hp)*log(wt)*qsec, data=mtcars)

AIC(fit1,fit2,fit3)
BIC(fit1,fit2,fit3)
adjR2(fit1,fit2,fit3)
```

advertising

Advertising

Description

The advertising data set consists of sales of that product in 200 different markets. It also includes advertising budgets for the product in each of those markets for three different media: TV, radio, and newspapers.

Usage

```
data(advertising)
```

Format

A data frame with 200 rows and 4 variables:

TV a numeric vector indicating the advertising budget on TV.

radio a numeric vector indicating the advertising budget on radio.

newspaper a numeric vector indicating the advertising budget on newspaper.

sales a numeric vector indicating the sales of the interest product.

Source

<https://www.statlearning.com/s/Advertising.csv>

References

James G., Witten D., Hastie T., Tibshirani R. (2013, page 15) *An Introduction to Statistical Learning with Applications in R*, Springer, New York.

Examples

```
data(advertising)
breaks <- with(advertising, quantile(radio, probs=c(0:3)/3))
labels <- c("low", "mid", "high")
advertising2 <- within(advertising, radioC <- cut(radio, breaks, labels, include.lowest=TRUE))
dev.new()
with(advertising2, plot(TV, sales, pch=16, col=as.numeric(radioC)))
legend("topleft", legend=c("low", "mid", "high"), fill=c(1:3), title="Radio", bty="n")
```

AGPC

AGPC for Generalized Estimating Equations

Description

Computes the Akaike-type penalized Gaussian pseudo-likelihood criterion (AGPC) for one or more objects of the class *glmgee*.

Usage

```
AGPC(..., k = 2, verbose = TRUE, digits = max(3, getOption("digits") - 2))
```

Arguments

<code>...</code>	one or several objects of the class <i>glmgee</i> .
<code>k</code>	an (optional) non-negative value giving the magnitude of the penalty. As default, <code>k</code> is set to 2.
<code>verbose</code>	an (optional) logical switch indicating if should the report of results be printed. As default, <code>verbose</code> is set to <code>TRUE</code> .
<code>digits</code>	an (optional) integer indicating the number of digits to print. As default, <code>digits</code> is set to <code>max(3, getOption("digits") - 2)</code> .

Details

If k is set to 0 then the AGPC reduces to the Gaussian pseudo-likelihood criterion (GPC), proposed by Carey and Wang (2011), which corresponds to the logarithm of the multivariate normal density function.

Value

A data frame with the values of the gaussian pseudo-likelihood, the number of parameters in the linear predictor plus the number of parameters in the correlation matrix, and the value of AGPC for each *glmgee* object in the input.

References

Carey V.J., Wang Y.-G. (2011) Working covariance model selection for generalized estimating equations. *Statistics in Medicine* 30:3117-3124.

Zhu X., Zhu Z. (2013) Comparison of Criteria to Select Working Correlation Matrix in Generalized Estimating Equations. *Chinese Journal of Applied Probability and Statistics* 29:515-530.

Fu L., Hao Y., Wang Y.-G. (2018) Working correlation structure selection in generalized estimating equations. *Computational Statistics* 33:983-996.

Vanegas L.H., Rondon L.M., Paula G.A. (2023) Generalized Estimating Equations using the new R package *glmtoolbox*. *The R Journal* 15:105-133.

See Also

[QIC](#), [CIC](#), [RJC](#), [GHYC](#), [SGPC](#)

Examples

```
##### Example 1: Effect of ozone-enriched atmosphere on growth of sitka spruces
data(spruces)
mod1 <- size ~ poly(days,4) + treat
fit1 <- glmgee(mod1, id=tree, family=Gamma(log), data=spruces)
fit2 <- update(fit1, corstr="AR-M-dependent")
fit3 <- update(fit1, corstr="Stationary-M-dependent(2)")
fit4 <- update(fit1, corstr="Exchangeable")
AGPC(fit1, fit2, fit3, fit4)

##### Example 2: Treatment for severe postnatal depression
data(depression)
mod2 <- depressd ~ visit + group
fit1 <- glmgee(mod2, id=subj, family=binomial(logit), data=depression)
fit2 <- update(fit1, corstr="AR-M-dependent")
fit3 <- update(fit1, corstr="Stationary-M-dependent(2)")
fit4 <- update(fit1, corstr="Exchangeable")
AGPC(fit1, fit2, fit3, fit4)

##### Example 3: Treatment for severe postnatal depression (2)
mod3 <- dep ~ visit*group
fit1 <- glmgee(mod3, id=subj, family=gaussian(identity), data=depression)
fit2 <- update(fit1, corstr="AR-M-dependent")
```

```
fit3 <- update(fit1, constr="Exchangeable")
AGPC(fit1, fit2, fit3)
```

amenorrhea

amenorrhea

Description

A total of 1151 women completed menstrual diaries. The diary data were used to generate a binary sequence for each woman, indicating whether or not she had experienced amenorrhea (the absence of menstrual bleeding for a specified number of days) on the day of randomization and three additional 90-day intervals. The goal of this trial was to compare the two treatments (100 mg or 150 mg of depot-medroxyprogesterone acetate (DMPA)) in terms of how the rates of amenorrhea change over time with continued use of the contraceptive method.

Usage

```
data(amenorrhea)
```

Format

A data frame with 4604 rows and 4 variables:

ID a numeric vector indicating the woman's ID.

Dose a factor with two levels: "100mg" for treatment with 100 mg injection; and "150mg" for treatment with 150 mg injection.

Time a numeric vector indicating the number of 90-day intervals since the trial began.

amenorrhea a numeric vector indicating the amenorrhea status (1 for amenorrhea; 0 otherwise).

References

Fitzmaurice G.M., Laird N.M., Ware J.H. (2011, page 397). *Applied Longitudinal Analysis*. 2nd ed. John Wiley & Sons.

Machin D., Farley T.M., Busca B., Campbell M.J., d'Arcangues C. (1988) Assessing changes in vaginal bleeding patterns in contracepting women. *Contraception*, 38, 165-79.

Examples

```
data(amenorrhea)
dev.new()
amenorrhea2 <- aggregate(amenorrhea ~ Time + Dose, mean, data=amenorrhea, na.rm=TRUE)
barplot(100*amenorrhea2 ~ Dose+Time, data=amenorrhea2, beside=TRUE, col=c("blue", "yellow"), ylab="%")
legend("topleft", legend=c("100 mg", "150 mg"), fill=c("blue", "yellow"), title="Dose", bty="n")
```

Description

Allows to compare nested generalized estimating equations using the Wald and generalized score tests.

Usage

```
## S3 method for class 'glmgee'
anova(
  object,
  ...,
  test = c("wald", "score"),
  verbose = TRUE,
  varest = c("robust", "df-adjusted", "model", "bias-corrected")
)
```

Arguments

object	an object of the class <i>glmgee</i> .
...	another objects of the class <i>glmgee</i> which are obtained from the fit of generalized estimating equations.
test	an (optional) character string indicating the required test. The available options are: Wald ("wald") and generalized score ("score") tests. As default, test is set to "wald".
verbose	an (optional) logical switch indicating if should the report of results be printed. As default, verbose is set to TRUE.
varest	an (optional) character string indicating the type of estimator which should be used to the variance-covariance matrix of the interest parameters in the Wald test. The available options are: robust sandwich-type estimator ("robust"), degrees-of-freedom-adjusted estimator ("df-adjusted"), bias-corrected estimator ("bias-corrected"), and the model-based or naive estimator ("model"). As default, varest is set to "robust". See vcov.glmgee .

Value

A matrix with three columns which contains the following:

Chi The value of the statistic of the test.

df The number of degrees of freedom.

Pr(>Chi) The p -value of the test computed using the Chi-square distribution.

References

Rotnitzky A., Jewell P. (1990) Hypothesis Testing of Regression Parameters in Semiparametric Generalized Linear Models for Cluster Correlated Data. *Biometrika* 77:485-497.

Boos D.D. (1992) On Generalized Score Tests. *The American Statistician* 46:327-333.

Vanegas L.H., Rondon L.M., Paula G.A. (2023) Generalized Estimating Equations using the new R package glmtoolbox. *The R Journal* 15:105-133.

Boos D. (1992) On Generalized Score Tests. *American Statistician* 46:327-33.

Rotnitzky A., Jewell N.P. (1990). Hypothesis Testing of Regression Parameters in Semiparametric Generalized Linear Models for Cluster Correlated Data. *Biometrika* 77:485-497.

Examples

```
##### Example 1: Effect of ozone-enriched atmosphere on growth of sitka spruces
data(spruces)
mod <- size ~ poly(days,4)
fit1 <- glmgee(mod, id=tree, family=Gamma(log), data=spruces, corstr="AR-M-dependent")
fit2 <- update(fit1, . ~ . + treat)
fit3 <- update(fit2, . ~ . + poly(days,4):treat)
anova(fit1,fit2,fit3,test="wald")
anova(fit3,test="wald")

##### Example 2: Treatment for severe postnatal depression
data(depression)
mod2 <- depressd ~ group
fit1 <- glmgee(mod2, id=subj, family=binomial(logit), corstr="AR-M-dependent", data=depression)
fit2 <- update(fit1, . ~ . + visit)
fit3 <- update(fit2, . ~ . + group:visit)
anova(fit1,fit2,fit3,test="score")
anova(fit3,test="score")
```

anova.gnm

Comparison of nested models in Generalized Nonlinear Models.

Description

Allows to use the likelihood-ratio test to compare nested models in generalized nonlinear models.

Usage

```
## S3 method for class 'gnm'
anova(object, ..., verbose = TRUE)
```

Arguments

object an object of the class *gnm*.
 ... another objects of the class *gnm*.
 verbose an (optional) logical indicating if should the report of results be printed. As default, verbose is set to TRUE.

Value

A matrix with the following three columns:

Chi The value of the statistic of the test,
 Df The number of degrees of freedom,
 Pr(>Chi) The *p*-value of the test-type test computed using the Chi-square distribution.

Examples

```
##### Example: The effects of fertilizers on coastal Bermuda grass
data(Grass)
fit1 <- gnm(Yield ~ b0 + b1/(Nitrogen + a1) + b2/(Phosphorus + a2) + b3/(Potassium + a3),
           family=gaussian(inverse), start=c(b0=0.1,b1=13,b2=1,b3=1,a1=45,a2=15,a3=30), data=Grass)

fit2 <- update(fit1,Yield ~ I(b0 + b2/(Phosphorus + a2) + b3/(Potassium + a3)),
              start=c(b0=0.1,b2=1,b3=1,a2=15,a3=30))

anova(fit2,fit1)
```

anova.overglm *Comparison of nested models for alternatives to the Poisson and Binomial Regression Models under the presence of Overdispersion.*

Description

Allows to compare nested models for regression models based on the negative binomial, beta-binomial, and random-clumped binomial distributions, which are alternatives to the Poisson and binomial regression models under the presence of overdispersion. The comparisons are performed by using the Wald, score, gradient or likelihood ratio tests.

Usage

```
## S3 method for class 'overglm'
anova(object, ..., test = c("wald", "lr", "score", "gradient"), verbose = TRUE)
```

Arguments

object	an object of the class <i>overglm</i> .
...	another objects of the class <i>overglm</i> .
test	an (optional) character string which allows to specify the required test. The available options are: Wald ("wald"), Rao's score ("score"), likelihood ratio ("lr") and Terrell's gradient ("gradient") tests. As default, test is set to "wald".
verbose	an (optional) logical indicating if should the report of results be printed. As default, verbose is set to TRUE.

Value

A matrix with the following three columns:

Chi	The value of the statistic of the test,
Df	The number of degrees of freedom,
Pr(>Chi)	The <i>p</i> -value of the test-type test computed using the Chi-square distribution.

References

Buse A. (1982) The Likelihood Ratio, Wald, and Lagrange Multiplier Tests: An Expository Note. *The American Statistician* 36, 153-157.

Terrell G.R. (2002) The gradient statistic. *Computing Science and Statistics* 34, 206–215.

Examples

```
## Example 1: Self diagnosed ear infections in swimmers
data(swimmers)
fit1 <- overglm(infections ~ frequency + location + age + gender, family="nb1(log)", data=swimmers)
anova(fit1, test="wald")
anova(fit1, test="score")
anova(fit1, test="lr")
anova(fit1, test="gradient")

## Example 2: Agents to stimulate cellular differentiation
data(cellular)
fit2 <- overglm(cbind(cells,200-cells) ~ tnf*ifn, family="bb(logit)", data=cellular)
anova(fit2, test="wald")
anova(fit2, test="score")
anova(fit2, test="lr")
anova(fit2, test="gradient")
```

anova.zeroinflation *Comparison of nested models for Regression Models to deal with Zero-Excess in Count Data*

Description

Allows to compare nested models for regression models used to deal with zero-excess in count data. The comparisons are performed by using the Wald, score, gradient or likelihood ratio tests.

Usage

```
## S3 method for class 'zeroinflation'
anova(
  object,
  ...,
  test = c("wald", "lr", "score", "gradient"),
  verbose = TRUE,
  submodel = c("counts", "zeros")
)
```

Arguments

object	an object of the class <i>zeroinflation</i> .
...	another objects of the class <i>zeroinflation</i> .
test	an (optional) character string which allows to specify the required test. The available options are: Wald ("wald"), Rao's score ("score"), likelihood ratio ("lr") and Terrell's gradient ("gradient") tests. As default, test is set to "wald".
verbose	an (optional) logical indicating if should the report of results be printed. As default, verbose is set to TRUE.
submodel	an (optional) character string which allows to specify the model: "counts" or "zeros". By default, submodel is set to "counts".

Value

A matrix with the following three columns:

Chi The value of the statistic of the test,

Df The number of degrees of freedom,

Pr(>Chi) The *p*-value of the test *test* computed using the Chi-square distribution.

References

Buse A. (1982) The Likelihood Ratio, Wald, and Lagrange Multiplier Tests: An Expository Note. *The American Statistician* 36, 153-157.

Terrell G.R. (2002) The gradient statistic. *Computing Science and Statistics* 34, 206–215.

Examples

```
##### Example 1: Article production by graduate students in biochemistry PhD programs
bioChemists <- pscl::bioChemists
fit1 <- zeroinf(art ~ fem + kid5 + ment | ment, family="nb1(log)", data = bioChemists)
anova(fit1, test="wald")
anova(fit1, test="lr")
anova(fit1, test="score")
anova(fit1, test="gradient")

fit2 <- zeroalt(art ~ fem + kid5 + ment, family="nb1(log)", data = bioChemists)
anova(fit2, submodel="zeros", test="wald")
anova(fit2, submodel="zeros", test="lr")
anova(fit2, submodel="zeros", test="score")
anova(fit2, submodel="zeros", test="gradient")
```

 anova2

Comparison of nested Generalized Linear Models

Description

Allows to compare nested generalized linear models using Wald, score, gradient, and likelihood ratio tests.

Usage

```
anova2(
  object,
  ...,
  test = c("wald", "lr", "score", "gradient"),
  verbose = TRUE
)
```

Arguments

object	an object of the class glm which is obtained from the fit of a generalized linear model.
...	another objects of the class glm which are obtained from the fit of generalized linear models.
test	an (optional) character string indicating the required type of test. The available options are: Wald ("wald"), Rao's score ("score"), Terrell's gradient ("gradient"), and likelihood ratio ("lr") tests. As default, test is set to "wald".
verbose	an (optional) logical indicating if should the report of results be printed. As default, verbose is set to TRUE.

Details

The Wald, Rao's score and Terrell's gradient tests are performed using the expected Fisher information matrix.

Value

A matrix with three columns which contains the following:

Chi The value of the statistic of the test.

Df The number of degrees of freedom.

Pr(>Chi) The p -value of the test computed using the Chi-square distribution.

References

Buse A. (1982) The Likelihood Ratio, Wald, and Lagrange Multiplier Tests: An Expository Note. *The American Statistician* 36, 153-157.

Terrell G.R. (2002) The gradient statistic. *Computing Science and Statistics* 34, 206 – 215.

Examples

```
## Example 1
Auto <- ISLR::Auto
fit1 <- glm(mpg ~ weight, family=inverse.gaussian("log"), data=Auto)
fit2 <- update(fit1, . ~ . + horsepower)
fit3 <- update(fit2, . ~ . + horsepower:weight)
anova2(fit1, fit2, fit3, test="lr")
anova2(fit1, fit2, fit3, test="score")
anova2(fit1, fit2, fit3, test="wald")
anova2(fit1, fit2, fit3, test="gradient")
```

```
## Example 2
burn1000 <- aplore3::burn1000
mod <- death ~ age + tbsa + inh_inj
fit1 <- glm(mod, family=binomial("logit"), data=burn1000)
fit2 <- update(fit1, . ~ . + inh_inj + age*inh_inj + tbsa*inh_inj)
anova2(fit1, fit2, test="lr")
anova2(fit1, fit2, test="score")
anova2(fit1, fit2, test="wald")
anova2(fit1, fit2, test="gradient")
```

```
## Example 3
data(aucuba)
fit <- glm(lesions ~ 1 + time, family=poisson("log"), data=aucuba)
anova2(fit, test="lr")
anova2(fit, test="score")
anova2(fit, test="wald")
anova2(fit, test="gradient")
```

aucuba	<i>Lesions of Aucuba mosaic virus</i>
--------	---------------------------------------

Description

The investigators counted the number of lesions of *Aucuba mosaic* virus developing after exposure to X rays for various times.

Usage

```
data(aucuba)
```

Format

A data frame with 7 rows and 2 variables:

time a numeric vector giving the minutes of exposure.

lesions a numeric vector giving the counts of lesions, in hundreds.

References

Snedecor G.W., Cochran W.G. (1989) *Statistical Methods, Eight Edition*, Iowa State University Press, Ames.

Examples

```
data(aucuba)
dev.new()
barplot(lesions ~ time, col="red", data=aucuba)
```

bestSubset	<i>Best Subset Selection</i>
------------	------------------------------

Description

Best subset selection by exhaustive search in generalized linear models.

Usage

```
bestSubset(
  object,
  nvmax = 8,
  nbest = 1,
  force.in = NULL,
  force.out = NULL,
  verbose = TRUE,
  digits = max(3, getOption("digits") - 2)
)
```

Arguments

object	one object of the class <i>glm</i> , which is assumed to be the full model.
nvmax	an (optional) positive integer value indicating the maximum size of subsets to examine.
nbest	an (optional) positive integer value indicating the number of subsets of each size to record.
force.in	an (optional) positive integers vector indicating the index of columns of model matrix that should be in all models.
force.out	an (optional) positive integers vector indicating the index of columns of model matrix that should be in no models.
verbose	an (optional) logical indicating if should the report of results be printed. As default, verbose is set to TRUE.
digits	an (optional) integer value indicating the number of decimal places to be used. As default, digits is set to $\max(3, \text{getOption("digits")} - 2)$.

Details

In order to apply the "best subset" selection, an exhaustive search is conducted, separately for every size from i to $nvmax$, to identify the model with the smallest deviance value. Therefore, if, for a fixed model size, the interest model selection criteria reduce to monotone functions of deviance, thus differing only in the way the sizes of the models are compared, then the results of the "best subset" selection do not depend upon the choice of the trade-off between goodness-of-fit and complexity on which they are based.

Examples

```
##### Example 1: Fuel consumption of automobiles
Auto <- ISLR::Auto
Auto2 <- within(Auto, origin <- factor(origin))
mod <- mpg ~ cylinders + displacement + acceleration + origin + horsepower*weight
fit1 <- glm(mod, family=inverse.gaussian(log), data=Auto2)
out1 <- bestSubset(fit1)
out1

##### Example 2: Patients with burn injuries
burn1000 <- aplore3::burn1000
burn1000 <- within(burn1000, death <- factor(death, levels=c("Dead", "Alive")))
mod <- death ~ gender + race + flame + age*tbsa*inh_inj
fit2 <- glm(mod, family=binomial(logit), data=burn1000)
out2 <- bestSubset(fit2)
out2

##### Example 3: Advertising
data(advertising)
fit3 <- glm(sales ~ log(TV)*radio*newspaper, family=gaussian(log), data=advertising)
out3 <- bestSubset(fit3)
out3
```

bladder

Bladder cancer in mice

Description

Female mice were continuously fed dietary concentrations of 2-Acetylaminofluorene (2-AAF), a carcinogenic and mutagenic derivative of fluorene. Serially sacrificed, dead or moribund mice were examined for tumors and deaths dates recorded. These data consist of the incidences of bladder neoplasms in mice observed during 33 months.

Usage

```
data(bladder)
```

Format

A data frame with 8 rows and 3 variables:

dose a numeric vector giving the dose, in parts per 10^4 , of 2-AAF.

exposed a numeric vector giving the number of mice exposed to each dose of 2-AAF.

cancer a numeric vector giving the number of mice with bladder cancer for each dose of 2-AAF.

References

Zhang H., Zelterman D. (1999) Binary Regression for Risks in Excess of Subject-Specific Thresholds. *Biometrics* 55:1247-1251.

See Also

[liver](#)

Examples

```
data(bladder)
dev.new()
barplot(100*cancer/exposed ~ dose, beside=TRUE, data=bladder, col="red",
        xlab="Dose of 2-AAF", ylab="% of mice with bladder cancer")
```

 BoxTidwell

Box-Tidwell transformations

Description

Computes the Box-Tidwell power transformations of the predictors in a regression model.

Usage

```
BoxTidwell(
  object,
  transf,
  epsilon = 1e-04,
  maxiter = 30,
  trace = FALSE,
  digits = max(3, getOption("digits") - 2),
  ...
)
```

Arguments

<code>object</code>	a model fit object.
<code>transf</code>	an one-sided formula giving the predictors that are candidates for transformation.
<code>epsilon</code>	an (optional) numerical value. If the maximum relative change in coefficients is less than <i>epsilon</i> , then convergence is declared. As default, <i>epsilon</i> is set to 0.0001.
<code>maxiter</code>	an (optional) positive integer value indicating the maximum number of iterations. By default, <i>maxiter</i> is set to 30.
<code>trace</code>	an (optional) logical indicating if should the record of iterations be printed. By default, <i>trace</i> is set to FALSE.
<code>digits</code>	an (optional) integer value indicating the number of decimal places to be used.
<code>...</code>	further arguments passed to or from other methods.

Value

Two matrices with the values of marginal and omnibus tests.

Description

Computes the Box-Tidwell power transformations of the predictors in a generalized linear model.

Usage

```
## S3 method for class 'glm'
BoxTidwell(
  object,
  transf,
  epsilon = 1e-04,
  maxiter = 30,
  trace = FALSE,
  digits = max(3, getOption("digits") - 2),
  ...
)
```

Arguments

<code>object</code>	an object of the class <i>glm</i> .
<code>transf</code>	an one-sided formula giving the quantitative predictors that are candidates for transformation.
<code>epsilon</code>	an (optional) numerical value. If the maximum relative change in coefficients is less than <i>epsilon</i> , then convergence is declared. As default, <i>epsilon</i> is set to 0.0001.
<code>maxiter</code>	an (optional) positive integer value indicating the maximum number of iterations. By default, <i>maxiter</i> is set to 30.
<code>trace</code>	an (optional) logical indicating if should the record of iterations be printed. By default, <i>trace</i> is set to FALSE.
<code>digits</code>	an (optional) integer value indicating the number of decimal places to be used.
<code>...</code>	further arguments passed to or from other methods.

Value

a list list with components including

`marginal` a matrix with estimates, standard errors, and 95 and the p-value of the Wald test to assess the hypothesis $H_0 : \tau =$

`omnibus` a matrix with the statistic and the p-value of the Wald test for null hypothesis that all powers are 1,

References

- Box G.E.P., Tidwell P.W. (1962) Transformation of the independent variables. *Technometrics* 4, 531-550.
- Fox J. (2016) *Applied Regression Analysis and Generalized Linear Models*, Third Edition. Sage.

See Also

[BoxTidwell.lm](#)

Examples

```
##### Example 1: Skin cancer in women
data(skincancer)
fit1 <- glm(cases ~ age + city, offset=log(population), family=poisson(log), data=skincancer)
AIC(fit1)
BoxTidwell(fit1, transf= ~ age)
fit1 <- update(fit1,formula=. ~ I(age^(-1/2)) + city)
AIC(fit1)

##### Example 3: Gas mileage
data(Auto, package="ISLR")
fit3 <- glm(mpg ~ horsepower + weight, family=inverse.gaussian(log), data=Auto)
AIC(fit3)
BoxTidwell(fit3, transf= ~ horsepower + weight)
fit3 <- update(fit3,formula=. ~ I(horsepower^(-1/3)) + weight)
AIC(fit3)

##### Example 4: Advertising
data(advertising)
fit4 <- glm(sales ~ TV + radio, family=gaussian(log), data=advertising)
AIC(fit4)
BoxTidwell(fit4, transf= ~ TV)
fit4 <- update(fit4,formula=. ~ I(TV^(1/10)) + radio)
AIC(fit4)

##### Example 5: Leukaemia Patients
data(leuk, package="MASS")
fit5 <- glm(ifelse(time>=52,1,0) ~ ag + wbc, family=binomial, data=leuk)
AIC(fit5)
BoxTidwell(fit5, transf= ~ wbc)
fit5 <- update(fit5,formula=. ~ ag + I(wbc^(-0.18)))
AIC(fit5)
```

BoxTidwell.lm

Box-Tidwell transformations in Normal Linear Models

Description

Computes the Box-Tidwell power transformations of the predictors in a normal linear model.

Usage

```
## S3 method for class 'lm'
BoxTidwell(
  object,
  transf,
  epsilon = 1e-04,
  maxiter = 30,
  trace = FALSE,
  digits = max(3, getOption("digits") - 2),
  ...
)
```

Arguments

object	an object of the class <i>lm</i> .
transf	an one-sided formula giving the quantitative predictors that are candidates for transformation.
epsilon	an (optional) numerical value. If the maximum relative change in coefficients is less than <i>epsilon</i> , then convergence is declared. As default, <i>epsilon</i> is set to 0.0001.
maxiter	an (optional) positive integer value indicating the maximum number of iterations. By default, <i>maxiter</i> is set to 30.
trace	an (optional) logical indicating if should the record of iterations be printed. By default, <i>trace</i> is set to FALSE.
digits	an (optional) integer value indicating the number of decimal places to be used.
...	further arguments passed to or from other methods.

Value

a list list with components including

marginal	a matrix with estimates, standard errors, and 95 and the p-value of the Wald test to assess the hypothesis $H_0 : \tau =$
omnibus	a matrix with the statistic and the p-value of the Wald test for null hypothesis that all powers are 1,

References

Box G.E.P., Tidwell P.W. (1962) Transformation of the independent variables. *Technometrics* 4, 531-550.

Fox J. (2016) *Applied Regression Analysis and Generalized Linear Models*, Third Edition. Sage.

See Also

[BoxTidwell.glm](#)

Examples

```
##### Example 1: Hill races in Scotland
data(races)
fit1 <- lm(rtime ~ distance + cclimb, data=races)
AIC(fit1)
BoxTidwell(fit1, transf= ~ distance + cclimb)
fit1 <- update(fit1,formula=rtime ~ distance + I(cclimb^2))
AIC(fit1)

##### Example 2: Gasoline yield
fit2 <- lm(mpg ~ hp + wt + am, data=mtcars)
AIC(fit2)
BoxTidwell(fit2, transf= ~ hp + wt)
fit2 <- update(fit2,formula=mpg ~ log(hp) + log(wt) + am)
AIC(fit2)

##### Example 3: New York Air Quality Measurements
fit3 <- lm(log(Ozone) ~ Solar.R + Wind + Temp, data=airquality)
AIC(fit3)
BoxTidwell(fit3, transf= ~ Solar.R + Wind + Temp)
fit3 <- update(fit3,formula=log(Ozone) ~ log(Solar.R) + Wind + Temp)
AIC(fit3)

##### Example 4: Heat capacity of hydrobromic acid
data(heatcap,package="GLMsData")
fit4 <- lm(Cp ~ Temp, data=heatcap)
AIC(fit4)
BoxTidwell(fit4, transf= ~ Temp)
fit4 <- update(fit4,formula=Cp ~ I(Temp^5))
AIC(fit4)

##### Example 5: Age and Eye Lens Weight of Rabbits in Australia
data(rabbits)
fit5 <- lm(log(wlens) ~ age, data=rabbits)
AIC(fit5)
BoxTidwell(fit5, transf= ~ age)
fit5 <- update(fit5,formula=log(wlens) ~ I(age^(-1/3)))
AIC(fit5)
```

 brains

Mammal brain and body weights

Description

These data correspond to the (average) body weight and the (average) brain weight for sixty-two species of mammals.

Usage

```
data(brains)
```

Format

A data frame with 62 rows and 3 variables:

Specie a character string giving the species name.

BrainWt a numeric vector indicating the average brain weight, in grams.

BodyWt a numeric vector indicating the average body weight, in kilograms.

References

Allison T., Cicchetti D. (1976). Sleep in mammals: Ecology and constitutional correlates. *Science* 194:732-734.

Weisberg S. (2005). *Applied Linear Regression*, 3rd edition. Wiley, New York.

Examples

```
data(brains)
xlab <- "log(Body Weight)"
ylab <- "log(Brain Weight)"
dev.new()
with(brains, plot(log(BodyWt), log(BrainWt), pch=20, xlab=xlab, ylab=ylab))
```

calls

Calls to a technical support help line

Description

Data on technical support calls after a product release. Using this information, new products could be allocated technical support resources.

Usage

```
data(calls)
```

Format

A data frame with 16 rows and 2 variables:

week a numeric vector indicating number of weeks that have elapsed since the product's release.

calls a numeric vector indicating the number of technical support calls.

Source

https://documentation.sas.com/doc/en/pgmsascdc/9.4_3.3/statug/statug_mcmc_examples12.htm

Examples

```
data(calls)
dev.new()
with(calls,plot(week,calls,xlab="The number of weeks since the release of the product",
  pch=16,col="blue",ylab="Technical support calls"))
```

cellular

*Agents to stimulate cellular differentiation***Description**

In a biomedical study of the immuno-activating ability of two agents, TNF (tumor necrosis factor) and IFN (interferon), to induce cell differentiation, the number of cells that exhibited markers of differentiation after exposure to TNF and IFN was recorded. At each of the 16 TNF/INF dose combinations, 200 cells were examined. The main question is whether the two agents stimulate cell differentiation synergistically or independently.

Usage

```
data(cellular)
```

Format

A data frame with 16 rows and 3 variables:

cells a numeric vector giving the number of cells that exhibited markers of differentiation after exposure to the dose of the two agents

tnf a numeric vector giving the dose (U/ml) of TNF

ifn a numeric vector giving the dose (U/ml) of IFN

References

Piegorsch W.W., Weinberg C.R., Margolin B.H. (1988) Exploring simple independent action in multifactor tables of proportions. *Biometrics* 44:595-603.

Vanegas L.H., Rondon L.M. (2020) A data transformation to deal with constant under/over-dispersion in binomial and poisson regression models. *Journal of Statistical Computation and Simulation* 90:1811-1833.

Examples

```
data(cellular)
dev.new()
barplot(100*cells/200 ~ ifn + tnf, beside=TRUE, data=cellular, col=terrain.colors(4),
  xlab="Dose of TNF", ylab="% of cells with markers of differentiation")
legend("topleft", legend=c("0","4","20","100"), fill=terrain.colors(4),
  title="Dose of IFN", bty="n")
```

cholecystectomy

Shoulder Pain after Laparoscopic Cholecystectomy

Description

Inflation of the abdomen during laparoscopic cholecystectomy (removal of the gallbladder) separates the liver from the diaphragm and strains the attachments that connect both. This strain is felt as a referred shoulder pain. Suction to remove residual gas may reduce shoulder pain. There were 22 subjects randomized in the active group (with abdominal suction) and 19 subjects randomized in the control group (without abdominal suction). After laparoscopic surgery, patients were asked to rate their shoulder pain on a visual analog scale morning and afternoon for three days after the operation (a total of six different times). The scale was coded into five ordered categories where a pain score of 1 indicated "low pain" and a score of 5 reflected "high pain".

Usage

```
data(cholecystectomy)
```

Format

A data frame with 246 rows and 7 variables:

id a numeric vector with the identifier of the patient.

treatment a factor indicating the treatment received by the patient: abdominal suction ("A") and placebo ("P").

gender a factor indicating the gender of the patient: female ("F") and male ("M").

age a numeric vector indicating the age of the patient, in years.

time a numeric vector indicating the occasion the patient was asked to rate their shoulder pain after the laparoscopic surgery: integers from 1 to 6.

pain a numeric vector indicating the shoulder pain rated by the patient on a scale coded into five ordered categories, where 1 indicated "low pain" and 5 reflected "high pain".

pain2 a numeric vector indicating the shoulder pain rated by the patient and coded as 1 for the two first categories of pain and 0 for other cases.

References

Jorgensen J.O., Gillies R.B., Hunt D.R., Caplehorn J.R.M., Lumley T. (1995) A simple and effective way to reduce postoperative pain after laparoscopic cholecystectomy. *Australian and New Zealand Journal of Surgery* 65:466–469.

Lumley T. (1996) Generalized Estimating Equations for Ordinal Data: A Note on Working Correlation Structures. *Biometrics* 52:354–361.

Morel J.G., Nagaraj N.K. (2012) *Overdispersion Models in SAS*. SAS Institute Inc., Cary, North Carolina, USA.

Examples

```

data(cholecystectomy)
out <- aggregate(pain2 ~ treatment + time, data=cholecystectomy, mean)
dev.new()
barplot(100*pain2 ~ treatment + time, beside=TRUE, data=out, xlab="Time",
        col=c("yellow","blue"), ylab="% of patients with low pain")
legend("topleft", c("Placebo","Abdominal suction"), fill=c("yellow","blue"),
       title="Treatment", cex=0.9, bty="n")

```

CIC	<i>Correlation Information Criterion for Generalized Estimating Equations</i>
-----	---

Description

Computes the Correlation Information Criterion (CIC) for one or more objects of the class *glmgee*.

Usage

```
CIC(..., verbose = TRUE, digits = max(3, getOption("digits") - 2))
```

Arguments

...	one or several objects of the class <i>glmgee</i> .
verbose	an (optional) logical switch indicating if should the report of results be printed. As default, verbose is set to TRUE.
digits	an (optional) integer indicating the number of digits to print. As default, digits is set to $\max(3, \text{getOption}(\text{"digits"}) - 2)$.

Value

A data.frame with the values of the CIC for each *glmgee* object in the input.

References

Hin L.-Y., Wang Y.-G. (2009) Working-Correlation-Structure Identification in Generalized Estimating Equations. *Statistics in Medicine*, 28:642-658.

Hin L.-Y., Carey V.J., Wang Y.-G. (2007) Criteria for Working-Correlation-Structure Selection in GEE: Assessment via Simulation. *The American Statistician* 61:360-364.

Vanegas L.H., Rondon L.M., Paula G.A. (2023) Generalized Estimating Equations using the new R package *glmtoolbox*. *The R Journal* 15:105-133.

See Also

[QIC](#), [GHYC](#), [RJC](#), [AGPC](#), [SGPC](#)

Examples

```
##### Example 1: Effect of ozone-enriched atmosphere on growth of sitka spruces
data(spruces)
mod1 <- size ~ poly(days,4) + treat
fit1 <- glmgee(mod1, id=tree, family=Gamma(log), data=spruces)
fit2 <- update(fit1, corstr="AR-M-dependent")
fit3 <- update(fit1, corstr="Stationary-M-dependent(2)")
fit4 <- update(fit1, corstr="Exchangeable")
CIC(fit1, fit2, fit3, fit4)

##### Example 2: Treatment for severe postnatal depression
data(depression)
mod2 <- depressd ~ visit + group
fit1 <- glmgee(mod2, id=subj, family=binomial(logit), data=depression)
fit2 <- update(fit1, corstr="AR-M-dependent")
fit3 <- update(fit1, corstr="Stationary-M-dependent(2)")
fit4 <- update(fit1, corstr="Exchangeable")
CIC(fit1, fit2, fit3, fit4)

##### Example 3: Treatment for severe postnatal depression (2)
mod3 <- dep ~ visit*group
fit1 <- glmgee(mod3, id=subj, family=gaussian(identity), data=depression)
fit2 <- update(fit1, corstr="AR-M-dependent")
fit3 <- update(fit1, corstr="Exchangeable")
CIC(fit1, fit2, fit3)
```

 confint.gnm

Confidence Intervals for Generalized Nonlinear Models

Description

Computes confidence intervals based on Wald test for a generalized nonlinear model.

Usage

```
## S3 method for class 'gnm'
confint(
  object,
  parm,
  level = 0.95,
  contrast,
  digits = max(3, getOption("digits") - 2),
  dispersion = NULL,
  verbose = TRUE,
  ...
)
```

Arguments

object	an object of the class <i>gnm</i> .
parm	a specification of which parameters are to be given confidence intervals, either a vector of numbers or a vector of names. If missing, all parameters are considered.
level	an (optional) value indicating the required confidence level. As default, level is set to 0.95.
contrast	an (optional) matrix indicating the linear combinations of parameters for which confidence intervals are required. The number of rows in this matrix corresponds to the number of linear combinations required.
digits	an (optional) integer value indicating the number of decimal places to be used. As default, digits is set to $\max(3, \text{getOption}(\text{"digits"}) - 2)$.
dispersion	an (optional) value indicating the estimate of the dispersion parameter. As default, dispersion is set to <code>summary(object)\$dispersion</code> .
verbose	an (optional) logical indicating if should the report of results be printed. As default, verbose is set to TRUE.
...	further arguments passed to or from other methods.

Details

The approximate $100(\text{level})\%$ confidence interval for β based on the Wald test.

Value

A matrix with so many rows as parameters in the "linear" predictor and two columns: "Lower limit" and "Upper limit".

Examples

```
##### Example 1: The effects of fertilizers on coastal Bermuda grass
data(Grass)
fit1 <- gnm(Yield ~ b0 + b1/(Nitrogen + a1) + b2/(Phosphorus + a2) + b3/(Potassium + a3),
           family=gaussian(inverse), start=c(b0=0.1,b1=13,b2=1,b3=1,a1=45,a2=15,a3=30), data=Grass)

confint(fit1, level=0.95)

##### Example 2: Assay of an Insecticide with a Synergist
data(Melanopus)
fit2 <- gnm(Killed/Exposed ~ b0 + b1*log(Insecticide-a1) + b2*Synergist/(a2 + Synergist),
           family=binomial(logit), weights=Exposed, start=c(b0=-3,b1=1.2,a1=1.7,b2=1.7,a2=2),
           data=Melanopus)

confint(fit2, level=0.95)

##### Example 3: Developmental rate of Drosophila melanogaster
data(Drosophila)
fit3 <- gnm(Duration ~ b0 + b1*Temp + b2/(Temp-a), family=Gamma(log),
           start=c(b0=3,b1=-0.25,b2=-210,a=55), weights=Size, data=Drosophila)
```



```

confint(fit3, level=0.95)

##### Example 4: Radioimmunological Assay of Cortisol
data(Cortisol)
fit4 <- gnm(Y ~ b0 + (b1-b0)/(1 + exp(b2+ b3*lDose))^b4, family=Gamma(identity),
           start=c(b0=130,b1=2800,b2=3,b3=3,b4=0.5), data=Cortisol)

### Confidence Interval for 'b1-b0'
confint(fit4, level=0.95, contrast=matrix(c(-1,1,0,0,0),1,5))

### Confidence Intervals for 'b0', 'b1', 'b2', 'b3', 'b4'
confint(fit4, level=0.95, contrast=diag(5))

```

 confint2

Confidence Intervals for Generalized Linear Models

Description

Computes confidence intervals based on Wald, likelihood-ratio, Rao's score or Terrell's gradient tests for a generalized linear model.

Usage

```

confint2(
  model,
  level = 0.95,
  test = c("wald", "lr", "score", "gradient"),
  digits = max(3, getOption("digits") - 2),
  verbose = TRUE
)

```

Arguments

model	an object of the class <i>glm</i> .
level	an (optional) value indicating the required confidence level. As default, level is set to 0.95.
test	an (optional) character string indicating the required type of test. The available options are: Wald ("wald"), Rao's score ("score"), Terrell's gradient ("gradient"), and likelihood ratio ("lr") tests. As default, test is set to "wald".
digits	an (optional) integer value indicating the number of decimal places to be used. As default, digits is set to $\max(3, \text{getOption}(\text{"digits"}) - 2)$.
verbose	an (optional) logical indicating if should the report of results be printed. As default, verbose is set to TRUE.

Details

The approximate $100(1-\text{level})\%$ confidence interval for β based on the test test is the set of values of β_0 for which the hypothesis $H_0: \beta = \beta_0$ versus $H_1: \beta \neq \beta_0$ is not rejected at the approximate significance level of $100(1-\text{level})\%$. The Wald, Rao's score and Terrell's gradient tests are performed using the expected Fisher information matrix.

Value

A matrix with so many rows as parameters in the linear predictor and two columns: "Lower limit" and "Upper limit".

References

Buse A. (1982) The Likelihood Ratio, Wald, and Lagrange Multiplier Tests: An Expository Note. *The American Statistician* 36, 153-157.

Terrell G.R. (2002) The gradient statistic. *Computing Science and Statistics* 34, 206 – 215.

Examples

```
##### Example 1: Fuel consumption of automobiles
Auto <- ISLR::Auto
fit1 <- glm(mpg ~ weight*horsepower, family=inverse.gaussian("log"), data=Auto)
confint2(fit1, test="lr")
confint2(fit1, test="score")

##### Example 2: Patients with burn injuries
burn1000 <- aplore3::burn1000
burn1000 <- within(burn1000, death <- factor(death, levels=c("Dead", "Alive")))
fit2 <- glm(death ~ age*inh_inj + tbsa*inh_inj, family=binomial("logit"), data=burn1000)
confint2(fit2, test="lr")
confint2(fit2, test="gradient")
```

cooks.distance.glmgee *Cook's Distance for Generalized Estimating Equations*

Description

Produces an approximation, better known as the *one-step approximation*, of the Cook's distance, which is aimed to measure the effect on the estimates of the parameters in the linear predictor of deleting each cluster/observation in turn. This function also can produce a cluster/observation-index plot of the Cook's distance for all parameters in the linear predictor or for some subset of them (via the argument `coefs`).

Usage

```
## S3 method for class 'glmgee'
cooks.distance(
  model,
  method = c("Preisser-Qaqish", "full"),
  level = c("clusters", "observations"),
  plot.it = FALSE,
  coefs,
  identify,
  varest = c("robust", "df-adjusted", "model", "bias-corrected"),
  ...
)
```

Arguments

<code>model</code>	an object of class <i>glmgee</i> .
<code>method</code>	an (optional) character string indicating the method of calculation for the <i>one-step approximation</i> . The options are: the <i>one-step approximation</i> described by Preisser and Qaqish (1996) in which the working-correlation matrix is assumed to be known ("Preisser-Qaqish"); and the "authentic" <i>one-step approximation</i> ("full"). As default, <code>method</code> is set to "Preisser-Qaqish".
<code>level</code>	an (optional) character string indicating the level for which the Cook's distance is required. The options are: cluster-level ("clusters") and observation-level ("observations"). As default, <code>level</code> is set to "clusters".
<code>plot.it</code>	an (optional) logical indicating if the plot of Cook's distance is required or just the data matrix in which that plot is based. As default, <code>plot.it</code> is set to FALSE.
<code>coefs</code>	an (optional) character string which (partially) match with the names of some of the parameters in the linear predictor.
<code>identify</code>	an (optional) integer indicating the number of clusters to identify on the plot of Cook's distance. This is only appropriate if <code>plot.it=TRUE</code> .
<code>varest</code>	an (optional) character string indicating the type of estimator which should be used to the variance-covariance matrix of the interest parameters. The available options are: robust sandwich-type estimator ("robust"), degrees-of-freedom-adjusted estimator ("df-adjusted"), bias-corrected estimator ("bias-corrected"), and the model-based or naive estimator ("model"). As default, <code>varest</code> is set to "robust".
<code>...</code>	further arguments passed to or from other methods. If <code>plot.it=TRUE</code> then ... may be used to include graphical parameters to customize the plot. For example, <code>col</code> , <code>pch</code> , <code>cex</code> , <code>main</code> , <code>sub</code> , <code>xlab</code> , <code>ylab</code> .

Details

The Cook's distance consists of the *distance* between two estimates of the parameters in the linear predictor using a metric based on the (estimate of the) variance-covariance matrix. For the cluster-level, the first one set of estimates is computed from a dataset including all clusters/observations, and the second one is computed from a dataset in which the *i*-th cluster is excluded. To avoid

computational burden, the second set of estimates is replaced by its *one-step approximation*. See the [dfbeta.glmgee](#) documentation.

Value

A matrix as many rows as clusters/observations in the sample and one column with the values of the Cook's distance.

References

- Pregibon D. (1981). Logistic regression diagnostics. *The Annals of Statistics* 9, 705-724.
- Preisser J.S., Qaqish B.F. (1996) Deletion diagnostics for generalised estimating equations. *Biometrika* 83:551–562.
- Hammill B.G., Preisser J.S. (2006) A SAS/IML software program for GEE and regression diagnostics. *Computational Statistics & Data Analysis* 51:1197-1212.
- Vanegas L.H., Rondon L.M., Paula G.A. (2023) Generalized Estimating Equations using the new R package `glmtoolbox`. *The R Journal* 15:105-133.

Examples

```
##### Example 1: Effect of ozone-enriched atmosphere on growth of sitka spruces
data(spruces)
mod1 <- size ~ poly(days,4) + treat
fit1 <- glmgee(mod1, id=tree, family=Gamma(log), data=spruces, corstr="AR-M-dependent")

### Cook's distance for all parameters in the linear predictor
cooks.distance(fit1, method="full", plot.it=TRUE, col="red", lty=1, lwd=1, cex=0.8,
               col.lab="blue", col.axis="blue", col.main="black", family="mono")

### Cook's distance for the parameter associated to the variable 'treat'
cooks.distance(fit1, coef="treat", method="full", plot.it=TRUE, col="red", lty=1,
               lwd=1, col.lab="blue", col.axis="blue", col.main="black", cex=0.8)

##### Example 2: Treatment for severe postnatal depression
data(depression)
mod2 <- depressd ~ visit + group
fit2 <- glmgee(mod2, id=subj, family=binomial(logit), corstr="AR-M-dependent", data=depression)

### Cook's distance for all parameters in the linear predictor
cooks.distance(fit2, method="full", plot.it=TRUE, col="red", lty=1, lwd=1, cex=0.8,
               col.lab="blue", col.axis="blue", col.main="black", family="mono")

### Cook's distance for the parameter associated to the variable 'group'
cooks.distance(fit2, coef="group", method="full", plot.it=TRUE, col="red", lty=1,
               lwd=1, col.lab="blue", col.axis="blue", col.main="black", cex=0.8)
```

 cooks.distance.gnm *Cook's Distance for Generalized Nonlinear Models*

Description

Produces an approximation of the Cook's distance, better known as the *one-step approximation*, for measuring the effect of deleting each observation in turn on the estimates of the parameters in a linear predictor. Additionally, this function can produce an index plot of Cook's distance for all or a subset of the parameters in the linear predictor (via the argument `coefs`).

Usage

```
## S3 method for class 'gnm'
cooks.distance(model, plot.it = FALSE, dispersion = NULL, coefs, identify, ...)
```

Arguments

<code>model</code>	an object of class <i>gnm</i> .
<code>plot.it</code>	an (optional) logical indicating if the plot is required or just the data matrix in which that plot is based. As default, <code>plot.it</code> is set to <code>FALSE</code> .
<code>dispersion</code>	an (optional) value indicating the estimate of the dispersion parameter. As default, <code>dispersion</code> is set to <code>summary(object)\$dispersion</code> .
<code>coefs</code>	an (optional) character string that matches (partially) some of the model parameter names.
<code>identify</code>	an (optional) integer indicating the number of individuals to identify on the plot of the Cook's distance. This is only appropriate if <code>plot.it=TRUE</code> .
<code>...</code>	further arguments passed to or from other methods. If <code>plot.it=TRUE</code> then <code>...</code> may be used to include graphical parameters to customize the plot. For example, <code>col</code> , <code>pch</code> , <code>cex</code> , <code>main</code> , <code>sub</code> , <code>xlab</code> , <code>ylab</code> .

Details

The Cook's distance consists of the *distance* between two estimates of the parameters in the linear predictor using a metric based on the (estimate of the) variance-covariance matrix. The first one set of estimates is computed from a dataset including all individuals, and the second one is computed from a dataset in which the *i*-th individual is excluded. To avoid computational burden, the second set of estimates is replaced by its *one-step approximation*. See the [dfbeta.overglm](#) documentation.

Value

A matrix as many rows as individuals in the sample and one column with the values of the Cook's distance.

Examples

```
##### Example 1: The effects of fertilizers on coastal Bermuda grass
data(Grass)
fit1 <- gnm(Yield ~ b0 + b1/(Nitrogen + a1) + b2/(Phosphorus + a2) + b3/(Potassium + a3),
           family=gaussian(inverse), start=c(b0=0.1,b1=13,b2=1,b3=1,a1=45,a2=15,a3=30), data=Grass)

cooks.distance(fit1, plot.it=TRUE, col="red", lty=1, lwd=1,
              col.lab="blue", col.axis="blue", col.main="black", family="mono", cex=0.8)

##### Example 2: Assay of an Insecticide with a Synergist
data(Melanopus)
fit2 <- gnm(Killed/Exposed ~ b0 + b1*log(Insecticide-a1) + b2*Synergist/(a2 + Synergist),
           family=binomial(logit), weights=Exposed, start=c(b0=-3,b1=1.2,a1=1.7,b2=1.7,a2=2),
           data=Melanopus)

### Cook's distance just for the parameter "b1"
cooks.distance(fit2, plot.it=TRUE, coef="b1", col="red", lty=1, lwd=1,
              col.lab="blue", col.axis="blue", col.main="black", family="mono", cex=0.8)

##### Example 3: Developmental rate of Drosophila melanogaster
data(Drosophila)
fit3 <- gnm(Duration ~ b0 + b1*Temp + b2/(Temp-a), family=Gamma(log),
           start=c(b0=3,b1=-0.25,b2=-210,a=55), weights=Size, data=Drosophila)

cooks.distance(fit3, plot.it=TRUE, col="red", lty=1, lwd=1,
              col.lab="blue", col.axis="blue", col.main="black", family="mono", cex=0.8)

##### Example 4: Radioimmunological Assay of Cortisol
data(Cortisol)
fit4 <- gnm(Y ~ b0 + (b1-b0)/(1 + exp(b2+ b3*1Dose))^b4, family=Gamma(identity),
           start=c(b0=130,b1=2800,b2=3,b3=3,b4=0.5), data=Cortisol)

cooks.distance(fit4, plot.it=TRUE, col="red", lty=1, lwd=1,
              col.lab="blue", col.axis="blue", col.main="black", family="mono", cex=0.8)
```

cooks.distance.overglm

Cook's Distance for alternatives to the Poisson and Binomial Regression Models under the presence of Overdispersion

Description

Produces an approximation, better known as the *one-step approximation*, of the Cook's distance, which is aimed to measure the effect on the estimates of the parameters in the linear predictor of deleting each observation in turn. This function also can produce an index plot of the Cook's distance for all parameters in the linear predictor or for some subset of them (via the argument `coefs`).

Usage

```
## S3 method for class 'overglm'
cooks.distance(model, plot.it = FALSE, coefs, identify, ...)
```

Arguments

model	an object of class <i>overglm</i> .
plot.it	an (optional) logical indicating if the plot is required or just the data matrix in which that plot is based. As default, <code>plot.it</code> is set to <code>FALSE</code> .
coefs	an (optional) character string which (partially) match with the names of some model parameters.
identify	an (optional) integer indicating the number of individuals to identify on the plot of the Cook's distance. This is only appropriate if <code>plot.it=TRUE</code> .
...	further arguments passed to or from other methods. If <code>plot.it=TRUE</code> then ... may be used to include graphical parameters to customize the plot. For example, <code>col</code> , <code>pch</code> , <code>cex</code> , <code>main</code> , <code>sub</code> , <code>xlab</code> , <code>ylab</code> .

Details

The Cook's distance consists of the *distance* between two estimates of the parameters in the linear predictor using a metric based on the (estimate of the) variance-covariance matrix. The first one set of estimates is computed from a dataset including all individuals, and the second one is computed from a dataset in which the *i*-th individual is excluded. To avoid computational burden, the second set of estimates is replaced by its *one-step approximation*. See the [dfbeta.overglm](#) documentation.

Value

A matrix as many rows as individuals in the sample and one column with the values of the Cook's distance.

Examples

```
##### Example 1: Self diagnosed ear infections in swimmers
data(swimmers)
fit1 <- overglm(infections ~ frequency + location, family="nb1(log)", data=swimmers)

### Cook's distance for all parameters in the linear predictor
cooks.distance(fit1, plot.it=TRUE, col="red", lty=1, lwd=1, col.lab="blue",
               col.axis="blue", col.main="black", family="mono", cex=0.8)

### Cook's distance just for the parameter associated with 'frequency'
cooks.distance(fit1, plot.it=TRUE, coef="frequency", col="red", lty=1, lwd=1,
               col.lab="blue", col.axis="blue", col.main="black", family="mono", cex=0.8)

##### Example 2: Article production by graduate students in biochemistry PhD programs
bioChemists <- pscl::bioChemists
fit2 <- overglm(art ~ fem + kid5 + ment, family="nb1(log)", data = bioChemists)

### Cook's distance for all parameters in the linear predictor
```

```

cooks.distance(fit2, plot.it=TRUE, col="red", lty=1, lwd=1, col.lab="blue",
               col.axis="blue", col.main="black", family="mono", cex=0.8)

### Cook's distance just for the parameter associated with 'fem'
cooks.distance(fit2, plot.it=TRUE, coef="fem", col="red", lty=1, lwd=1,
               col.lab="blue", col.axis="blue", col.main="black", family="mono", cex=0.8)

##### Example 3: Agents to stimulate cellular differentiation
data(cellular)
fit3 <- overglm(cbind(cells,200-cells) ~ tnf + ifn, family="bb(logit)", data=cellular)

### Cook's distance for all parameters in the linear predictor
cooks.distance(fit3, plot.it=TRUE, col="red", lty=1, lwd=1, col.lab="blue",
               col.axis="blue", col.main="black", family="mono", cex=0.8)

### Cook's distance just for the parameter associated with 'tnf'
cooks.distance(fit3, plot.it=TRUE, coef="tnf", col="red", lty=1, lwd=1,
               col.lab="blue", col.axis="blue", col.main="black", family="mono", cex=0.8)

```

```
cooks.distance.zeroinflation
```

*Cook's Distance for Regression Models to deal with Zero-Excess in
Count Data*

Description

Produces an approximation, better known as the *one-step approximation*, of the Cook's distance, which is aimed to measure the effect on the estimates of the parameters in the linear predictor of deleting each observation in turn. This function also can produce an index plot of the Cook's distance for all parameters in the linear predictor or for some subset of them (via the argument `coefs`).

Usage

```

## S3 method for class 'zeroinflation'
cooks.distance(
  model,
  submodel = c("counts", "zeros", "full"),
  plot.it = FALSE,
  coefs,
  identify,
  ...
)

```

Arguments

`model` an object of class *zeroinflation*.

<code>submodel</code>	an (optional) character string which allows to specify the model: "counts", "zeros" or "full". By default, <code>submodel</code> is set to "counts".
<code>plot.it</code>	an (optional) logical indicating if the plot is required or just the data matrix in which that plot is based. As default, <code>plot.it</code> is set to FALSE.
<code>coefs</code>	an (optional) character string which (partially) match with the names of some model parameters.
<code>identify</code>	an (optional) integer indicating the number of individuals to identify on the plot of the Cook's distance. This is only appropriate if <code>plot.it=TRUE</code> .
<code>...</code>	further arguments passed to or from other methods. If <code>plot.it=TRUE</code> then <code>...</code> may be used to include graphical parameters to customize the plot. For example, <code>col</code> , <code>pch</code> , <code>cex</code> , <code>main</code> , <code>sub</code> , <code>xlab</code> , <code>ylab</code> .

Details

The Cook's distance consists of the *distance* between two estimates of the parameters in the linear predictor using a metric based on the (estimate of the) variance-covariance matrix. The first one set of estimates is computed from a dataset including all individuals, and the second one is computed from a dataset in which the *i*-th individual is excluded. To avoid computational burden, the second set of estimates is replaced by its *one-step approximation*. See the [dfbeta.zeroinflation](#) documentation.

Value

A matrix as many rows as individuals in the sample and one column with the values of the Cook's distance.

Examples

```
##### Example 1: Self diagnosed ear infections in swimmers
data(swimmers)
fit <- zeroinf(infections ~ frequency + location, family="nb1(log)", data=swimmers)

### Cook's distance for all parameters in the "counts" model
cooks.distance(fit, submodel="counts", plot.it=TRUE, col="red", lty=1, lwd=1,
               col.lab="blue", col.axis="blue", col.main="black", family="mono", cex=0.8)

### Cook's distance for all parameters in the "zeros" model
cooks.distance(fit, submodel="zeros", plot.it=TRUE, col="red", lty=1, lwd=1,
               col.lab="blue", col.axis="blue", col.main="black", family="mono", cex=0.8)
```

Description

The amount of hormone contained in a preparation cannot be measured directly, so estimating an unknown dose of hormone involves a two-step process. A calibration curve must first be established, then the curve must be inverted to determine the hormone dose. The calibration curve is estimated using a radioimmunological assay.

Usage

```
data(Cortisol)
```

Format

A data frame with 64 rows and 2 variables:

IDose a numeric vector indicating the logarithm in base 10 of the dose.

Y a numeric vector indicating the response, in counts per minute.

References

Huet S., Bouvier A., Poursat M.-A., Jolivet E. (2004). *Statistical tools for nonlinear regression : a practical guide with S-PLUS and R examples. 2nd Edition.* Springer, New York.

Examples

```
data(Cortisol)
dev.new()
with(Cortisol, plot(lDose,Y,xlab="Log10(Dose, in ng/0.1 ml)",pch=16,col="blue",
                  ylab="Response, in counts per minute"))
```

coupons

Discount coupons

Description

The market research department of a soft drink manufacturer is investigating the effectiveness of a price discount coupon on the purchase of a two-litre beverage product. A sample of 5500 costumers received coupons for varying price discounts between 5 and 25 cents. The main objective of the analysis is to determine if the price discount affects the proportion of redeemed coupons after one month.

Usage

```
data(coupons)
```

Format

A data frame with 11 rows and 3 variables:

discounts a numeric vector indicating the price discount, in cents.

costumers a numeric vector indicating the number of customers who received coupons.

redeemed a numeric vector indicating the number of redeemed coupons.

References

Montgomery D.C., Peck E.A., Vining G. (2012, page 464) *Introduction to linear regression analysis. 5th ed.* Berlin, Wiley.

Examples

```
dev.new()
data(coupons)
barplot(100*redeemed/costumers ~ discounts, data=coupons, xlab="Discount price",
        ylab="(%) Redeemed coupons", col="blue")
```

depression

Treatment for severe postnatal depression

Description

These data arose from a study on the efficacy of oestrogen given transdermally for the treatment of severe postnatal depression. Women with major depression were randomly assigned to a placebo control group or an oestrogen patch group. Prior to the treatment all women were assessed by self-rated depressive symptoms on the Edinburgh Postnatal Depression Scale (EPDS). EPDS data were collected monthly for six months once treatment began. Higher EDPS scores are indicative of higher depression levels.

Usage

```
data(depression)
```

Format

A data frame with 427 rows and 5 variables:

subj a numeric vector giving the identifier of each woman.

group a factor giving the received treatment: "placebo" or "oestrogen".

visit a numeric vector giving the number of months since the treatment began, where -1 indicates the pretreatment assessment of the EDPS.

dep a numeric vector giving the value of the EDPS.

depressd a numeric vector coded as 1 when the value of the EDPS is greater than or equal to 11 and coded as 0 in other cases.

Source

<https://stats.oarc.ucla.edu/spss/library/spss-librarypanel-data-analysis-using-gee/>

References

Gregoire A.J.P., Kumar R., Everitt B., Henderson A.F., Studd J.W.W. (1996) Transdermal oestrogen for treatment of severe postnatal depression, *The Lancet* 347:930-933.

Examples

```
data(depression)
dev.new()
boxplot(dep ~ visit, data=subset(depression,group=="placebo"), at=c(0:6) - 0.2,
        col="yellow", boxwex=0.3, xaxt="n", ylim=range(na.omit(depression$dep)),
        xlab="Months since the treatment began", ylab="EDPS")
boxplot(dep ~ visit, data=subset(depression,group=="oestrogen"), add=TRUE,
        at=c(0:6) + 0.2, col="blue", boxwex=0.3, xaxt="n")
axis(1, at=c(0:6), labels=c(-1,1:6))
legend("bottomleft", legend=c("placebo","oestrogen"), fill=c("yellow","blue"),
       title="Treatment", bty="n")
```

dfbeta.glmgee

Dfbeta for Generalized Estimating Equations

Description

Produces an approximation, better known as the *one-step approximation*, of the effect on the parameter estimates of deleting each cluster/observation in turn. This function also can produce an index plot of the Dfbeta Statistic for some parameters via the argument `coefs`.

Usage

```
## S3 method for class 'glmgee'
dfbeta(
  model,
  level = c("clusters", "observations"),
  method = c("Preisser-Qaqish", "full"),
  coefs,
  identify,
  ...
)
```

Arguments

model	an object of class <i>glmgee</i> .
level	an (optional) character string indicating the level for which the Dfbeta statistic is required. The options are: cluster-level ("clusters") and observation-level ("observations"). As default, level is set to "clusters".
method	an (optional) character string indicating the method of calculation for the <i>one-step approximation</i> . The options are: the <i>one-step approximation</i> described by Preisser and Qaqish (1996) in which the working-correlation matrix is assumed to be known ("Preisser-Qaqish"); and the "authentic" <i>one-step approximation</i> ("full"). As default, method is set to "Preisser-Qaqish".
coefs	an (optional) character string which (partially) match with the names of some parameters in the linear predictor.
identify	an (optional) integer indicating the number of clusters/observations to identify on the plot of the Dfbeta statistic. This is only appropriate if coefs is specified.
...	further arguments passed to or from other methods. If coefs is specified then ... may be used to include graphical parameters to customize the plot. For example, col, pch, cex, main, sub, xlab, ylab.

Details

The *one-step approximation* (with the method "full") of the estimates of the parameters in the linear predictor of a GEE when the i -th cluster is excluded from the dataset is given by the vector obtained as the result of the first iteration of the fitting algorithm of that GEE when it is performed using: (1) a dataset in which the i -th cluster is excluded; and (2) a starting value which is the solution to the same GEE but based on the dataset including all clusters.

Value

A matrix with so many rows as clusters/observations in the sample and so many columns as parameters in the linear predictor. For clusters, the i -th row of that matrix corresponds to the difference between the estimates of the parameters in the linear predictor using all clusters and the *one-step approximation* of those estimates when the i -th cluster is excluded from the dataset.

References

- Pregibon D. (1981). Logistic regression diagnostics. *The Annals of Statistics* 9, 705-724.
- Preisser J.S., Qaqish B.F. (1996) Deletion diagnostics for generalised estimating equations. *Biometrika* 83:551–562.
- Hammill B.G., Preisser J.S. (2006) A SAS/IML software program for GEE and regression diagnostics. *Computational Statistics & Data Analysis* 51:1197-1212.
- Vanegas L.H., Rondon L.M., Paula G.A. (2023) Generalized Estimating Equations using the new R package glmtoolbox. *The R Journal* 15:105-133.

Examples

```
##### Example 1: Effect of ozone-enriched atmosphere on growth of sitka spruces
data(spruces)
mod1 <- size ~ poly(days,4) + treat
fit1 <- glmgee(mod1, id=tree, family=Gamma(log), corstr="AR-M-dependent", data=spruces)
dfbs1 <- dfbeta(fit1, method="full", coefs="treat", col="red", lty=1, lwd=1, col.lab="blue",
               col.axis="blue", col.main="black", family="mono", cex=0.8, main="treat")

### Calculation by hand of dfbeta for the tree labeled by "N1T01"
onestep1 <- glmgee(mod1, id=tree, family=Gamma(log), corstr="AR-M-dependent",
                  data=spruces, start=coef(fit1), subset=c(tree!="N1T01"), maxit=1)

coef(fit1)-coef(onestep1)
dfbs1[rownames(dfbs1)=="N1T01",]

##### Example 2: Treatment for severe postnatal depression
data(depression)
mod2 <- depressd ~ visit + group
fit2 <- glmgee(mod2, id=subj, family=binomial(logit), corstr="AR-M-dependent",
               data=depression)

dfbs2 <- dfbeta(fit2, method="full", coefs="group", col="red", lty=1, lwd=1, col.lab="blue",
               col.axis="blue", col.main="black", family="mono", cex=0.8, main="group")

### Calculation by hand of dfbeta for the woman labeled by "18"
onestep2 <- glmgee(mod2, id=subj, family=binomial(logit), corstr="AR-M-dependent",
                  data=depression, start=coef(fit2), subset=c(subj!=18), maxit=1)

coef(fit2)-coef(onestep2)
dfbs2[rownames(dfbs2)=="18",]

##### Example 3: Treatment for severe postnatal depression (2)
mod3 <- dep ~ visit*group
fit3 <- glmgee(mod3, id=subj, family=gaussian(identity), corstr="AR-M-dependent",
               data=depression)

dfbs3 <- dfbeta(fit3, method="full", coefs="visit:group", col="red", lty=1, lwd=1, col.lab="blue",
               col.axis="blue", col.main="black", family="mono", cex=0.8, main="visit:group")

### Calculation by hand of dfbeta for the woman labeled by "18"
onestep3 <- glmgee(mod3, id=subj, family=gaussian(identity), corstr="AR-M-dependent",
                  data=depression, start=coef(fit3), subset=c(subj!=18), maxit=1)

coef(fit3)-coef(onestep3)
dfbs3[rownames(dfbs3)=="18",]
```

Description

Calculates an approximation of the parameter estimates that would be produced by deleting each case in turn, which is known as the *one-step approximation*. Additionally, the function can produce an index plot of the Dfbeta statistic for some parameter specified by the argument `coefs`.

Usage

```
## S3 method for class 'gnm'
dfbeta(model, coefs, identify, ...)
```

Arguments

<code>model</code>	an object of class <i>gnm</i> .
<code>coefs</code>	an (optional) character string which (partially) match with the names of some model parameters.
<code>identify</code>	an (optional) integer indicating the number of individuals to identify on the plot of the Dfbeta statistic. This is only appropriate if <code>coefs</code> is specified.
<code>...</code>	further arguments passed to or from other methods. If <code>plot.it=TRUE</code> then <code>...</code> may be used to include graphical parameters to customize the plot. For example, <code>col</code> , <code>pch</code> , <code>cex</code> , <code>main</code> , <code>sub</code> , <code>xlab</code> , <code>ylab</code> .

Details

The *one-step approximation* of the parameters estimates when the *i*-th case is excluded from the dataset consists of the vector obtained as a result of the first iteration of the Fisher Scoring algorithm when it is performed using: (1) a dataset in which the *i*-th case is excluded; and (2) a starting value that is the estimate of the same model but based on the dataset including all cases.

Value

A matrix with as many rows as cases in the sample and as many columns as parameters in the linear predictor. The *i*-th row in that matrix corresponds to the difference between the parameters estimates obtained using all cases and the *one-step approximation* of those estimates when excluding the *i*-th case from the dataset.

References

Pregibon D. (1981). Logistic regression diagnostics. *The Annals of Statistics*, 9, 705-724.
 Wei B.C. (1998). *Exponential Family Nonlinear Models*. Springer, Singapore.

Examples

```
##### Example 1: The effects of fertilizers on coastal Bermuda grass
data(Grass)
fit1 <- gnm(Yield ~ b0 + b1/(Nitrogen + a1) + b2/(Phosphorus + a2) + b3/(Potassium + a3),
          family=gaussian(inverse), start=c(b0=0.1,b1=13,b2=1,b3=1,a1=45,a2=15,a3=30), data=Grass)

fit1a <- update(fit1, subset=-c(1), start=coef(fit1), maxit=1)
coef(fit1) - coef(fit1a)
```

```

dfbetas <- dfbeta(fit1)
round(dfbetas[1,],5)

##### Example 2: Assay of an Insecticide with a Synergist
data(Melanopus)
fit2 <- gnm(Killed/Exposed ~ b0 + b1*log(Insecticide-a1) + b2*Synergist/(a2 + Synergist),
            family=binomial(logit), weights=Exposed, start=c(b0=-3,b1=1.2,a1=1.7,b2=1.7,a2=2),
            data=Melanopus)

fit2a <- update(fit2, subset=-c(2), start=coef(fit2), maxit=1)
coef(fit2) - coef(fit2a)

dfbetas <- dfbeta(fit2)
round(dfbetas[2,],5)

##### Example 3: Developmental rate of Drosophila melanogaster
data(Drosophila)
fit3 <- gnm(Duration ~ b0 + b1*Temp + b2/(Temp-a), family=Gamma(log),
            start=c(b0=3,b1=-0.25,b2=-210,a=55), weights=Size, data=Drosophila)

fit3a <- update(fit3, subset=-c(3), start=coef(fit3), maxit=1)
coef(fit3) - coef(fit3a)

dfbetas <- dfbeta(fit3)
round(dfbetas[3,],5)

##### Example 4: Radioimmunological Assay of Cortisol
data(Cortisol)
fit4 <- gnm(Y ~ b0 + (b1-b0)/(1 + exp(b2+ b3*lDose))^b4, family=Gamma(identity),
            start=c(b0=130,b1=2800,b2=3,b3=3,b4=0.5), data=Cortisol)

fit4a <- update(fit4, subset=-c(4), start=coef(fit4), maxit=1)
coef(fit4) - coef(fit4a)

dfbetas <- dfbeta(fit4)
round(dfbetas[4,],5)

```

dfbeta.overglm

Dfbeta statistic for alternatives to the Poisson and Binomial Regression Models under the presence of Overdispersion.

Description

Produces an approximation, better known as the *one-step approximation*, of the effect on the parameter estimates of deleting each individual in turn. This function also can produce an index plot of the Dfbeta statistic for some parameter chosen via the argument `coefs`.

Usage

```
## S3 method for class 'overglm'
dfbeta(model, coefs, identify, ...)
```

Arguments

model	an object of class <i>overglm</i> .
coefs	an (optional) character string which (partially) match with the names of some model parameters.
identify	an (optional) integer indicating the number of individuals to identify on the plot of the Dfbeta statistic. This is only appropriate if coefs is specified.
...	further arguments passed to or from other methods. If <code>plot.it=TRUE</code> then ... may be used to include graphical parameters to customize the plot. For example, <code>col</code> , <code>pch</code> , <code>cex</code> , <code>main</code> , <code>sub</code> , <code>xlab</code> , <code>ylab</code> .

Details

The *one-step approximation* of the estimates of the parameters when the i -th individual is excluded from the dataset consists of the vector obtained as result of the first iteration of the Newton-Raphson algorithm when it is performed using: (1) a dataset in which the i -th individual is excluded; and (2) a starting value which is the estimate of the same model but based on the dataset including all individuals.

Value

A matrix with so many rows as individuals in the sample and so many columns as parameters in the linear predictor. The i -th row of that matrix corresponds to the difference between the estimates of the parameters in the linear predictor using all individuals and the *one-step approximation* of those estimates when the i -th individual is excluded from the dataset.

References

Pregibon D. (1981). Logistic regression diagnostics. *The Annals of Statistics*, 9, 705-724.

Examples

```
##### Example 1: Self diagnosed ear infections in swimmers
data(swimmers)
fit1 <- overglm(infections ~ frequency + location, family="nb1(log)", data=swimmers)
dfbeta(fit1, coefs="frequency", col="red", lty=1, lwd=1, col.lab="blue",
       col.axis="blue", col.main="black", family="mono", cex=0.8, main="frequency")

##### Example 2: Article production by graduate students in biochemistry PhD programs
bioChemists <- pscl::bioChemists
fit2 <- overglm(art ~ fem + kid5 + ment, family="nb1(log)", data = bioChemists)
dfbeta(fit2, coefs="fem", col="red", lty=1, lwd=1, col.lab="blue",
       col.axis="blue", col.main="black", family="mono", cex=0.8, main="fem")

##### Example 3: Agents to stimulate cellular differentiation
```

```
data(cellular)
fit3 <- overglm(cbind(cells,200-cells) ~ tnf + ifn, family="bb(logit)", data=cellular)
dfbeta(fit3, coefs="tnf", col="red", lty=1, lwd=1, col.lab="blue",
       col.axis="blue", col.main="black", family="mono", cex=0.8, main="tnf")
```

dfbeta.zeroinflation *Dfbeta statistic for Regression Models to deal with Zero-Excess in Count Data*

Description

Produces an approximation, better known as the *one-step approximation*, of the effect on the parameter estimates of deleting each individual in turn. This function also can produce an index plot of the Dfbeta statistic for some parameter chosen via the argument `coefs`.

Usage

```
## S3 method for class 'zeroinflation'
dfbeta(model, submodel = c("counts", "zeros"), coefs, identify, ...)
```

Arguments

<code>model</code>	an object of class <i>zeroinflation</i> .
<code>submodel</code>	an (optional) character string which allows to specify the model: "counts" or "zeros". By default, <code>submodel</code> is set to "counts".
<code>coefs</code>	an (optional) character string which (partially) match with the names of some model parameters.
<code>identify</code>	an (optional) integer indicating the number of individuals to identify on the plot of the Dfbeta statistic. This is only appropriate if <code>coefs</code> is specified.
<code>...</code>	further arguments passed to or from other methods. If <code>plot.it=TRUE</code> then <code>...</code> may be used to include graphical parameters to customize the plot. For example, <code>col</code> , <code>pch</code> , <code>cex</code> , <code>main</code> , <code>sub</code> , <code>xlab</code> , <code>ylab</code> .

Details

The *one-step approximation* of the estimates of the parameters when the i -th individual is excluded from the dataset consists of the vector obtained as result of the first iteration of the Newton-Raphson algorithm when it is performed using: (1) a dataset in which the i -th individual is excluded; and (2) a starting value which is the estimate of the same model but based on the dataset including all individuals.

Value

A matrix with so many rows as individuals in the sample and so many columns as parameters in the linear predictor. The i -th row of that matrix corresponds to the difference between the estimates of the parameters in the linear predictor using all individuals and the *one-step approximation* of those estimates when the i -th individual is excluded from the dataset.

References

Pregibon D. (1981). Logistic regression diagnostics. *The Annals of Statistics*, 9, 705-724.

Examples

```
##### Example 1: Self diagnosed ear infections in swimmers
data(swimmers)
fit <- zeroinf(infections ~ frequency + location, family="nb1(log)", data=swimmers)

dfbeta(fit, submodel="counts", coefs="frequency", col="red", lty=1, lwd=1,
        col.lab="blue", col.axis="blue", col.main="black", family="mono", cex=0.8)

dfbeta(fit, submodel="zeros", coefs="location", col="red", lty=1, lwd=1,
        col.lab="blue", col.axis="blue", col.main="black", family="mono", cex=0.8)
```

dilution

Dilution Assay

Description

These data are counts of virus particles at 5 different dilutions. There are 4 replicate counts at each dilution except the last for which there are 5 counts. The aim is to estimate the expected number of virus particles per unit volume.

Usage

```
data(dilution)
```

Format

A data frame with 21 rows and 2 variables:

Count a numeric vector indicating the count of virus particles.

Dilution a numeric vector indicating the dilution volume.

Source

https://sada2013.sciencesconf.org/16138/glmSession4_Cotonou.pdf

Examples

```
data(dilution)
xlab <- "Dilution volume"
ylab <- "Count of virus particles"
dev.new()
with(dilution,plot(Dilution,Count,pch=20,xlab=xlab,ylab=ylab))
```

Drosophila

Developmental rate of Drosophila melanogaster

Description

Drosophila melanogaster developmental stages were monitored as part of an experiment to determine the effect of temperature on their duration. The eggs were laid at approximately 25 degrees Celsius and remained at that temperature for 20-30 minutes. The eggs were then brought to the experimental temperature, which remained constant throughout the experiment.

Usage

```
data(Drosophila)
```

Format

A data frame with 23 rows and 3 variables:

Temp a numeric vector indicating the temperature, in degrees Celsius.

Duration a numeric vector indicating the average duration of the embryonic period, in hours, measured from the time at which the eggs were laid.

Size a numeric vector indicating how many eggs each batch contained.

References

Powsner L. (1935) The effects of temperature on the durations of the developmental stages of *Drosophila melanogaster*. *Physiological Zoology*, 8, 474-520.

McCullagh P., Nelder J.A. (1989). *Generalized Linear Models. 2nd Edition*. Chapman and Hall, London.

Wei B.C. (1998). *Exponential Family Nonlinear Models*. Springer, Singapore.

Examples

```
data(Drosophila)
dev.new()
with(Drosophila, plot(Temp,Duration,xlab="Temperature, in degrees Celsius",pch=16,col="blue",
                     ylab="Average duration of the embryonic period"))
```

envelope	<i>Normal QQ-plot with simulated envelope of model residuals</i>
----------	--

Description

Generic function for building a normal QQ-plot with simulated envelope of residuals obtained from a fitted model.

Usage

```
envelope(object, ...)
```

Arguments

object	a fitted model object.
...	further arguments passed to or from other methods.

Value

A matrix with the simulated envelope and, optionally, a plot of it.

envelope.glm	<i>Normal QQ-plot with simulated envelope of residuals in Generalized Linear Models</i>
--------------	---

Description

Produces a normal QQ-plot with simulated envelope of residuals for generalized linear models.

Usage

```
## S3 method for class 'glm'
envelope(
  object,
  rep = 25,
  conf = 0.95,
  type = c("quantile", "deviance", "pearson"),
  standardized = FALSE,
  plot.it = TRUE,
  identify,
  ...
)
```

Arguments

<code>object</code>	an object of the class <i>glm</i> .
<code>rep</code>	an (optional) positive integer which allows to specify the number of replicates which should be used to build the simulated envelope. As default, <code>rep</code> is set to 25.
<code>conf</code>	an (optional) value in the interval (0,1) indicating the confidence level which should be used to build the pointwise confidence intervals, which form the envelope. As default, <code>conf</code> is set to 0.95.
<code>type</code>	an (optional) character string indicating the type of residuals which should be used. The available options are: randomized quantile ("quantile"), deviance ("deviance") and pearson ("pearson") residuals. As default, <code>type</code> is set to "quantile".
<code>standardized</code>	an (optional) logical switch indicating if the residuals should be standardized by dividing by the square root of $(1 - h)$, where h is a measure of leverage. As default, <code>standardized</code> is set to FALSE.
<code>plot.it</code>	an (optional) logical switch indicating if the normal QQ-plot with simulated envelope of residuals is required or just the data matrix in which it is based. As default, <code>plot.it</code> is set to TRUE.
<code>identify</code>	an (optional) positive integer indicating the number of individuals to identify on the QQ-plot with simulated envelope of residuals. This is only appropriate if <code>plot.it=TRUE</code> .
<code>...</code>	further arguments passed to or from other methods. If <code>plot.it=TRUE</code> then <code>...</code> may be used to include graphical parameters to customize the plot. For example, <code>col</code> , <code>pch</code> , <code>cex</code> , <code>main</code> , <code>sub</code> , <code>xlab</code> , <code>ylab</code> .

Details

In order to construct the simulated envelope, `rep` independent realizations of the response variable for each individual are simulated, which is done by considering (1) the model assumption about the distribution of the response variable; (2) the estimation of the linear predictor parameters; and (3) the estimation of the dispersion parameter. Each time, the vector of observed responses is replaced with one of the simulated samples, re-fitting the interest model `rep` times. For each $i = 1, 2, \dots, n$, where n is the number of individuals in the sample, the i -th order statistic of the `type`-type residuals is computed and then sorted for each replicate, giving a random sample of size `rep` of the i -th order statistic. In other words, the simulated envelope is comprised of the quantiles $(1 - \text{conf})/2$ and $(1 + \text{conf})/2$ of the random sample of size `rep` of the i -th order statistic of the `type`-type residuals for $i = 1, 2, \dots, n$.

Value

A matrix with the following four columns:

<code>Lower limit</code>	the quantile $(1 - \text{conf})/2$ of the random sample of size <code>rep</code> of the i -th order statistic of the <code>type</code> -type residuals for $i = 1, 2, \dots, n$,
<code>Median</code>	the quantile 0.5 of the random sample of size <code>rep</code> of the i -th order

- statistic of the type-type residuals for $i = 1, 2, \dots, n$,
- Upper limit the quantile $(1 + \text{conf})/2$ of the random sample of size rep of the i -th order statistic of the type-type residuals for $i = 1, 2, \dots, n$,
- Residuals the observed type-type residuals,

References

- Atkinson A.C. (1985) *Plots, Transformations and Regression*. Oxford University Press, Oxford.
- Davison A.C., Gigli A. (1989) Deviance Residuals and Normal Scores Plots. *Biometrika* 76, 211-221.
- Dunn P.K., Smyth G.K. (1996) Randomized Quantile Residuals. *Journal of Computational and Graphical Statistics* 5, 236-244.
- Pierce D.A., Schafer D.W. (1986) Residuals in Generalized Linear Models. *Journal of the American Statistical Association* 81, 977-986.
- Wei B.C. (1998). *Exponential Family Nonlinear Models*. Springer, Singapore.

See Also

[envelope.lm](#), [envelope.gnm](#), [envelope.overglm](#)

Examples

```
##### Example 1:
burn1000 <- aplore3::burn1000
burn1000 <- within(burn1000, death <- factor(death, levels=c("Dead","Alive")))
fit1 <- glm(death ~ age*inh_inj + tbsa*inh_inj, family=binomial("logit"), data=burn1000)
envelope(fit1, rep=50, conf=0.95, type="pearson", col="red", pch=20, col.lab="blue",
         col.axis="blue", col.main="black", family="mono", cex=0.8)

##### Example 2: Fuel consumption of automobiles
Auto <- ISLR::Auto
fit2 <- glm(mpg ~ horsepower*weight, family=inverse.gaussian("log"), data=Auto)
envelope(fit2, rep=50, conf=0.95, type="pearson", col="red", pch=20, col.lab="blue",
         col.axis="blue", col.main="black", family="mono", cex=0.8)

##### Example 3: Skin cancer in women
data(skincancer)
fit3 <- glm(cases ~ city + ageC, offset=log(population), family=poisson, data=skincancer)
envelope(fit3, rep=100, conf=0.95, type="quantile", col="red", pch=20, col.lab="blue",
         col.axis="blue", col.main="black", family="mono", cex=0.8)

##### Example 4: Self diagnosed ear infections in swimmers
data(swimmers)
fit4 <- glm(infections ~ frequency + location, family=poisson(log), data=swimmers)
envelope(fit4, rep=100, conf=0.95, type="quantile", col="red", pch=20, col.lab="blue",
         col.axis="blue", col.main="black", family="mono", cex=0.8)
```

```
##### Example 5: Agents to stimulate cellular differentiation
data(cellular)
fit5 <- glm(cbind(cells,200-cells) ~ tnf + ifn, family=binomial(logit), data=cellular)
envelope(fit5, rep=100, conf=0.95, type="quantile", col="red", pch=20, col.lab="blue",
         col.axis="blue", col.main="black", family="mono", cex=0.8)
```

envelope.gnm	<i>Normal QQ-plot with simulated envelope of residuals in Generalized Nonlinear Models</i>
--------------	--

Description

Produces a normal QQ-plot with simulated envelope of residuals for generalized nonlinear models.

Usage

```
## S3 method for class 'gnm'
envelope(
  object,
  rep = 25,
  conf = 0.95,
  type = c("quantile", "deviance", "pearson"),
  standardized = FALSE,
  plot.it = TRUE,
  identify,
  ...
)
```

Arguments

object	an object of the class <i>gnm</i> .
rep	an (optional) positive integer which allows to specify the number of replicates which should be used to build the simulated envelope. As default, rep is set to 25.
conf	an (optional) value in the interval (0,1) indicating the confidence level which should be used to build the pointwise confidence intervals, which form the envelope. As default, conf is set to 0.95.
type	a character string indicating the type of residuals which should be used. The available options are: randomized quantile ("quantile"), deviance ("deviance") and pearson ("pearson") residuals. As default, type is set to "quantile".
standardized	an (optional) logical switch indicating if the residuals should be standardized by dividing by the square root of $(1 - h)$, where h is a measure of leverage. As default, standardized is set to FALSE.
plot.it	an (optional) logical switch indicating if the normal QQ-plot with simulated envelope of residuals is required or just the data matrix in which it is based. As default, plot.it is set to TRUE.

identify	an (optional) positive integer indicating the number of individuals to identify on the QQ-plot with simulated envelope of residuals. This is only appropriate if <code>plot.it=TRUE</code> .
...	further arguments passed to or from other methods. If <code>plot.it=TRUE</code> then ... may be used to include graphical parameters to customize the plot. For example, <code>col</code> , <code>pch</code> , <code>cex</code> , <code>main</code> , <code>sub</code> , <code>xlab</code> , <code>ylab</code> .

Details

In order to construct the simulated envelope, `rep` independent realizations of the response variable for each individual are simulated, which is done by considering (1) the model assumption about the distribution of the response variable; (2) the estimation of the "linear" predictor parameters; and (3) the estimation of the dispersion parameter. Each time, the vector of observed responses is replaced with one of the simulated samples, re-fitting the interest model `rep` times. For each $i = 1, 2, \dots, n$, where n is the number of individuals in the sample, the i -th order statistic of the type-type residuals is computed and then sorted for each replicate, giving a random sample of size `rep` of the i -th order statistic. In other words, the simulated envelope is comprised of the quantiles $(1 - \text{conf})/2$ and $(1 + \text{conf})/2$ of the random sample of size `rep` of the i -th order statistic of the type-type residuals for $i = 1, 2, \dots, n$.

Value

A matrix with the following four columns:

Lower limit	the quantile $(1 - \text{conf})/2$ of the random sample of size <code>rep</code> of the i -th order statistic of the type-type residuals for $i = 1, 2, \dots, n$,
Median	the quantile 0.5 of the random sample of size <code>rep</code> of the i -th order statistic of the type-type residuals for $i = 1, 2, \dots, n$,
Upper limit	the quantile $(1 + \text{conf})/2$ of the random sample of size <code>rep</code> of the i -th order statistic of the type-type residuals for $i = 1, 2, \dots, n$,
Residuals	the observed type-type residuals,

References

- Atkinson A.C. (1985) *Plots, Transformations and Regression*. Oxford University Press, Oxford.
- Davison A.C., Gigli A. (1989) Deviance Residuals and Normal Scores Plots. *Biometrika* 76, 211-221.
- Dunn P.K., Smyth G.K. (1996) Randomized Quantile Residuals. *Journal of Computational and Graphical Statistics* 5, 236-244.
- Pierce D.A., Schafer D.W. (1986) Residuals in Generalized Linear Models. *Journal of the American Statistical Association* 81, 977-986.
- Wei B.C. (1998). *Exponential Family Nonlinear Models*. Springer, Singapore.

See Also

[envelope.lm](#), [envelope.overglm](#)

Examples

```
##### Example 1: The effects of fertilizers on coastal Bermuda grass
data(Grass)
fit1 <- gnm(Yield ~ b0 + b1/(Nitrogen + a1) + b2/(Phosphorus + a2) + b3/(Potassium + a3),
           family=gaussian(inverse), start=c(b0=0.1,b1=13,b2=1,b3=1,a1=45,a2=15,a3=30), data=Grass)

#envelope(fit1, rep=50, conf=0.95, type="quantile", col="red", pch=20, col.lab="blue",
#         col.axis="blue", col.main="black", family="mono", cex=0.8)

##### Example 2: Assay of an Insecticide with a Synergist
data(Melanopus)
fit2 <- gnm(Killed/Exposed ~ b0 + b1*log(Insecticide-a1) + b2*Synergist/(a2 + Synergist),
           family=binomial(logit), weights=Exposed, start=c(b0=-3,b1=1.2,a1=1.7,b2=1.7,a2=2),
           data=Melanopus)

#envelope(fit2, rep=50, conf=0.95, type="pearson", col="red", pch=20, col.lab="blue",
#         col.axis="blue", col.main="black", family="mono", cex=0.8)

##### Example 3: Developmental rate of Drosophila melanogaster
data(Drosophila)
fit3 <- gnm(Duration ~ b0 + b1*Temp + b2/(Temp-a), family=Gamma(log),
           start=c(b0=3,b1=-0.25,b2=-210,a=55), weights=Size, data=Drosophila)

#envelope(fit3, rep=50, conf=0.95, type="quantile", col="red", pch=20, col.lab="blue",
#         col.axis="blue", col.main="black", family="mono", cex=0.8)

##### Example 4: Radioimmunological Assay of Cortisol
data(Cortisol)
fit4 <- gnm(Y ~ b0 + (b1-b0)/(1 + exp(b2+ b3*1Dose))^b4, family=Gamma(identity),
           start=c(b0=130,b1=2800,b2=3,b3=3,b4=0.5), data=Cortisol)

#envelope(fit4, rep=50, conf=0.95, type="quantile", col="red", pch=20, col.lab="blue",
#         col.axis="blue", col.main="black", family="mono", cex=0.8)
```

envelope.lm

Normal QQ-plot with simulated envelope of residuals for normal linear models

Description

Produces a normal QQ-plot with simulated envelope of residuals obtained from the fit of a normal linear model.

Usage

```
## S3 method for class 'lm'
envelope(
  object,
  rep = 100,
  conf = 0.95,
  type = c("external", "internal"),
  plot.it = TRUE,
  identify,
  ...
)
```

Arguments

<code>object</code>	an object of the class <i>lm</i> .
<code>rep</code>	an (optional) positive integer indicating the number of replicates which should be used to build the simulated envelope. As default, <code>rep</code> is set to 100.
<code>conf</code>	an (optional) value in the interval (0,1) indicating the confidence level which should be used to build the pointwise confidence intervals, which form the envelope. As default, <code>conf</code> is set to 0.95.
<code>type</code>	a character string indicating the type of residuals which should be used. The available options are: internally Studentized ("internal") and externally Studentized ("external") residuals. See Cook and Weisberg (1982, pages 18-20).
<code>plot.it</code>	an (optional) logical switch indicating if the normal QQ-plot with simulated envelope of residuals is required or just the data matrix in which it is based. As default, <code>plot.it</code> is set to TRUE.
<code>identify</code>	an (optional) positive integer value indicating the number of individuals to identify on the QQ-plot with simulated envelope of residuals. This is only appropriate if <code>plot.it=TRUE</code> .
<code>...</code>	further arguments passed to or from other methods. If <code>plot.it=TRUE</code> then <code>...</code> may be used to include graphical parameters to customize the plot. For example, <code>col</code> , <code>pch</code> , <code>cex</code> , <code>main</code> , <code>sub</code> , <code>xlab</code> , <code>ylab</code> .

Details

The simulated envelope is built by simulating `rep` independent realizations of the response variable for each individual, which is accomplished taking into account the following: (1) the model assumption about the distribution of the response variable; (2) the estimates of the parameters in the linear predictor; and (3) the estimate of the dispersion parameter. The interest model is re-fitted `rep` times, as each time the vector of observed responses is replaced by one of the simulated samples. The type-type residuals are computed and then sorted for each replicate, so that for each $i = 1, 2, \dots, n$, where n is the number of individuals in the sample, there is a random sample of size `rep` of the i -th order statistic of the type-type residuals. Therefore, the simulated envelope is composed of the quantiles $(1 - \text{conf})/2$ and $(1 + \text{conf})/2$ of the random sample of size `rep` of the i -th order statistic of the type-type residuals for $i = 1, 2, \dots, n$.

Value

A matrix with the following four columns:

Lower limit	the quantile $(1 - \text{conf})/2$ of the random sample of size rep of the i -th order statistic of the type-type residuals for $i = 1, 2, \dots, n$,
Median	the quantile 0.5 of the random sample of size rep of the i -th order statistic of the type-type residuals for $i = 1, 2, \dots, n$,
Upper limit	the quantile $(1 + \text{conf})/2$ of the random sample of size rep of the i -th order statistic of the type-type residuals for $i = 1, 2, \dots, n$,
Residuals	the observed type-type residuals,

References

Atkinson A.C. (1985) *Plots, Transformations and Regression*. Oxford University Press, Oxford.

Cook R.D., Weisberg S. (1982) *Residuals and Influence in Regression*. Chapman and Hall, New York.

See Also

[envelope.glm](#), [envelope.overglm](#)

Examples

```
##### Example 1: Fuel consumption of automobiles
fit1 <- lm(mpg ~ log(hp) + log(wt), data=mtcars)
envelope(fit1, rep=100, conf=0.95, type="external", col="red", pch=20, col.lab="blue",
         col.axis="blue", col.main="black", family="mono", cex=0.8)

##### Example 2: Species richness in plots
data(richness)
fit2 <- lm(Species ~ Biomass + pH + Biomass*pH, data=richness)
envelope(fit2, rep=100, conf=0.95, type="internal", col="red", pch=20, col.lab="blue",
         col.axis="blue", col.main="black", family="mono", cex=0.8)

##### Example 3: Gas consumption in a home before and after insulation
whiteside <- MASS::whiteside
fit3 <- lm(Gas ~ Temp + Insul + Temp*Insul, data=whiteside)
envelope(fit3, rep=100, conf=0.95, type="internal", col="red", pch=20, col.lab="blue",
         col.axis="blue", col.main="black", family="mono", cex=0.8)
```

envelope.overglm	<i>Normal QQ-plot with Simulated Envelope of Residuals for alternatives to the Poisson and Binomial Regression Models under the presence of Overdispersion</i>
------------------	--

Description

Produces a normal QQ-plot with simulated envelope of residuals for regression models based on the negative binomial, beta-binomial, and random-clumped binomial distributions, which are alternatives to the Poisson and binomial regression models under the presence of overdispersion.

Usage

```
## S3 method for class 'overglm'
envelope(
  object,
  rep = 25,
  conf = 0.95,
  type = c("quantile", "response", "standardized"),
  plot.it = TRUE,
  identify,
  ...
)
```

Arguments

object	an object of class <i>overglm</i> .
rep	an (optional) positive integer which allows to specify the number of replicates which should be used to build the simulated envelope. As default, rep is set to 25.
conf	an (optional) value in the interval (0, 1) indicating the confidence level which should be used to build the pointwise confidence intervals, which conform the simulated envelope. As default, conf is set to 0.95.
type	an (optional) character string which allows to specify the required type of residuals. The available options are: (1) the difference between the observed response and the fitted mean ("response"); (2) the standardized difference between the observed response and the fitted mean ("standardized"); and (3) the randomized quantile residual ("quantile"). As default, type is set to "quantile".
plot.it	an (optional) logical switch indicating if the normal QQ-plot with simulated envelope of residuals is required or just the data matrix in which it is based. As default, plot.it is set to TRUE.
identify	an (optional) positive integer value indicating the number of individuals to identify on the QQ-plot with simulated envelope of residuals. This is only appropriate if plot.it=TRUE.
...	further arguments passed to or from other methods. If plot.it=TRUE then ... may be used to include graphical parameters to customize the plot. For example, col, pch, cex, main, sub, xlab, ylab.

Details

The simulated envelope is builded by simulating rep independent realizations of the response variable for each individual, which is accomplished taking into account the following: (1) the model assumption about the distribution of the response variable; (2) the estimates of the parameters in the linear predictor; and (3) the estimate of the dispersion parameter. The interest model is re-fitted rep times, as each time the vector of observed responses is replaced by one of the simulated samples. The type-type residuals are computed and then sorted for each replicate, so that for each $i = 1, 2, \dots, n$, where n is the number of individuals in the sample, there is a random sample of size rep of the i -th order statistic of the type-type residuals. Therefore, the simulated envelope is composed of the quantiles $(1 - \text{conf})/2$ and $(1 + \text{conf})/2$ of the random sample of size rep of the i -th order statistic of the type-type residuals for $i = 1, 2, \dots, n$.

Value

A matrix with the following four columns:

Lower limit	the quantile $(1 - \text{conf})/2$ of the random sample of size rep of the i -th order statistic of the type-type residuals for $i = 1, 2, \dots, n$,
Median	the quantile 0.5 of the random sample of size rep of the i -th order statistic of the type-type residuals for $i = 1, 2, \dots, n$,
Upper limit	the quantile $(1 + \text{conf})/2$ of the random sample of size rep of the i -th order statistic of the type-type residuals for $i = 1, 2, \dots, n$,
Residuals	the observed type-type residuals,

References

- Atkinson A.C. (1985) *Plots, Transformations and Regression*. Oxford University Press, Oxford.
- Dunn P.K., Smyth G.K. (1996) Randomized Quantile Residuals. *Journal of Computational and Graphical Statistics* 5, 236-244.

See Also

[envelope.lm](#), [envelope.glm](#), [envelope.zeroinflation](#)

Examples

```
##### Example 1: Self diagnosed ear infections in swimmers
data(swimmers)
fit1 <- overglm(infections ~ frequency + location, family="nb1(log)", data=swimmers)
envelope(fit1, rep=30, conf=0.95, type="quantile", col="red", pch=20, col.lab="blue",
         col.axis="blue", col.main="black", family="mono", cex=0.8, plot.it=TRUE)

##### Example 2: Article production by graduate students in biochemistry PhD programs
bioChemists <- pscl::bioChemists
fit2 <- overglm(art ~ fem + kid5 + ment, family="nb1(log)", data = bioChemists)
```

```

envelope(fit2, rep=30, conf=0.95, type="quantile", col="red", pch=20, col.lab="blue",
         col.axis="blue", col.main="black", family="mono", cex=0.8, plot.it=TRUE)

##### Example 3: Agents to stimulate cellular differentiation
data(cellular)
fit3 <- overglm(cbind(cells,200-cells) ~ tnf + ifn, family="bb(logit)", data=cellular)
envelope(fit3, rep=30, conf=0.95, type="quantile", col="red", pch=20, col.lab="blue",
         col.axis="blue", col.main="black", family="mono", cex=0.8, plot.it=TRUE)

```

envelope.zeroinflation

Normal QQ-plot with Simulated Envelope of Residuals for Regression Models to deal with Zero-Excess in Count Data

Description

Produces a normal QQ-plot with simulated envelope of residuals for regression models used to deal with zero-excess in count data.

Usage

```

## S3 method for class 'zeroinflation'
envelope(
  object,
  rep = 20,
  conf = 0.95,
  type = c("quantile", "response", "standardized"),
  plot.it = TRUE,
  identify,
  ...
)

```

Arguments

object	an object of the class <i>zeroinflation</i> .
rep	an (optional) positive integer which allows to specify the number of replicates which should be used to build the simulated envelope. As default, rep is set to 25.
conf	an (optional) value in the interval (0,1) indicating the confidence level which should be used to build the pointwise confidence intervals, which conform the simulated envelope. As default, conf is set to 0.95.
type	an (optional) character string which allows to specify the required type of residuals. The available options are: (1) the difference between the observed response and the fitted mean ("response"); (2) the standardized difference between the observed response and the fitted mean ("standardized"); (3) the randomized quantile residual ("quantile"). As default, type is set to "quantile".

<code>plot.it</code>	an (optional) logical switch indicating if the normal QQ-plot with simulated envelope of residuals is required or just the data matrix in which it is based. As default, <code>plot.it</code> is set to TRUE.
<code>identify</code>	an (optional) positive integer value indicating the number of individuals to identify on the QQ-plot with simulated envelope of residuals. This is only appropriate if <code>plot.it=TRUE</code> .
<code>...</code>	further arguments passed to or from other methods. If <code>plot.it=TRUE</code> then <code>...</code> may be used to include graphical parameters to customize the plot. For example, <code>col</code> , <code>pch</code> , <code>cex</code> , <code>main</code> , <code>sub</code> , <code>xlab</code> , <code>ylab</code> .

Details

The simulated envelope is builded by simulating `rep` independent realizations of the response variable for each individual, which is accomplished taking into account the following: (1) the model assumption about the distribution of the response variable; (2) the estimates of the parameters in the linear predictor; and (3) the estimate of the dispersion parameter. The interest model is re-fitted `rep` times, as each time the vector of observed responses is replaced by one of the simulated samples. The type-type residuals are computed and then sorted for each replicate, so that for each $i = 1, 2, \dots, n$, where n is the number of individuals in the sample, there is a random sample of size `rep` of the i -th order statistic of the type-type residuals. Therefore, the simulated envelope is composed of the quantiles $(1 - \text{conf})/2$ and $(1 + \text{conf})/2$ of the random sample of size `rep` of the i -th order statistic of the type-type residuals for $i = 1, 2, \dots, n$.

Value

A matrix with the following four columns:

Lower limit	the quantile $(1 - \text{conf})/2$ of the random sample of size <code>rep</code> of the i -th order statistic of the type-type residuals for $i = 1, 2, \dots, n$,
Median	the quantile 0.5 of the random sample of size <code>rep</code> of the i -th order statistic of the type-type residuals for $i = 1, 2, \dots, n$,
Upper limit	the quantile $(1 + \text{conf})/2$ of the random sample of size <code>rep</code> of the i -th order statistic of the type-type residuals for $i = 1, 2, \dots, n$,
Residuals	the observed type-type residuals.

References

- Atkinson A.C. (1985) *Plots, Transformations and Regression*. Oxford University Press, Oxford.
- Dunn P.K., Smyth G.K. (1996) Randomized Quantile Residuals. *Journal of Computational and Graphical Statistics* 5, 236-244.

See Also

[envelope.lm](#), [envelope.glm](#), [envelope.overglm](#)

Examples

```
##### Example 1: Self diagnosed ear infections in swimmers
data(swimmers)
fit <- zeroinf(infections ~ frequency | location, family="nb1(log)", data=swimmers)
envelope(fit, rep=30, conf=0.95, type="quantile", col="red", pch=20, col.lab="blue",
         col.axis="blue", col.main="black", family="mono", cex=0.8)
```

 estequa

Function to extract estimating equations

Description

Extracts estimating equations evaluated at the parameter estimates and the observed data for a fitted model object.

Usage

```
estequa(object, ...)
```

Arguments

`object` a fitted model object.
`...` further arguments passed to or from other methods.

Value

A vector with the value of the estimating equations evaluated at the parameter estimates and the observed data.

 estequa.glm

Estimating Equations in Generalized Linear Models

Description

Extracts estimating equations evaluated at the parameter estimates and the observed data for a generalized linear model fitted to the data.

Usage

```
## S3 method for class 'glm'
estequa(object, ...)
```

Arguments

object an object of the class `glm` which is obtained from the fit of a generalized linear model.

... further arguments passed to or from other methods.

Value

A vector with the value of the estimating equations evaluated at the parameter estimates and the observed data.

Examples

```
## Example 1
Auto <- ISLR::Auto
mod <- mpg ~ cylinders + displacement + acceleration + origin + horsepower*weight
fit1 <- glm(mod, family=inverse.gaussian("log"), data=Auto)
estequa(fit1)

## Example 2
burn1000 <- aplore3::burn1000
burn1000 <- within(burn1000, death <- factor(death, levels=c("Dead", "Alive")))
mod2 <- death ~ age + gender + race + tbsa + inh_inj + flame + age*inh_inj + tbsa*inh_inj
fit2 <- glm(mod2, family=binomial("logit"), data=burn1000)
estequa(fit2)

## Example 3
data(skincancer)
fit3 <- glm(cases ~ offset(log(population)) + city + age, family=poisson("log"), data=skincancer)
estequa(fit3)
```

estequa.glmgee

Estimating Equations in Generalized Estimating Equations

Description

Extracts estimating equations evaluated at the parameter estimates and the observed data for a generalized estimating equation fitted to the data.

Usage

```
## S3 method for class 'glmgee'
estequa(object, ...)
```

Arguments

object an object of class *glmgee*.

... further arguments passed to or from other methods.

Value

A vector with the value of the estimating equations evaluated at the parameter estimates and the observed data.

Examples

```
##### Example 1: Effect of ozone-enriched atmosphere on growth of sitka spruces
data(spruces)
mod1 <- size ~ poly(days,4) + treat
fit1 <- glmgee(mod1, id=tree, family=Gamma(log), corstr="AR-M-dependent", data=spruces)
estequa(fit1)
```

```
##### Example 2: Treatment for severe postnatal depression
data(depression)
mod2 <- depressd ~ visit + group
fit2 <- glmgee(mod2, id=subj, family=binomial(logit), corstr="AR-M-dependent", data=depression)
estequa(fit2)
```

```
##### Example 3: Treatment for severe postnatal depression (2)
mod3 <- dep ~ visit*group
fit3 <- glmgee(mod3, id=subj, family=gaussian(identity), corstr="AR-M-dependent", data=depression)
estequa(fit3)
```

```
##### Example 4: Dental Clinical Trial
data(rinse)
mod4 <- score/3.6 ~ rinse*time
fit4 <- glmgee(mod4, family=binomial(log), id=subject, corstr="Exchangeable", data=rinse)
estequa(fit4)
```

```
##### Example 5: Shoulder Pain after Laparoscopic Cholecystectomy
data(cholecystectomy)
mod5 <- pain2 ~ treatment + age + time
corstr <- "Stationary-M-dependent(2)"
fit5 <- glmgee(mod5, family=binomial(logit), id=id, corstr=corstr, data=cholecystectomy)
estequa(fit5)
```

```
##### Example 6: Guidelines for Urinary Incontinence Discussion and Evaluation
data(GUIDE)
mod6 <- bothered ~ gender + age + dayacc + severe + toilet
fit6 <- glmgee(mod6, family=binomial(logit), id=practice, corstr="Exchangeable", data=GUIDE)
estequa(fit6)
```

```
##### Example 7: Tests of Auditory Perception in Children with OME
OME <- MASS::OME
mod7 <- cbind(Correct, Trials-Correct) ~ Loud + Age + OME
fit7 <- glmgee(mod7, family = binomial(cloglog), id = ID, corstr = "Exchangeable", data = OME)
estequa(fit7)
```

estequa.overglm	<i>Estimating Equations for alternatives to the Poisson and Binomial Regression Models under the presence of Overdispersion.</i>
-----------------	--

Description

Computes the estimating equations evaluated at the parameter estimates and the observed data for regression models based on the negative binomial, beta-binomial, and random-clumped binomial distributions, which are alternatives to the Poisson and binomial regression models under the presence of overdispersion.

Usage

```
## S3 method for class 'overglm'
estequa(object, ...)
```

Arguments

object	an object of the class <i>overglm</i> .
...	further arguments passed to or from other methods.

Value

A vector with the values of the estimating equations evaluated at the parameter estimates and the observed data.

Examples

```
### Example 1: Ability of retinyl acetate to prevent mammary cancer in rats
data(mammary)
fit1 <- overglm(tumors ~ group, family="nb1(identity)", data=mammary)
estequa(fit1)

### Example 2: Self diagnosed ear infections in swimmers
data(swimmers)
fit2 <- overglm(infections ~ frequency + location, family="nb1(log)", data=swimmers)
estequa(fit2)

### Example 3: Urinary tract infections in HIV-infected men
data(uti)
fit3 <- overglm(episodes ~ cd4 + offset(log(time)), family="nb1(log)", data = uti)
estequa(fit3)

### Example 4: Article production by graduate students in biochemistry PhD programs
bioChemists <- pscl::bioChemists
fit4 <- overglm(art ~ fem + kid5 + ment, family="nb1(log)", data = bioChemists)
estequa(fit4)

### Example 5: Agents to stimulate cellular differentiation
```

```

data(cellular)
fit5 <- overglm(cbind(cells,200-cells) ~ tnf + ifn, family="bb(logit)", data=cellular)
estequa(fit5)

### Example 6: Teratogenic effects of phenytoin and trichloropropene oxide
data(ossification)
model6 <- cbind(fetuses,litter-fetuses) ~ pht + tcpo
fit6 <- overglm(model6, family="rcb(cloglog)", data=ossification)
estequa(fit6)

### Example 7: Germination of orobanche seeds
data(orobanche)
model7 <- cbind(germinated,seeds-germinated) ~ specie + extract
fit7 <- overglm(model7, family="rcb(cloglog)", data=orobanche)
estequa(fit7)

```

*estequa.zeroinflation Estimating Equations in Regression Models to deal with Zero-Excess
in Count Data*

Description

Computes the estimating equations evaluated at the parameter estimates and the observed data for regression models to deal with zero-excess in count data.

Usage

```
## S3 method for class 'zeroinflation'
estequa(object, submodel = c("counts", "zeros"), ...)
```

Arguments

<code>object</code>	an object of the class <i>zeroinflation</i> .
<code>submodel</code>	an (optional) character string which allows to specify the model: "counts" or "zeros". By default, submodel is set to "counts".
<code>...</code>	further arguments passed to or from other methods.

Value

A vector with the values of the estimating equations evaluated at the parameter estimates and the observed data.

Examples

```
##### Example 1: Roots Produced by the Columnar Apple Cultivar Trajan
data(Trajan)
fit1 <- zeroalt(roots ~ photoperiod, family="nbf(log)", zero.link="logit", data=Trajan)
estequa(fit1)

fit1a <- zeroinf(roots ~ photoperiod, family="nbf(log)", zero.link="logit", data=Trajan)
estequa(fit1a)

##### Example 2: Self diagnosed ear infections in swimmers
data(swimmers)
fit2 <- zeroalt(infections ~ frequency | location, family="nb1(log)", data=swimmers)
estequa(fit2)

fit2a <- zeroinf(infections ~ frequency | location, family="nb1(log)", data=swimmers)
estequa(fit2a)

##### Example 3: Article production by graduate students in biochemistry PhD programs
bioChemists <- pscl::bioChemists
fit3 <- zeroalt(art ~ fem + kid5 + ment, family="nb1(log)", data = bioChemists)
estequa(fit3)

fit3a <- zeroinf(art ~ fem + kid5 + ment | ment, family="nb1(log)", data = bioChemists)
estequa(fit3a)
```

fabric

Fabric faults

Description

The main objective of the analysis of this dataset is to assess if there is an association between the number of faults in fabric rolls and their length.

Usage

```
data(fabric)
```

Format

A data frame with 32 rows and 2 variables:

roll a numeric vector indicating the length of the rolls.

faults a numeric vector indicating the number of faults.

References

Hinde J., Demetrio C.G.B. (1998) Over-dispersion: models and estimation. *Computational Statistics & Data Analysis* 27:151–170.

Examples

```
dev.new()
data(fabric)
with(fabric,plot(roll, faults, pch=16, xlab="Length of roll", ylab="Number of faults"))
```

FisherScoring

Fisher Scoring algorithm in Generalized Linear Models

Description

This function displays the entire path performed by the Fisher Scoring algorithm for parameter estimation in Generalized Linear Models. It starts with the starting value until convergence is achieved or the maximum number of iterations is exceeded.

Usage

```
FisherScoring(object, verbose = TRUE, digits = max(3, getOption("digits") - 2))
```

Arguments

object	one object of the class <i>glm</i> .
verbose	an (optional) logical indicating if should the report of results be printed. As default, verbose is set to TRUE.
digits	an (optional) integer value indicating the number of decimal places to be used. As default, digits is set to $\max(3, \text{getOption}(\text{"digits"}) - 2)$.

Value

a matrix whose first three columns are the following

Iteration	the iteration number,
Deviance	value of the (unscaled) deviance computed using the current value of the parameter vector,
Tolerance	value of $ deviance - deviance_{old} / (deviance_{old} + 0.1)$,

Examples

```
##### Example 1: Fuel efficiency of cars
Auto <- ISLR::Auto
fit1 <- glm(mpg ~ horsepower + weight + horsepower*weight, family=Gamma(inverse), data=Auto,
           control=list(trace=TRUE))
FisherScoring(fit1)

##### Example 2: Hill races in Scotland
data(races)
```

```

fit2 <- glm(rtime ~ log(distance) + cclimb, family=Gamma(log), data=races,
           control=list(trace=TRUE))
FisherScoring(fit2)

##### Example 3:
burn1000 <- aplore3::burn1000
burn1000 <- within(burn1000, death <- factor(death, levels=c("Dead", "Alive")))
fit3 <- glm(death ~ age*inh_inj + tbsa*inh_inj, family=binomial("logit"), data=burn1000,
           control=list(trace=TRUE))
FisherScoring(fit3)

##### Example 4: Skin cancer in women
data(skincancer)
fit4 <- glm(cases ~ offset(log(population)) + city + age, family=poisson, data=skincancer,
           control=list(trace=TRUE))
FisherScoring(fit4)

##### Example 5: Agents to stimulate cellular differentiation
data(cellular)
fit5 <- glm(cbind(cells,200-cells) ~ tnf + ifn, family=binomial(logit), data=cellular,
           control=list(trace=TRUE))
FisherScoring(fit5)

##### Example 6: Advertising
data(advertising)
fit6 <- glm(sales ~ log(TV) + radio + log(TV)*radio, family=gaussian(log), data=advertising,
           control=list(trace=TRUE))
FisherScoring(fit6)

```

GHYC

Gosho-Hamada-Yoshimura's Criterion for Generalized Estimating Equations

Description

Computes the Gosho-Hamada-Yoshimura's criterion (GHYC) for one or more objects of the class `glmgee`.

Usage

```
GHYC(..., verbose = TRUE, digits = max(3, getOption("digits") - 2))
```

Arguments

<code>...</code>	one or several objects of the class <code>glmgee</code> .
<code>verbose</code>	an (optional) logical switch indicating if should the report of results be printed. As default, <code>verbose</code> is set to <code>TRUE</code> .
<code>digits</code>	an (optional) integer indicating the number of digits to print. As default, <code>digits</code> is set to <code>max(3, getOption("digits") - 2)</code> .

Value

A data frame with the values of the GHYC for each *glmgee* object in the input.

References

Gosho M., Hamada C., Yoshimura I. (2011) Criterion for the Selection of a Working Correlation Structure in the Generalized Estimating Equation Approach for Longitudinal Balanced Data. *Communications in Statistics — Theory and Methods* 40:3839-3856.

Gosho M. (2014) Criteria to Select a Working Correlation Structure in SAS. *Journal of Statistical Software, Code Snippets* 57:1548-7660.#' @references [Vanegas L.H.](#), [Rondon L.M.](#), [Paula G.A.](#) (2023) Generalized Estimating Equations using the new R package *glmtoolbox*. *The R Journal* 15:105-133.

See Also

[QIC](#), [CIC](#), [RJC](#), [AGPC](#), [SGPC](#)

Examples

```
##### Example 1: Effect of ozone-enriched atmosphere on growth of sitka spruces
data(spruces)
mod1 <- size ~ poly(days,4) + treat
fit1 <- glmgee(mod1, id=tree, family=Gamma(log), data=spruces)
fit2 <- update(fit1, corstr="AR-M-dependent")
fit3 <- update(fit1, corstr="Stationary-M-dependent(2)")
fit4 <- update(fit1, corstr="Exchangeable")
GHYC(fit1, fit2, fit3, fit4)

##### Example 2: Treatment for severe postnatal depression
data(depression)
mod2 <- depressd ~ visit + group
fit1 <- glmgee(mod2, id=subj, family=binomial(logit), data=depression)
fit2 <- update(fit1, corstr="AR-M-dependent")
fit3 <- update(fit1, corstr="Stationary-M-dependent(2)")
fit4 <- update(fit1, corstr="Exchangeable")
GHYC(fit1, fit2, fit3, fit4)

##### Example 3: Treatment for severe postnatal depression (2)
mod3 <- dep ~ visit*group
fit1 <- glmgee(mod3, id=subj, family=gaussian(identity), data=depression)
fit2 <- update(fit1, corstr="AR-M-dependent")
fit3 <- update(fit1, corstr="Exchangeable")
GHYC(fit1, fit2, fit3)
```

glmgee

*Fit Generalized Estimating Equations***Description**

Produces an object of the class `glmgee` in which the main results of a Generalized Estimating Equation (GEE) fitted to the data are stored.

Usage

```
glmgee(
  formula,
  family = gaussian(),
  weights,
  id,
  waves,
  data,
  subset,
  corstr,
  corr,
  start = NULL,
  scale.fix = FALSE,
  scale.value = 1,
  toler = 1e-05,
  maxit = 50,
  trace = FALSE,
  ...
)
```

Arguments

<code>formula</code>	a formula expression of the form $\text{response} \sim x_1 + x_2 + \dots$, which is a symbolic description of the linear predictor of the model to be fitted to the data.
<code>family</code>	an (optional) family object, that is, a list of functions and expressions for defining link and variance functions. Families (and links) supported are the same supported by <code>glm</code> using its <code>family</code> argument, that is, <code>gaussian</code> , <code>binomial</code> , <code>poisson</code> , <code>Gamma</code> , <code>inverse.gaussian</code> , and <code>quasi</code> . The family <code>negative.binomial</code> in the library MASS are also available. As default, the argument <code>family</code> is set to <code>gaussian(identity)</code> .
<code>weights</code>	an (optional) vector of positive "prior weights" to be used in the fitting process. The length of <code>weights</code> should be the same as the total number of observations.
<code>id</code>	a vector which identifies the subjects or clusters. The length of <code>id</code> should be the same as the number of observations.
<code>waves</code>	an (optional) positive integer-valued variable that is used to identify the order and spacing of observations within clusters. This argument is crucial when there are missing values and gaps in the data. As default, <code>waves</code> is equal to the integers from 1 to the size of each cluster.

data	an (optional) data frame in which to look for variables involved in the formula expression, as well as for variables specified in the arguments <code>id</code> and <code>weights</code> . The data are assumed to be sorted by <code>id</code> and time.
subset	an (optional) vector specifying a subset of observations to be used in the fitting process.
corstr	an (optional) character string which allows to specify the working-correlation structure. The available options are: "Independence", "Unstructured", "Stationary-M-dependent(<i>m</i>)", "Non-Stationary-M-dependent(<i>m</i>)", "AR-M-dependent(<i>m</i>)", "Exchangeable" and "User-defined", where <i>m</i> represents the lag of the dependence. As default, <code>corstr</code> is set to "Independence".
corr	an (optional) square matrix of the same dimension of the maximum cluster size containing the user specified correlation. This is only appropriate if <code>corstr</code> is specified to be "User-defined".
start	an (optional) vector of starting values for the parameters in the linear predictor.
scale.fix	an (optional) logical variable. If TRUE, the scale parameter is fixed at the value of <code>scale.value</code> . As default, <code>scale.fix</code> is set to FALSE.
scale.value	an (optional) numeric value at which the scale parameter should be fixed. This is only appropriate if <code>scale.fix</code> =TRUE. As default, <code>scale.value</code> is set to 1.
toler	an (optional) positive value which represents the <i>convergence tolerance</i> . The convergence is reached when the maximum of the absolute relative differences between the values of the parameters in the linear predictor in consecutive iterations of the fitting algorithm is lower than <code>toler</code> . As default, <code>toler</code> is set to 0.00001.
maxit	an (optional) integer value which represents the maximum number of iterations allowed for the fitting algorithm. As default, <code>maxit</code> is set to 50.
trace	an (optional) logical variable. If TRUE, output is produced for each iteration of the estimating algorithm.
...	further arguments passed to or from other methods.

Details

The values of the multivariate response variable measured on n subjects or clusters, denoted by $y_i = (y_{i1}, \dots, y_{in_i})^\top$ for $i = 1, \dots, n$, are assumed to be realizations of independent random vectors denoted by $Y_i = (Y_{i1}, \dots, Y_{in_i})^\top$ for $i = 1, \dots, n$. The random variables associated to the i -th subject or cluster, Y_{ij} for $j = 1, \dots, n_i$, are assumed to satisfy $\mu_{ij} = E(Y_{ij})$, $\text{Var}(Y_{ij}) = \frac{\phi}{\omega_{ij}} V(\mu_{ij})$ and $\text{Corr}(Y_{ij}, Y_{ik}) = r_{jk}(\rho)$, where $\phi > 0$ is the dispersion parameter, $V(\mu_{ij})$ is the variance function, $\omega_{ij} > 0$ is a known weight, and $\rho = (\rho_1, \dots, \rho_q)^\top$ is a parameter vector. In addition, μ_{ij} is assumed to be dependent on the regressors vector x_{ij} by $g(\mu_{ij}) = z_{ij} + x_{ij}^\top \beta$, where $g(\cdot)$ is the link function, z_{ij} is a known *offset* and $\beta = (\beta_1, \dots, \beta_p)^\top$ is a vector of regression parameters. The parameter estimates are obtained by iteratively solving the estimating equations described by Liang and Zeger (1986).

If the maximum cluster size is 6 and for a cluster of size 4 the value of `waves` is set to 2, 4, 5, 6, then it means that the data at times 1 and 3 are missing, which should be taken into account by `glmgee` when the structure of the correlation matrix is assumed to be "Unstructured", "Stationary-M-dependent", "Non-Stationary-M-dependent" or "AR-M-dependent". If in this scenario `waves` is

not specified then `glmgee` assumes that the available data for this cluster were taken at times 1, 2, 3 and 4.

A set of standard extractor functions for fitted model objects is available for objects of class `glmgee`, including methods to generic functions such as `print`, `summary`, `model.matrix`, `estequa`, `coef`, `vcov`, `loglik`, `fitted`, `confint` and `predict`. In addition, the model may be assessed using functions such as [anova.glmgee](#), [residuals.glmgee](#), [dfbeta.glmgee](#), [cooks.distance.glmgee](#) and [localInfluence.glmgee](#). The variable selection may be accomplished using the routine [stepCriterion.glmgee](#).

Value

an object of class `glmgee` in which the main results of the GEE model fitted to the data are stored, i.e., a list with components including

<code>coefficients</code>	a vector with the estimates of β_1, \dots, β_p ,
<code>fitted.values</code>	a vector with the estimates of μ_{ij} for $i = 1, \dots, n$ and $j = 1, \dots, n_i$,
<code>start</code>	a vector with the starting values used,
<code>iter</code>	a numeric constant with the number of iterations,
<code>prior.weights</code>	a vector with the values of ω_{ij} for $i = 1, \dots, n$ and $j = 1, \dots, n_i$,
<code>offset</code>	a vector with the values of z_{ij} for $i = 1, \dots, n$ and $j = 1, \dots, n_i$,
<code>terms</code>	an object containing the terms objects,
<code>loglik</code>	the value of the quasi-log-likelihood function evaluated at the parameter estimates and the observed data,
<code>estfun</code>	a vector with the estimating equations evaluated at the parameter estimates and the observed data,
<code>formula</code>	the formula,
<code>levels</code>	the levels of the categorical regressors,
<code>contrasts</code>	an object containing the contrasts corresponding to levels,
<code>converged</code>	a logical indicating successful convergence,
<code>model</code>	the full model frame,
<code>y</code>	a vector with the values of y_{ij} for $i = 1, \dots, n$ and $j = 1, \dots, n_i$,
<code>family</code>	an object containing the family object used,
<code>linear.predictors</code>	a vector with the estimates of $g(\mu_{ij})$ for $i = 1, \dots, n$ and $j = 1, \dots, n_i$,

R	a matrix with the (robust) estimate of the variance-covariance,
corr	a matrix with the estimate of the working-correlation,
corstr	a character string specifying the working-correlation structure,
id	a vector which identifies the subjects or clusters,
sizes	a vector with the values of n_i for $i = 1, \dots, n$,
call	the original function call,

References

Liang K.Y., Zeger S.L. (1986) Longitudinal data analysis using generalized linear models. *Biometrika* 73:13-22.

Zeger S.L., Liang K.Y. (1986) Longitudinal data analysis for discrete and continuous outcomes. *Biometrics* 42:121-130.

Vanegas L.H., Rondon L.M., Paula G.A. (2023) Generalized Estimating Equations using the new R package `glmtoolbox`. *The R Journal* 15:105-133.

See Also

[gmmgee](#), [wglmgee](#)

Examples

```
##### Example 1: Effect of ozone-enriched atmosphere on growth of sitka spruces
data(spruces)
mod1 <- size ~ poly(days,4) + treat
fit1 <- glmgee(mod1, id=tree, family=Gamma(log), corstr="AR-M-dependent(1)", data=spruces)
summary(fit1, corr.digits=2)
```

```
##### Example 2: Treatment for severe postnatal depression
data(depression)
mod2 <- depressd ~ visit + group
fit2 <- glmgee(mod2, id=subj, family=binomial(logit), corstr="AR-M-dependent(1)", data=depression)
summary(fit2, corr.digits=2)
```

```
##### Example 3: Treatment for severe postnatal depression (2)
data(depression)
mod3 <- dep ~ visit*group
fit3 <- glmgee(mod3, id=subj, family=gaussian, corstr="AR-M-dependent(1)", data=depression)
summary(fit3, corr.digits=2)
```

```
##### Example 4: Dental Clinical Trial
data(rinse)
mod4 <- score/3.6 ~ rinse*time
```

```

fit4 <- glmgee(mod4, family=binomial(log), id=subject, corstr="Exchangeable", data=rinse)
summary(fit4, corr.digits=2)

##### Example 5: Shoulder Pain after Laparoscopic Cholecystectomy
data(cholecystectomy)
mod5 <- pain2 ~ treatment + age + time
corstr <- "Stationary-M-dependent(2)"
fit5 <- glmgee(mod5, family=binomial(logit), id=id, corstr=corstr, data=cholecystectomy)
summary(fit5, varest="bias-corrected")

##### Example 6: Guidelines for Urinary Incontinence Discussion and Evaluation
data(GUIDE)
mod6 <- bothered ~ gender + age + dayacc + severe + toilet
fit6 <- glmgee(mod6, family=binomial(logit), id=practice, corstr="Exchangeable", data=GUIDE)
summary(fit6)

##### Example 7: Tests of Auditory Perception in Children with OME
OME <- MASS::OME
mod7 <- cbind(Correct, Trials-Correct) ~ Loud + Age + OME
fit7 <- glmgee(mod7, family = binomial(cloglog), id = ID, corstr = "Exchangeable", data = OME)
summary(fit7, corr=FALSE)

##### Example 8: Epileptic seizures
data(Seizures)
Seizures2 <- within(Seizures, time4 <- ifelse(time==4,1,0))
mod8 <- seizures ~ log(age) + time4 + log(base/4)*treatment
fit8 <- glmgee(mod8, family=poisson(log), id=id, corstr="Exchangeable", data=Seizures2)
summary(fit8)

```

gnm

Generalized Nonlinear Models.

Description

gnm is used to fit generalized nonlinear models, specified by giving a symbolic description of the "linear" predictor and a description of the error distribution.

Usage

```

gnm(
  formula,
  family = gaussian(),
  offset = NULL,
  weights = NULL,
  data,
  subset = NULL,
  start = NULL,
  toler = 1e-05,

```

```

    maxit = 50,
    trace = FALSE,
    ...
)

```

Arguments

formula	a formula expression which is a symbolic description of the "linear" predictor of the model to be fitted to the data.
family	a description of the error distribution and link function to be used in the model. For gnm this can be a character string naming a family function, a family function or the result of a call to a family function. As default, family is set to <code>gaussian(identity)</code> .
offset	this can be used to specify an <i>a priori</i> known component to be included in the linear predictor during fitting. This should be NULL or a numeric vector of length equal to the number of cases.
weights	an (optional) vector of "prior weights" to be used in the fitting process. The length of weights should be the same as the number of observations.
data	an (optional) data frame, list or environment (or object coercible by as.data.frame to a data frame) containing the variables in the model. If not found in data, the variables are taken from <code>environment(formula)</code> , typically the environment from which gnm is called.
subset	an (optional) vector specifying a subset of observations to be used in the fitting process.
start	an (optional) vector of starting values for the parameters in the "linear" predictor.
toler	an (optional) positive value which represents the <i>convergence tolerance</i> . The convergence is reached when the maximum of the absolute relative differences between the values of the parameters in the "linear" predictor in consecutive iterations of the fitting algorithm is lower than toler. As default, toler is set to 0.00001.
maxit	an (optional) integer value which represents the maximum number of iterations allowed for the fitting algorithm. As default, maxit is set to 50.
trace	an (optional) logical variable. If TRUE, output is produced for each iteration of the estimating algorithm.
...	further arguments passed to or from other methods.

Details

A set of standard extractor functions for fitted model objects is available for objects of class *gnm*, including methods to the generic functions such as `summary`, `model.matrix`, `estequa`, `coef`, `vcov`, `logLik`, `fitted`, `confint`, `AIC`, `BIC` and `predict`. In addition, the model fitted to the data may be assessed using functions such as `adjR2.gnm`, [anova.gnm](#), [residuals.gnm](#), [dfbeta.gnm](#), [cooks.distance.gnm](#), [localInfluence.gnm](#) and [envelope.gnm](#).

Value

an object of class *gnm* in which the main results of the model fitted to the data are stored, i.e., a list with components including

coefficients	a vector containing the parameter estimates,
fitted.values	a vector containing the estimates of μ_1, \dots, μ_n ,
start	a vector containing the starting values used,
prior.weights	a vector containing the case weights used,
offset	a vector containing the offset used,
terms	an object containing the terms objects,
loglik	the value of the log-likelihood function evaluated at the parameter estimates,
estfun	a vector containing the estimating functions evaluated at the parameter estimates and the observed data,
formula	the formula,
converged	a logical indicating successful convergence,
model	the full model frame,
y	the response vector,
family	an object containing the family object used,
linear.predictors	a vector containing the estimates of $g(\mu_1), \dots, g(\mu_n)$,
R	a matrix with unscaled estimate of the variance-covariance matrix of model parameters,
call	the original function call.

See Also

[glm](#), [glmgee](#), [gnmgee](#)

Examples

```
##### Example 1: The effects of fertilizers on coastal Bermuda grass
data(Grass)
fit1 <- gnm(Yield ~ b0 + b1/(Nitrogen + a1) + b2/(Phosphorus + a2) + b3/(Potassium + a3),
           family=gaussian(inverse), start=c(b0=0.1,b1=13,b2=1,b3=1,a1=45,a2=15,a3=30), data=Grass)
summary(fit1)
```

```
##### Example 2: Assay of an Insecticide with a Synergist
data(Melanopus)
fit2 <- gnm(Killed/Exposed ~ b0 + b1*log(Insecticide-a1) + b2*Synergist/(a2 + Synergist),
```

```

        family=binomial(logit), weights=Exposed, start=c(b0=-3,b1=1.2,a1=1.7,b2=1.7,a2=2),
        data=Melanopus)
summary(fit2)

##### Example 3: Developmental rate of Drosophila melanogaster
data(Drosophila)
fit3 <- gnm(Duration ~ b0 + b1*Temp + b2/(Temp-a), family=Gamma(log),
            start=c(b0=3,b1=-0.25,b2=-210,a=55), weights=Size, data=Drosophila)
summary(fit3)

##### Example 4: Radioimmunological Assay of Cortisol
data(Cortisol)
fit4 <- gnm(Y ~ b0 + (b1-b0)/(1 + exp(b2+ b3*lDose))^b4, family=Gamma(identity),
            start=c(b0=130,b1=2800,b2=3,b3=3,b4=0.5), data=Cortisol)
summary(fit4)

##### Example 5: Age and Eye Lens Weight of Rabbits in Australia
data(rabbits)
fit5 <- gnm(wlens ~ b1 - b2/(age + b3), family=Gamma(log),
            start=c(b1=5.5,b2=130,b3=35), data=rabbits)
summary(fit5)

##### Example 6: Calls to a technical support help line
data(calls)
fit6 <- gnm(calls ~ SSlogis(week, Asym, xmid, scal), family=poisson(identity), data=calls)
summary(fit6)

```

gnmgee

Fit Nonlinear Generalized Estimating Equations

Description

Produces an object of the class `glmgee` in which the main results of a Nonlinear Generalized Estimating Equation (GEE) fitted to the data are stored.

Usage

```

gnmgee(
  formula,
  family = gaussian(),
  offset = NULL,
  weights = NULL,
  id,
  waves,
  data,
  subset = NULL,
  corstr,
  corr,

```

```

    start = NULL,
    scale.fix = FALSE,
    scale.value = 1,
    toler = 1e-05,
    maxit = 50,
    trace = FALSE,
    ...
)

```

Arguments

formula	a nonlinear model formula including variables and parameters, which is a symbolic description of the nonlinear predictor of the model to be fitted to the data.
family	an (optional) family object, that is, a list of functions and expressions for defining link and variance functions. Families (and links) supported are the same supported by <code>glm</code> using its <code>family</code> argument, that is, <code>gaussian</code> , <code>binomial</code> , <code>poisson</code> , <code>Gamma</code> , <code>inverse.gaussian</code> , and <code>quasi</code> . The family <code>negative.binomial</code> in the library MASS are also available. As default, the argument <code>family</code> is set to <code>gaussian(identity)</code> .
offset	an (optional) numeric vector of length equal to the number of cases, which can be used to specify an a priori known component to be included in the linear predictor during fitting.
weights	an (optional) vector of positive "prior weights" to be used in the fitting process. The length of <code>weights</code> should be the same as the total number of observations.
id	a vector which identifies the subjects or clusters. The length of <code>id</code> should be the same as the number of observations.
waves	an (optional) positive integer-valued variable that is used to identify the order and spacing of observations within clusters. This argument is crucial when there are missing values and gaps in the data. As default, <code>waves</code> is equal to the integers from 1 to the size of each cluster.
data	an (optional) data frame in which to look for variables involved in the <code>formula</code> expression, as well as for variables specified in the arguments <code>id</code> and <code>weights</code> . The data are assumed to be sorted by <code>id</code> and time.
subset	an (optional) vector specifying a subset of observations to be used in the fitting process.
corstr	an (optional) character string which allows to specify the working-correlation structure. The available options are: "Independence", "Unstructured", "Stationary-M-dependent(<i>m</i>)", "Non-Stationary-M-dependent(<i>m</i>)", "AR-M-dependent(<i>m</i>)", "Exchangeable" and "User-defined", where <i>m</i> represents the lag of the dependence. As default, <code>corstr</code> is set to "Independence".
corr	an (optional) square matrix of the same dimension of the maximum cluster size containing the user specified correlation. This is only appropriate if <code>corstr</code> is specified to be "User-defined".
start	an (optional) vector of starting values for the parameters in the nonlinear predictor. When <code>start</code> is missing (and <code>formula</code> is not a self-starting model, see <code>nls</code> and <code>selfStart</code>), a very cheap guess for <code>start</code> is tried.

<code>scale.fix</code>	an (optional) logical variable. If TRUE, the scale parameter is fixed at the value of <code>scale.value</code> . As default, <code>scale.fix</code> is set to FALSE.
<code>scale.value</code>	an (optional) numeric value at which the scale parameter should be fixed. This is only appropriate if <code>scale.fix</code> =TRUE. As default, <code>scale.value</code> is set to 1.
<code>toler</code>	an (optional) positive value which represents the <i>convergence tolerance</i> . The convergence is reached when the maximum of the absolute relative differences between the values of the parameters in the nonlinear predictor in consecutive iterations of the fitting algorithm is lower than <code>toler</code> . As default, <code>toler</code> is set to 0.00001.
<code>maxit</code>	an (optional) integer value which represents the maximum number of iterations allowed for the fitting algorithm. As default, <code>maxit</code> is set to 50.
<code>trace</code>	an (optional) logical variable. If TRUE, output is produced for each iteration of the estimating algorithm.
<code>...</code>	further arguments passed to or from other methods.

Details

The values of the multivariate response variable measured on n subjects or clusters, denoted by $y_i = (y_{i1}, \dots, y_{in_i})^\top$ for $i = 1, \dots, n$, are assumed to be realizations of independent random vectors denoted by $Y_i = (Y_{i1}, \dots, Y_{in_i})^\top$ for $i = 1, \dots, n$. The random variables associated to the i -th subject or cluster, Y_{ij} for $j = 1, \dots, n_i$, are assumed to satisfy $\mu_{ij} = E(Y_{ij})$, $\text{Var}(Y_{ij}) = \frac{\phi}{\omega_{ij}} V(\mu_{ij})$ and $\text{Corr}(Y_{ij}, Y_{ik}) = r_{jk}(\rho)$, where $\phi > 0$ is the dispersion parameter, $V(\mu_{ij})$ is the variance function, $\omega_{ij} > 0$ is a known weight, and $\rho = (\rho_1, \dots, \rho_q)^\top$ is a parameter vector. In addition, μ_{ij} is assumed to be dependent on the regressors vector x_{ij} by $g(\mu_{ij}) = z_{ij} + m(x_{ij}, \beta)$, where $g(\cdot)$ is the link function, z_{ij} is a known *offset*, $\beta = (\beta_1, \dots, \beta_p)^\top$ is a vector of regression parameters and $m(x_{ij}, \beta)$ is a known nonlinear function of β . The parameter estimates are obtained by iteratively solving the estimating equations described by Liang and Zeger (1986).

If the maximum cluster size is 6 and for a cluster of size 4 the value of waves is set to 2, 4, 5, 6, then it means that the data at times 1 and 3 are missing, which should be taken into account by `gnmgee` when the structure of the correlation matrix is assumed to be "Unstructured", "Stationary-M-dependent", "Non-Stationary-M-dependent" or "AR-M-dependent". If in this scenario waves is not specified then `gnmgee` assumes that the available data for this cluster were taken at times 1, 2, 3 and 4.

A set of standard extractor functions for fitted model objects is available for objects of class `glmgee`, including methods to generic functions such as `print`, `summary`, `model.matrix`, `estequa`, `coef`, `vcov`, `logLik`, `fitted`, `confint` and `predict`. In addition, the model may be assessed using functions such as [anova.glmgee](#), [residuals.glmgee](#), [dfbeta.glmgee](#) and [cooks.distance.glmgee](#).

Value

an object of class `glmgee` in which the main results of the GEE model fitted to the data are stored, i.e., a list with components including

<code>coefficients</code>	a vector with the estimates of β_1, \dots, β_p ,
<code>fitted.values</code>	a vector with the estimates of μ_{ij} for $i = 1, \dots, n$ and $j = 1, \dots, n_i$,

start	a vector with the starting values used,
iter	a numeric constant with the number of iterations,
prior.weights	a vector with the values of ω_{ij} for $i = 1, \dots, n$ and $j = 1, \dots, n_i$,
offset	a vector with the values of z_{ij} for $i = 1, \dots, n$ and $j = 1, \dots, n_i$,
terms	an object containing the terms objects,
loglik	the value of the quasi-log-likelihood function evaluated at the parameter estimates and the observed data,
estfun	a vector with the estimating equations evaluated at the parameter estimates and the observed data,
formula	the formula,
levels	the levels of the categorical regressors,
contrasts	an object containing the contrasts corresponding to levels,
converged	a logical indicating successful convergence,
model	the full model frame,
y	a vector with the values of y_{ij} for $i = 1, \dots, n$ and $j = 1, \dots, n_i$,
family	an object containing the family object used,
linear.predictors	a vector with the estimates of $g(\mu_{ij})$ for $i = 1, \dots, n$ and $j = 1, \dots, n_i$,
R	a matrix with the (robust) estimate of the variance-covariance,
corr	a matrix with the estimate of the working-correlation,
corstr	a character string specifying the working-correlation structure,
id	a vector which identifies the subjects or clusters,
sizes	a vector with the values of n_i for $i = 1, \dots, n$,
call	the original function call,

References

Liang K.Y., Zeger S.L. (1986) Longitudinal data analysis using generalized linear models. *Biometrika* 73:13-22.

Zeger S.L., Liang K.Y. (1986) Longitudinal data analysis for discrete and continuous outcomes. *Biometrics* 42:121-130.

Hardin J.W., Hilbe J.M. (2013) *Generalized Estimating Equations*. Chapman & Hall, London.

Vanegas L.H., Rondon L.M., Paula G.A. (2023) Generalized Estimating Equations using the new R package `glmtoolbox`. *The R Journal* 15:105-133.

See Also

[glmgee](#), [wglmgee](#)

Examples

```
##### Example : Orange trees grown at Riverside, California
data(Oranges)
mod <- Trunk ~ b1/(1 + exp((b2-Days)/b3))
start <- c(b1=200,b2=760,b3=375)
fit1 <- gnmgee(mod, start=start, id=Tree, family=Gamma(identity), corstr="Exchangeable",
              data=Oranges)
summary(fit1, corr.digits=2)

mod <- Trunk ~ SSlogis(Days,b1,b2,b3)
fit2 <- gnmgee(mod, id=Tree, family=Gamma(identity), corstr="Exchangeable", data=Oranges)
summary(fit2, corr.digits=2)
```

Grass

The effects of fertilizers on coastal Bermuda grass

Description

These data arose from a 4³ factorial experiment with the three major plant nutrients, nitrogen (N), phosphorus (P), and potassium (K), on the yield of coastal Bermuda grass. The experiment was performed to produce a response surface for the effects of the three nutrients, so that an optimal dressing could be predicted. The grass was cut about every five weeks and oven-dried.

Usage

```
data(Grass)
```

Format

A data frame with 64 rows and 4 variables:

Nitrogen a numeric vector indicating the Nitrogen level, in lb/acre.

Phosphorus a numeric vector indicating the Phosphorus level, in lb/acre.

Potassium a numeric vector indicating the Potassium level, in lb/acre.

Yield a numeric vector indicating the yields, in tons/acre.

References

- Welch L.F., Adams W.E., Carmon J.L. (1963) Yield Response Surfaces, Isoquants, and Economic Fertilizer Optima for Coastal Bermuda grass. *Agronomy Journal*, 55, 63-67.
- McCullagh P., Nelder J.A. (1989). *Generalized Linear Models. 2nd Edition.* Chapman and Hall, London.
- Wei B.C. (1998). *Exponential Family Nonlinear Models.* Springer, Singapore.

 GUIDE

Guidelines for Urinary Incontinence Discussion and Evaluation

Description

These data arose from a randomized controlled trial that assessed if provider adherence to a set of guidelines for treatment of patients with urinary incontinence (UI) affected patient outcomes. Data were collected on 137 elderly patients from 38 medical practices. The number of patients per practice ranged from 1 to 8 and the median was 4 patients. The statistical analysis aims to determine what predicts whether or not a patient considers their UI a problem that interferes with him/her daily life.

Usage

data(GUIDE)

Format

A data frame with 137 rows and 7 variables:

bothered a numeric vector giving the answer to the following: Do you consider this accidental loss of urine a problem that interferes with your day to day activities or bothers you in other ways? 1 for "Yes" and 0 for "No".

gender a factor giving the patient's gender: "Male" or "Female".

age a numeric vector giving the standardized age: (age in years - 76)/10.

dayacc a numeric vector giving the patient's report of the number of leaking accidents they experience in an average day (derived from number of accidents reported per week).

severe a factor giving the severity of the loss of urine: "1" if there is only some moisture; "2" if the patient wet the underwear; "3" if the urine trickled down the thigh; and "4" if the patient wet the floor.

toilet a numeric vector giving the patient's report on the number of times during the day he (or she) usually go to the toilet to urinate.

practice a character string giving the identifier of the medical practice.

Source

<http://www.bios.unc.edu/~preisser/personal/uidata/preqaq99.dat>

References

Hammill B.G., Preisser J.S. (2006) A SAS/IML software program for GEE and regression diagnostics. *Computational Statistics & Data Analysis* 51:1197-1212.

Jung K.-M. (2008) Local Influence in Generalized Estimating Equations. *Scandinavian Journal of Statistics* 35:286-294.

Examples

```
data(GUIDE)
mod <- bothered ~ gender + age + dayacc + severe + toilet
fit <- glmgee(mod, family=binomial(logit), id=practice, corstr="Exchangeable", data=GUIDE)
summary(fit)
```

gvif	<i>Generalized Variance Inflation Factor</i>
------	--

Description

Computes the generalized variance inflation factor (GVIF) for a fitted model object.

Usage

```
gvif(model, ...)
```

Arguments

model	a fitted model object.
...	further arguments passed to or from other methods.

Value

An object with the values of the GVIF for all effects in the model.

gvif.glm	<i>Generalized Variance Inflation Factor</i>
----------	--

Description

Computes the generalized variance inflation factor (GVIF) for a generalized linear model.

Usage

```
## S3 method for class 'glm'
gvif(model, verbose = TRUE, ...)
```


Arguments

model	an object of the class <i>glm</i> .
verbose	an (optional) logical switch indicating if should the report of results be printed. As default, verbose is set to TRUE.
...	further arguments passed to or from other methods.

Details

If the number of degrees of freedom is 1 then the GVIF reduces to the Variance Inflation Factor (VIF).

Value

A matrix with so many rows as effects in the model and the following columns:

GVIF	the values of GVIF,
df	the number of degrees of freedom,
GVIF ^{1/(2*df)}	the values of GVIF ^{1/2df} ,

References

Fox J., Monette G. (1992) Generalized collinearity diagnostics, *JASA* 87, 178–183.

See Also

[gvif.lm](#)

Examples

```
##### Example 1: Fuel consumption of automobiles
Auto <- ISLR::Auto
Auto2 <- within(Auto, origin <- factor(origin))
mod <- mpg ~ cylinders + displacement + acceleration + origin + horsepower*weight
fit1 <- glm(mod, family=inverse.gaussian("log"), data=Auto2)
gvif(fit1)

##### Example 2: Patients with burn injuries
burn1000 <- aplore3::burn1000
burn1000 <- within(burn1000, death <- factor(death, levels=c("Dead","Alive")))
mod2 <- death ~ gender + race + flame + age*inh_inj + tbsa*inh_inj
fit2 <- glm(mod2, family=binomial("logit"), data=burn1000)
gvif(fit2)

##### Example 3: Hill races in Scotland
data(races)
fit3 <- glm(rtime ~ log(distance) + cclimb, family=Gamma(log), data=races)
gvif(fit3)
```

gvif.lm

Generalized Variance Inflation Factor

Description

Computes the generalized variance inflation factor (GVIF) for a weighted or unweighted normal linear model.

Usage

```
## S3 method for class 'lm'
gvif(model, verbose = TRUE, ...)
```

Arguments

model	an object of the class <i>lm</i> .
verbose	an (optional) logical switch indicating if should the report of results be printed. As default, verbose is set to TRUE.
...	further arguments passed to or from other methods.

Details

If the number of degrees of freedom is 1 then the GVIF reduces to the Variance Inflation Factor (VIF).

Value

A matrix with so many rows as effects in the model and the following columns:

GVIF	the values of GVIF,
df	the number of degrees of freedom,
GVIF^(1/(2*df))	the values of $GVIF^{1/2df}$,

References

Fox J., Monette G. (1992) Generalized collinearity diagnostics, *JASA* 87, 178–183.

See Also

[gvif.glm](#)

Examples

```
##### Example 1: New York air quality measurements
fit1 <- lm(log(Ozone) ~ Solar.R + Temp + Wind, data=airquality)
gvif(fit1)

##### Example 2: Fuel consumption of automobiles
fit2 <- lm(mpg ~ log(hp) + log(wt) + qsec, data=mtcars)
gvif(fit2)

##### Example 3: Credit card balance
Credit <- ISLR::Credit
fit3 <- lm(Balance ~ Cards + Age + Rating + Income + Student + Limit, data=Credit)
gvif(fit3)
```

gvif.overglm	<i>Generalized Variance Inflation Factor for alternatives to the Poisson and Binomial Regression Models under the presence of Overdispersion</i>
--------------	--

Description

Computes the generalized variance inflation factor (GVIF) for regression models based on the negative binomial, beta-binomial, and random-clumped binomial distributions, which are alternatives to the Poisson and binomial regression models under the presence of overdispersion. The GVIF is aimed to identify collinearity problems.

Usage

```
## S3 method for class 'overglm'
gvif(model, verbose = TRUE, ...)
```

Arguments

model	an object of class <i>overglm</i> .
verbose	an (optional) logical switch indicating if should the report of results be printed. As default, verbose is set to TRUE.
...	further arguments passed to or from other methods.

Details

If the number of degrees of freedom is 1 then the GVIF reduces to the Variance Inflation Factor (VIF).

Value

A matrix with so many rows as effects in the model and the following columns:

GVIF	the values of GVIF,
df	the number of degrees of freedom,
$GVIF^{1/(2*df)}$	the values of $GVIF^{1/2df}$,

References

Fox J., Monette G. (1992) Generalized collinearity diagnostics, *JASA* 87, 178–183.

See Also

[gvif.lm](#), [gvif.glm](#)

Examples

```
##### Example 1: Self diagnosed ear infections in swimmers
data(swimmers)
fit1 <- overglm(infections ~ frequency + location, family="nb1(log)", data=swimmers)
gvif(fit1)

##### Example 2: Article production by graduate students in biochemistry PhD programs
bioChemists <- pscl::bioChemists
fit2 <- overglm(art ~ fem + kid5 + ment, family="nb1(log)", data = bioChemists)
gvif(fit2)

##### Example 3: Agents to stimulate cellular differentiation
data(cellular)
fit3 <- overglm(cbind(cells,200-cells) ~ tnf + ifn, family="bb(logit)", data=cellular)
gvif(fit3)
```

 hltest

The Hosmer-Lemeshow Goodness-of-Fit Test

Description

Computes the Hosmer-Lemeshow goodness-of-fit test for a generalized linear model fitted to binary responses.

Usage

```
hltest(model, verbose = TRUE, ...)
```

Arguments

model	an object of the class <i>glm</i> , which is obtained from the fit of a generalized linear model where the distribution for the response variable is assumed to be binomial.
verbose	an (optional) logical switch indicating if should the report of results be printed. As default, verbose is set to TRUE.
...	further arguments passed to or from other methods.

Value

A matrix with the following four columns:

hm	a matrix with the values of Group, Size, Observed and Expected, which are required to compute the statistic of t
statistic	the value of the statistic of the test,
df	the number of degrees of freedom, given by the number of groups minus 2,
p.value	the <i>p</i> -value of the test computed using the Chi-square distribution,

References

Hosmer D.W., Lemeshow S. (2000) *Applied Logistic Regression. 2nd ed.* John Wiley & Sons, New York.

Examples

```
##### Example 1: Patients with burn injuries
burn1000 <- aplore3::burn1000
burn1000 <- within(burn1000, death <- factor(death, levels=c("Dead","Alive")))
fit1 <- glm(death ~ age*inh_inj + tbsa*inh_inj, family=binomial("logit"), data=burn1000)
hltest(fit1)

##### Example 2: Bladder cancer in mice
data(bladder)
fit2 <- glm(cancer/exposed ~ dose, weights=exposed, family=binomial("cloglog"), data=bladder)
hltest(fit2)

##### Example 3: Liver cancer in mice
data(liver)
fit3 <- glm(cancer/exposed ~ dose, weights=exposed, family=binomial("probit"), data=liver)
hltest(fit3)
```

ldh

*ldh***Description**

The data consists of the proportion of lactic dehydrogenase enzyme leakage obtained as a response of hepatocyte cell toxicity to the effects of different combinations of carbon tetrachloride (CCl₄) and chloroform (CHCl₃). Thus, the main objective of the data analysis is to evaluate the effects of CCl₄, CHCl₃ and their interactions on the response.

Usage

```
data(ldh)
```

Format

A data frame with 448 rows and 5 variables:

LDH a numeric vector indicating the proportion of lactic dehydrogenase enzyme leakage, a surrogate for cell toxicity.

CCl₄ a numeric vector indicating the carbon tetrachloride at 0, 1, 2.5 and 5 mM.

CHCl₃ a numeric vector indicating the chloroform at 0, 5, 10 and 25 mM.

Flask a numeric vector indicating the flask of isolated hepatocyte suspensions.

Time a numeric vector indicating the time at 0, 0.01, 0.25, 0.50, 1, 2 and 3 hours.

Source

Gennings, C., Chinchilli, V.M., Carter, W.H. (1989). Response Surface Analysis with Correlated Data: A Nonlinear Model Approach. *Journal of the American Statistical Association*, 84, 805–809.

References

Vonesh E.F. (2012) Generalized Linear and Nonlinear Models for Correlated Data: Theory and Applications Using SAS. *Cary, NC: SAS Institute Inc.*

Examples

```
data(ldh)
opt <- unique(ldh$CCl4)
dev.new()
par(mfrow=c(1,length(opt)))
for(i in 1:length(opt))
  boxplot(LDH ~ Time, data=subset(ldh,CCl4==opt[i]), ylim=c(0,0.8), main=paste("CCl4=",opt[i]))

dev.new()
opt <- unique(ldh$CHCl3)
par(mfrow=c(1,length(opt)))
for(i in 1:length(opt))
```

```
boxplot(LDH ~ Time, data=subset(ldh,CHCl3==opt[i]), ylim=c(0,0.8), main=paste("CHCl3=",opt[i]))
```

leverage	<i>Leverage</i>
----------	-----------------

Description

Computes leverage measures for a fitted model object.

Usage

```
leverage(object, ...)
```

Arguments

object	a fitted model object.
...	further arguments passed to or from other methods.

Value

An object with the values of the leverage measures.

leverage.glmgee	<i>Leverage for Generalized Estimating Equations</i>
-----------------	--

Description

Computes and, optionally, displays a graph of the leverage measures at the cluster- and observation-level.

Usage

```
## S3 method for class 'glmgee'
leverage(
  object,
  level = c("clusters", "observations"),
  plot.it = FALSE,
  identify,
  ...
)
```

Arguments

object	an object of class <i>glmgee</i> .
level	an (optional) character string indicating the level for which the leverage measures are required. The options are: cluster-level ("clusters") and observation-level ("observations"). As default, level is set to "clusters".
plot.it	an (optional) logical indicating if the plot of the measures of leverage are required or just the data matrix in which that plot is based. As default, plot.it is set to FALSE.
identify	an (optional) integer indicating the number of (level="clusters") or observations (level="observations") to identify on the plot of the leverage measures. This is only appropriate if plot.it is specified to be TRUE.
...	further arguments passed to or from other methods. If plot.it is specified to be TRUE then ... may be used to include graphical parameters to customize the plot. For example, col, pch, cex, main, sub, xlab, ylab.

Value

A vector with the values of the leverage measures with so many rows as clusters (level="clusters") or observations (level="observations") in the sample.

References

Preisser J.S., Qaqish B.F. (1996). Deletion diagnostics for generalised estimating equations. *Biometrika*, 83:551-562.

Hammill B.G., Preisser J.S. (2006). A SAS/IML software program for GEE and regression diagnostics. *Computational Statistics & Data Analysis*, 51:1197-1212.

Vanegas L.H., Rondon L.M., Paula G.A. (2023) Generalized Estimating Equations using the new R package glmtoolbox. *The R Journal* 15:105-133.

Examples

```
##### Example 1: Tests of Auditory Perception in Children with OME
OME <- MASS::OME
mod <- cbind(Correct, Trials-Correct) ~ Loud + Age + OME
fit1 <- glmgee(mod, family = binomial(cloglog), id = ID, corstr = "Exchangeable", data = OME)
leverage(fit1, level="clusters", plot.it=TRUE)

##### Example 2: Guidelines for Urinary Incontinence Discussion and Evaluation
data(GUIDE)
mod <- bothered ~ gender + age + dayacc + severe + toilet
fit2 <- glmgee(mod, family=binomial(logit), id=practice, corstr="Exchangeable", data=GUIDE)
leverage(fit2, level="clusters", plot.it=TRUE)
leverage(fit2, level="observations", plot.it=TRUE)
```

`liver`*Liver cancer in mice*

Description

Female mice were continuously fed dietary concentrations of 2-Acetylaminofluorene (2-AAF), a carcinogenic and mutagenic derivative of fluorene. Serially sacrificed, dead or moribund mice were examined for tumors and deaths dates recorded. These data consist of the incidences of liver neoplasms in mice observed during 18 months.

Usage

```
data(liver)
```

Format

A data frame with 8 rows and 3 variables:

dose a numeric vector giving the dose, in parts per 10^4 , of 2-AAF.

exposed a numeric vector giving the number of mice exposed to each dose of 2-AAF.

cancer a numeric vector giving the number of mice with liver cancer for each dose of 2-AAF.

References

Zhang H., Zelterman D. (1999) Binary Regression for Risks in Excess of Subject-Specific Thresholds. *Biometrics* 55:1247-1251.

See Also

[bladder](#)

Examples

```
data(liver)
dev.new()
barplot(100*cancer/exposed ~ dose, beside=TRUE, data=liver, col="red",
        xlab="Dose of 2-AAF", ylab="% of mice with liver cancer")
```

localInfluence	<i>Local Influence</i>
----------------	------------------------

Description

Computes measures of local influence for a fitted model object.

Usage

```
localInfluence(object, ...)
```

Arguments

object	a fitted model object.
...	further arguments passed to or from other methods.

Value

An object with the measures of local influence.

localInfluence.glm	<i>Local Influence for Generalized Linear Models</i>
--------------------	--

Description

Computes some measures and, optionally, display graphs of them to perform influence analysis based on the approaches described by Cook (1986).

Usage

```
## S3 method for class 'glm'
localInfluence(
  object,
  type = c("total", "local"),
  perturbation = c("case-weight", "response", "covariate"),
  covariate,
  coefs,
  plot.it = FALSE,
  identify,
  ...
)
```

Arguments

object	an object of class <i>glm</i> .
type	an (optional) character string indicating the type of approach to study the local influence. The options are: the absolute value of the elements of the eigenvector which corresponds to the maximum absolute eigenvalue ("local"); and the absolute value of the elements of the main diagonal ("total"). As default, type is set to "total".
perturbation	an (optional) character string indicating the perturbation scheme to apply. The options are: case weight perturbation of observations ("case-weight"); perturbation of covariates ("covariate"); and perturbation of response ("response"). As default, perturbation is set to "case-weight".
covariate	an character string which (partially) match with the names of one of the parameters in the linear predictor. This is only appropriate if perturbation="covariate".
coefs	an (optional) character string which (partially) match with the names of some of the parameters in the linear predictor.
plot.it	an (optional) logical indicating if the plot of the measures of local influence is required or just the data matrix in which that plot is based. By default, plot.it is set to FALSE.
identify	an (optional) integer indicating the number of observations to identify on the plot of the measures of local influence. This is only appropriate if plot.it=TRUE.
...	further arguments passed to or from other methods. If plot.it=TRUE then ... may be used to include graphical parameters to customize the plot. For example, col, pch, cex, main, sub, xlab, ylab.

Value

A matrix as many rows as observations in the sample and one column with the values of the measures of local influence.

References

- Cook D. (1986) Assessment of Local Influence. *Journal of the Royal Statistical Society: Series B (Methodological)* 48, 133-155.
- Thomas W., Cook D. (1989) Assessing Influence on Regression Coefficients in Generalized Linear Models. *Biometrika* 76, 741-749.

localInfluence.glmgee *Local Influence for Generalized Estimating Equations*

Description

Computes some measures and, optionally, display graphs of them to perform influence analysis based on the approaches described in Cook (1986) and Jung (2008).

Usage

```
## S3 method for class 'glmgee'
localInfluence(
  object,
  type = c("total", "local"),
  perturbation = c("cw-clusters", "cw-observations", "response"),
  coefs,
  plot.it = FALSE,
  identify,
  ...
)
```

Arguments

object	an object of class <i>glmgee</i> .
type	an (optional) character string indicating the type of approach to study the local influence. The options are: the absolute value of the elements of the eigenvector which corresponds to the maximum absolute eigenvalue ("local"); and the elements of the main diagonal ("total"). As default, type is set to "total".
perturbation	an (optional) character string indicating the perturbation scheme to apply. The options are: case weight perturbation of clusters ("cw-clusters"); Case weight perturbation of observations ("cw-observations"); and perturbation of response ("response"). As default, perturbation is set to "cw-clusters".
coefs	an (optional) character string which (partially) match with the names of some of the parameters in the linear predictor.
plot.it	an (optional) logical indicating if the plot of the measures of local influence is required or just the data matrix in which that plot is based. As default, plot.it is set to FALSE.
identify	an (optional) integer indicating the number of clusters/observations to identify on the plot of the measures of local influence. This is only appropriate if plot.it=TRUE.
...	further arguments passed to or from other methods. If plot.it=TRUE then ... may be used to include graphical parameters to customize the plot. For example, col, pch, cex, main, sub, xlab, ylab.

Value

A matrix as many rows as clusters/observations in the sample and one column with the values of the measures of local influence.

References

- Cook D. (1986) Assessment of Local Influence. *Journal of the Royal Statistical Society: Series B (Methodological)* 48:133-155.
- Jung K.-M. (2008) Local Influence in Generalized Estimating Equations. *Scandinavian Journal of Statistics* 35:286-294.

Vanegas L.H., Rondon L.M., Paula G.A. (2023) Generalized Estimating Equations using the new R package glmtoolbox. *The R Journal* 15:105-133.

Examples

```
##### Example 1: Effect of ozone-enriched atmosphere on growth of sitka spruces
data(spruces)
mod1 <- size ~ poly(days,4) + treat
fit1 <- glmgee(mod1, id=tree, family=Gamma(log), corstr="AR-M-dependent", data=spruces)
localInfluence(fit1,type="total",perturbation="cw-clusters",coefs="treat",plot.it=TRUE)

##### Example 2: Treatment for severe postnatal depression
data(depression)
mod2 <- depressd ~ visit + group
fit2 <- glmgee(mod2, id=subj, family=binomial(logit), corstr="AR-M-dependent", data=depression)
localInfluence(fit2,type="total",perturbation="cw-clusters",coefs="group",plot.it=TRUE)

##### Example 3: Treatment for severe postnatal depression (2)
mod3 <- dep ~ visit*group
fit3 <- glmgee(mod3, id=subj, family=gaussian(identity), corstr="AR-M-dependent", data=depression)
localInfluence(fit3,type="total",perturbation="cw-clusters",coefs="visit:group",plot.it=TRUE)
```

localInfluence.gnm *Local Influence for Generalized Nonlinear Models*

Description

Computes some measures and, optionally, display graphs of them to perform influence analysis based on the approaches described by Cook (1986).

Usage

```
## S3 method for class 'gnm'
localInfluence(
  object,
  type = c("total", "local"),
  perturbation = c("case-weight", "response"),
  coefs,
  plot.it = FALSE,
  identify,
  ...
)
```

Arguments

object an object of class *gnm*.

type	an (optional) character string indicating the type of approach to study the local influence. The options are: the absolute value of the elements of the eigenvector which corresponds to the maximum absolute eigenvalue ("local"); and the absolute value of the elements of the main diagonal ("total"). As default, type is set to "total".
perturbation	an (optional) character string indicating the perturbation scheme to apply. The options are: case weight perturbation of observations ("case-weight") and perturbation of response ("response"). As default, perturbation is set to "case-weight".
coefs	an (optional) character string which (partially) match with the names of some of the parameters in the 'linear' predictor.
plot.it	an (optional) logical indicating if the plot of the measures of local influence is required or just the data matrix in which that plot is based. As default, plot.it is set to FALSE.
identify	an (optional) integer indicating the number of observations to identify on the plot of the measures of local influence. This is only appropriate if plot.it=TRUE.
...	further arguments passed to or from other methods. If plot.it=TRUE then ... may be used to include graphical parameters to customize the plot. For example, col, pch, cex, main, sub, xlab, ylab.

Value

A matrix as many rows as observations in the sample and one column with the values of the measures of local influence.

References

Cook D. (1986) Assessment of Local Influence. *Journal of the Royal Statistical Society: Series B (Methodological)* 48, 133-155.

Thomas W., Cook D. (1989) Assessing Influence on Regression Coefficients in Generalized Linear Models. *Biometrika* 76, 741-749.

Examples

```
##### Example 1: The effects of fertilizers on coastal Bermuda grass
data(Grass)
fit1 <- gnm(Yield ~ b0 + b1/(Nitrogen + a1) + b2/(Phosphorus + a2) + b3/(Potassium + a3),
           family=gaussian(inverse), start=c(b0=0.1,b1=13,b2=1,b3=1,a1=45,a2=15,a3=30), data=Grass)

localInfluence(fit1, type="local", perturbation="case-weight", plot.it=TRUE, col="red",
              lty=1, lwd=1, col.lab="blue", col.axis="blue", col.main="black", family="mono")

##### Example 2: Assay of an Insecticide with a Synergist
data(Melanopus)
fit2 <- gnm(Killed/Exposed ~ b0 + b1*log(Insecticide-a1) + b2*Synergist/(a2 + Synergist),
           family=binomial(logit), weights=Exposed, start=c(b0=-3,b1=1.2,a1=1.7,b2=1.7,a2=2),
           data=Melanopus)

### Local Influence just for the parameter "b1"
```

```

localInfluence(fit2, type="local", perturbation="case-weight", plot.it=TRUE, coefs="b1", col="red",
               lty=1, lwd=1, col.lab="blue", col.axis="blue", col.main="black", family="mono")

##### Example 3: Developmental rate of Drosophila melanogaster
data(Drosophila)
fit3 <- gnm(Duration ~ b0 + b1*Temp + b2/(Temp-a), family=Gamma(log),
            start=c(b0=3,b1=-0.25,b2=-210,a=55), weights=Size, data=Drosophila)

localInfluence(fit3, type="total", perturbation="case-weight", plot.it=TRUE, col="red",
               lty=1, lwd=1, col.lab="blue", col.axis="blue", col.main="black", family="mono")

##### Example 4: Radioimmunological Assay of Cortisol
data(Cortisol)
fit4 <- gnm(Y ~ b0 + (b1-b0)/(1 + exp(b2+ b3*lDose))^b4, family=Gamma(identity),
            start=c(b0=130,b1=2800,b2=3,b3=3,b4=0.5), data=Cortisol)

localInfluence(fit4, type="total", perturbation="case-weight", plot.it=TRUE, col="red",
               lty=1, lwd=1, col.lab="blue", col.axis="blue", col.main="black", family="mono")

```

localInfluence.overglm

Local Influence for alternatives to the Poisson and Binomial Regression Models under the presence of Overdispersion

Description

Computes local influence measures under the case-weight perturbation scheme for alternatives to the Poisson and Binomial Regression Models under the presence of Overdispersion. Those local influence measures may be chosen to correspond to all parameters in the linear predictor or (via `coefs`) for just some subset of them.

Usage

```

## S3 method for class 'overglm'
localInfluence(
  object,
  type = c("total", "local"),
  coefs,
  plot.it = FALSE,
  identify,
  ...
)

```

Arguments

`object` an object of class *overglm*.

type	an (optional) character string which allows to specify the local influence approach: the absolute value of the elements of the main diagonal of the normal curvature matrix ("total") or the eigenvector which corresponds to the maximum absolute eigenvalue of the normal curvature matrix ("local"). As default, type is set to "total".
coefs	an (optional) character string which (partially) match with the names of some model parameters.
plot.it	an (optional) logical indicating if the plot is required or just the data matrix in which that plot is based. As default, plot.it is set to FALSE.
identify	an (optional) integer indicating the number of individuals to identify on the plot. This is only appropriate if plot.it=TRUE.
...	further arguments passed to or from other methods. If plot.it=TRUE then ... may be used to include graphical parameters to customize the plot. For example, col, pch, cex, main, sub, xlab, ylab.

Value

A matrix as many rows as individuals in the sample and one column with the values of the local influence measure.

References

Cook R.D. (1986) Assessment of Local Influence. *Journal of the Royal Statistical Society: Series B (Methodological)* 48, 133-155.

Examples

```
##### Example 1: Self diagnosed ear infections in swimmers
data(swimmers)
fit1 <- overglm(infections ~ frequency + location, family="nb1(log)", data=swimmers)

### Local influence for all parameters in the linear predictor
localInfluence(fit1, type="local", plot.it=TRUE, col="red", lty=1, lwd=1, col.lab="blue",
               col.axis="blue", col.main="black", family="mono", cex=0.8)

### Local influence for the parameter associated with 'frequency'
localInfluence(fit1, type="local", plot.it=TRUE, col="red", lty=1, lwd=1, col.lab="blue",
               coef="frequency", col.axis="blue", col.main="black", family="mono", cex=0.8)

##### Example 2: Article production by graduate students in biochemistry PhD programs
bioChemists <- pscl::bioChemists
fit2 <- overglm(art ~ fem + kid5 + ment, family="nb1(log)", data = bioChemists)

### Local influence for all parameters in the linear predictor
localInfluence(fit2, type="local", plot.it=TRUE, col="red", lty=1, lwd=1, col.lab="blue",
               col.axis="blue", col.main="black", family="mono", cex=0.8)

### Local influence for the parameter associated with 'fem'
localInfluence(fit2, type="local", plot.it=TRUE, col="red", lty=1, lwd=1, col.lab="blue",
               coef="fem", col.axis="blue", col.main="black", family="mono", cex=0.8)
```



```
##### Example 3: Agents to stimulate cellular differentiation
data(cellular)
fit3 <- overglm(cbind(cells,200-cells) ~ tnf + ifn, family="bb(logit)", data=cellular)

### Local influence for all parameters in the linear predictor
localInfluence(fit3, type="local", plot.it=TRUE, col="red", lty=1, lwd=1, col.lab="blue",
               col.axis="blue", col.main="black", family="mono", cex=0.8)

### Local influence for the parameter associated with 'tnf'
localInfluence(fit3, type="local", plot.it=TRUE, col="red", lty=1, lwd=1, col.lab="blue",
               coef="tnf", col.axis="blue", col.main="black", family="mono", cex=0.8)
```

 mammary

Ability of retinyl acetate to prevent mammary cancer in rats

Description

A total of 76 female rats were injected with a carcinogen for mammary cancer. Then, all animals were given retinyl acetate (retinoid) to prevent mammary cancer for 60 days. After this phase, the 48 animals that remained tumor-free were randomly assigned to continue retinoid prophylaxis or control. Rats were then palpated for tumors twice weekly, and observations ended 182 days after initial carcinogen injections began. The main objective of the analysis was to assess the difference in tumor development between the treated and control groups.

Usage

```
data(mammary)
```

Format

A data frame with 48 rows and 2 variables:

group a factor giving the group to which the rat was assigned: "retinoid" or "control".

tumors a numeric vector giving the number of tumors identified on the rat.

References

Lawless J.F. (1987) Regression Methods for Poisson Process Data. *Journal of the American Statistical Association* 82:808-815.

Morel J.G., Nagaraj N.K. (2012) *Overdispersion Models in SAS*. SAS Institute Inc., Cary, North Carolina, USA.

Examples

```
data(mammary)
dev.new()
boxplot(tumors ~ group, data=mammary, outline=FALSE, xlab="Group",
        ylab="Number of tumors", col=c("yellow","blue"))
```

 Melanopus

Assay of an Insecticide with a Synergist

Description

These data are concerned with the estimation of the lowest-cost mixtures of insecticides and synergists. They relate to assays on a grasshopper *Melanopus sanguinipes* with carbofuran and piperonyl butoxide, which enhances carbofuran's toxicity.

Usage

data(Melanopus)

Format

A data frame with 15 rows and 4 variables:

Killed a numeric vector indicating how many grasshoppers were killed.

Exposed a numeric vector indicating how many grasshoppers were exposed.

Insecticide a numeric vector indicating the dose of insecticide.

Synergist a numeric vector indicating the dose of synergist.

References

McCullagh P., Nelder J.A. (1989). *Generalized Linear Models. 2nd Edition.* Chapman and Hall, London.

Wei B.C. (1998). *Exponential Family Nonlinear Models.* Springer, Singapore.

 Oranges

Oranges

Description

The data arose from five orange trees grown in Riverside, California, during 1969-1973. The response is the trunk circumference, in millimeters, and the predictor variable is time, in days. The predictor variable has an arbitrary origin and was taken on December 31, 1968.

Usage

data(Oranges)

Format

A data frame with 35 rows and 3 variables:

Trunk a numeric vector indicating the trunk circumference, in millimeters.

Days a numeric vector indicating the time, in days, since December 31, 1968.

Tree a numeric vector with the identifier of each orange tree.

References

Draper N., Smith H. (1998) Applied Regression Analysis, Third Edition. *John Wiley & Sons*.

Examples

```
dev.new()
data(Oranges)
with(Oranges,plot(Days, Trunk, pch=16, col="blue"))
```

orobanche

Germination of Orobanche Seeds

Description

These data arose from a study of the germination of two species of Orobanche seeds (*O. aegyptiaca* 75 and *O. aegyptiaca* 73) grown on 1/125 dilutions of two different root extract media (cucumber and bean) in a 2×2 factorial layout with replicates. The data consist of the number of seeds and germinating seeds for each replicate. Interest is focused on the possible differences in germination rates for the two types of seed and root extract and whether there is any interaction.

Usage

```
data(orobanche)
```

Format

A data frame with 21 rows and 4 variables:

specie a factor indicating the specie of Orobanche seed: *O. aegyptiaca* 75 ("Aegyptiaca 75") and *O. aegyptiaca* 73 ("Aegyptiaca 73").

extract a factor indicating the root extract: cucumber ("Cucumber") and bean ("Bean").

seeds a numeric vector indicating the total number of seeds.

germinated a numeric vector indicating the number of germinated seeds.

References

Crowder M.J. (1978) Beta-binomial anova for proportions. *Journal of the Royal Statistical Society, Series C (Applied Statistics)* 27:34-37.

Hinde J., Demetrio C.G.B. (1998) Overdispersion: Models and estimation. *Computational Statistics & Data Analysis* 27:151-170.

Examples

```
data(orobanche)
out <- aggregate(cbind(germinated,seeds) ~ extract + specie, data=orobanche, sum)
dev.new()
barplot(100*germinated/seeds ~ extract + specie, beside=TRUE, data=out, width=0.3,
        col=c("yellow","blue"), xlab="Specie", ylab="% of germinated seeds")
legend("topleft",c("Bean","Cucumber"),fill=c("yellow","blue"),title="Extract",bty="n")
```

ossification

Teratogenic effects of phenytoin and trichloropropene oxide

Description

The data come from a 2x2 factorial design with 81 pregnant mice. In the experiment each pregnant mouse was randomly allocated to a control group and three treated groups. These groups received daily, by gastric gavage, 60 mg/kg of phenytoin, 100 mg/kg of trichloropropene oxide, or 60 mg/kg of phenytoin and 100 mg/kg of trichloropropene oxide. On day 18 of gestation, the fetuses were recovered, stained, and cleared. Then, by visual inspection, the presence or absence of ossification was determined for the different joints of the right and left forepaws. The experiment investigated the synergy of phenytoin and trichloropropene oxide to produce ossification at the phalanges, teratogenic effects.

Usage

```
data(ossification)
```

Format

A data frame with 81 rows and 4 variables:

fetuses a numeric vector giving the number of fetuses showing ossification on the left middle third phalanx.

litter a numeric vector giving the litter size.

pht a factor giving the dose (mg/kg) of phenytoin: "0 mg/kg" or "60 mg/kg".

tcpo a factor giving the dose (mg/kg) of trichloropropene oxide: "0 mg/kg" or "100 mg/kg".

References

Morel J.G., Neerchal N.K. (1997) Clustered binary logistic regression in teratology data using a finite mixture distribution. *Statistics in Medicine* 16:2843-2853.

Morel J.G., Nagaraj N.K. (2012) *Overdispersion Models in SAS*. SAS Institute Inc., Cary, North Carolina, USA.

Examples

```

data(ossification)
dev.new()
boxplot(100*fetuses/litter ~ pht, data=subset(ossification,tcpo=="0 mg/kg"),
        at=c(1:2) - 0.2, col="yellow", boxwex=0.25, xaxt="n",
        xlab="Dose of PHT", ylab="% of fetuses showing ossification")
boxplot(100*fetuses/litter ~ pht, data=subset(ossification,tcpo=="100 mg/kg"),
        add=TRUE, at=c(1:2) + 0.2, col="blue", boxwex=0.25, xaxt="n")
axis(1, at=c(1:2), labels=levels(ossification$pht))
legend("bottomleft", legend=c("0 mg/kg","100 mg/kg"), fill=c("yellow","blue"),
       title="Dose of TCPO", bty="n", cex=0.9)

```

overglm

Alternatives to the Poisson and Binomial Regression Models under the presence of Overdispersion.

Description

Allows to fit regression models based on the negative binomial, beta-binomial, and random-clumped binomial. distributions, which are alternatives to the Poisson and binomial regression models under the presence of overdispersion.

Usage

```

overglm(
  formula,
  offset,
  family = "nb1(log)",
  weights,
  data,
  subset,
  na.action = na.omit(),
  reltol = 1e-13,
  start = NULL,
  ...
)

```

Arguments

formula	a formula expression of the form $\text{response} \sim x_1 + x_2 + \dots$, which is a symbolic description of the linear predictor of the model to be fitted to the data.
offset	this can be used to specify an <i>a priori</i> known component to be included in the linear predictor during fitting. This should be NULL or a numeric vector of length equal to the number of cases.
family	A character string that allows you to specify the distribution describing the response variable. In addition, it allows you to specify the link function to be used in the model for μ . The following distributions are supported: negative

	binomial I ("nb1"), negative binomial II ("nb2"), negative binomial ("nbf"), zero-truncated negative binomial I ("ztnb1"), zero-truncated negative binomial II ("ztnb2"), zero-truncated negative binomial ("ztnbf"), zero-truncated poisson ("ztpoi"), beta-binomial ("bb") and random-clumped binomial ("rcb"). Link functions available for these models are the same as those available for Poisson and binomial models via <code>glm</code> . See family documentation.
weights	an (optional) vector of positive "prior weights" to be used in the fitting process. The length of weights should be the same as the number of observations.
data	an (optional) data frame in which to look for variables involved in the formula expression, as well as for variables specified in the arguments weights and subset.
subset	an (optional) vector specifying a subset of individuals to be used in the fitting process.
na.action	a function which indicates what should happen when the data contain NAs. By default <code>na.action</code> is set to <code>na.omit()</code> .
reltol	an (optional) positive value which represents the <i>relative convergence tolerance</i> for the BFGS method in <code>optim</code> . As default, <code>reltol</code> is set to <code>1e-13</code> .
start	an (optional) vector of starting values for the parameters in the linear predictor.
...	further arguments passed to or from other methods.

Details

The negative binomial distribution can be obtained as mixture of the Poisson and Gamma distributions. If $Y|\lambda \sim \text{Poisson}(\lambda)$, where $E(Y|\lambda) = \text{Var}(Y|\lambda) = \lambda$, and $\lambda \sim \text{Gamma}(\theta, \nu)$, in which $E(\lambda) = \theta$ and $\text{Var}(\lambda) = \nu\theta^2$, then Y is distributed according to the negative binomial distribution. As follows, some special cases are described:

- (1) If $\theta = \mu$ and $\nu = \phi$ then $Y \sim \text{Negative Binomial I}$, $E(Y) = \mu$ and $\text{Var}(Y) = \mu(1 + \phi\mu)$.
- (2) If $\theta = \mu$ and $\nu = \phi/\mu$ then $Y \sim \text{Negative Binomial II}$, $E(Y) = \mu$ and $\text{Var}(Y) = \mu(1 + \phi)$.
- (3) If $\theta = \mu$ and $\nu = \phi\mu^\tau$ then $Y \sim \text{Negative Binomial}$, $E(Y) = \mu$ and $\text{Var}(Y) = \mu(1 + \phi\mu^{\tau+1})$.

Therefore, the regression models based on the negative binomial and zero-truncated negative binomial distributions are alternatives, under overdispersion, to those based on the Poisson and zero-truncated Poisson distributions, respectively.

The beta-binomial distribution can be obtained as a mixture of the binomial and beta distributions. If $mY|\pi \sim \text{Binomial}(m, \pi)$, where $E(Y|\pi) = \pi$ and $\text{Var}(Y|\pi) = m^{-1}\pi(1-\pi)$, and $\pi \sim \text{Beta}(\mu, \phi)$, in which $E(\pi) = \mu$ and $\text{Var}(\pi) = (\phi+1)^{-1}\mu(1-\mu)$, with $\phi > 0$, then $mY \sim \text{Beta-Binomial}(m, \mu, \phi)$, so that $E(Y) = \mu$ and $\text{Var}(Y) = m^{-1}\mu(1-\mu)[1 + (\phi+1)^{-1}(m-1)]$. Therefore, the regression model based on the beta-binomial distribution is an alternative, under overdispersion, to the binomial regression model.

The random-clumped binomial distribution can be obtained as a mixture of the binomial and Bernoulli distributions. If $mY|\pi \sim \text{Binomial}(m, \pi)$, where $E(Y|\pi) = \pi$ and $\text{Var}(Y|\pi) = m^{-1}\pi(1-\pi)$, whereas $\pi = (1-\phi)\mu + \phi$ with probability μ , and $\pi = (1-\phi)\mu$ with probability $1-\mu$, in which $E(\pi) = \mu$ and $\text{Var}(\pi) = \phi^2\mu(1-\mu)$, with $\phi \in (0, 1)$, then $mY \sim \text{Random-clumped Binomial}(m, \mu, \phi)$, so that $E(Y) = \mu$ and $\text{Var}(Y) = m^{-1}\mu(1-\mu)[1 + \phi^2(m-1)]$. Therefore, the regression model based on the random-clumped binomial distribution is an alternative, under overdispersion, to the binomial regression model.

In all cases, even where the response variable is described by a zero-truncated distribution, the fitted model describes the way in which μ is dependent on some covariates. Parameter estimation is performed using the maximum likelihood method. The model parameters are estimated by maximizing the log-likelihood function through the BFGS method available in the routine `optim`. The accuracy and speed of the BFGS method are increased because the call to the routine `optim` is performed using analytical instead of the numerical derivatives. The variance-covariance matrix estimate is obtained as being minus the inverse of the (analytical) hessian matrix evaluated at the parameter estimates and the observed data.

A set of standard extractor functions for fitted model objects is available for objects of class `zeroinflation`, including methods to the generic functions such as `print`, `summary`, `model.matrix`, `estepqua`, `coef`, `vcov`, `logLik`, `fitted`, `confint`, `AIC`, `BIC` and `predict`. In addition, the model fitted to the data may be assessed using functions such as `anova.overglm`, `residuals.overglm`, `df-beta.overglm`, `cooks.distance.overglm`, `localInfluence.overglm`, `gvif.overglm` and `envelope.overglm`. The variable selection may be accomplished using the routine `stepCriterion.overglm`.

Value

an object of class `overglm` in which the main results of the model fitted to the data are stored, i.e., a list with components including

<code>coefficients</code>	a vector containing the parameter estimates,
<code>fitted.values</code>	a vector containing the estimates of μ_1, \dots, μ_n ,
<code>start</code>	a vector containing the starting values used,
<code>prior.weights</code>	a vector containing the case weights used,
<code>offset</code>	a vector containing the offset used,
<code>terms</code>	an object containing the terms objects,
<code>loglik</code>	the value of the log-likelihood function evaluated at the parameter estimates,
<code>estfun</code>	a vector containing the estimating functions evaluated at the parameter estimates and the observed data,
<code>formula</code>	the formula,
<code>levels</code>	the levels of the categorical regressors,
<code>contrasts</code>	an object containing the contrasts corresponding to levels,
<code>converged</code>	a logical indicating successful convergence,
<code>model</code>	the full model frame,
<code>y</code>	the response count vector,

family	an object containing the family object used,
linear.predictors	a vector containing the estimates of $g(\mu_1), \dots, g(\mu_n)$,
R	a matrix with the Cholesky decomposition of the inverse of the variance-covariance matrix of all parameters in the model,
call	the original function call.

References

- Crowder M. (1978) Beta-binomial anova for proportions, *Journal of the Royal Statistical Society Series C (Applied Statistics)* 27, 34-37.
- Lawless J.F. (1987) Negative binomial and mixed poisson regression, *The Canadian Journal of Statistics* 15, 209-225.
- Morel J.G., Neerchal N.K. (1997) Clustered binary logistic regression in teratology data using a finite mixture distribution, *Statistics in Medicine* 16, 2843-2853.
- Morel J.G., Nagaraj N.K. (2012) *Overdispersion Models in SAS*. SAS Institute Inc., Cary, North Carolina, USA.

See Also

[zeroalt](#), [zeroinf](#)

Examples

```
### Example 1: Ability of retinyl acetate to prevent mammary cancer in rats
data(mammary)
fit1 <- overglm(tumors ~ group, family="nb1(identity)", data=mammary)
summary(fit1)

### Example 2: Self diagnosed ear infections in swimmers
data(swimmers)
fit2 <- overglm(infections ~ frequency + location, family="nb1(log)", data=swimmers)
summary(fit2)

### Example 3: Urinary tract infections in HIV-infected men
data(uti)
fit3 <- overglm(episodes ~ cd4 + offset(log(time)), family="nb1(log)", data = uti)
summary(fit3)

### Example 4: Article production by graduate students in biochemistry PhD programs
bioChemists <- pscl::bioChemists
fit4 <- overglm(art ~ fem + kid5 + ment, family="nb1(log)", data = bioChemists)
summary(fit4)

### Example 5: Agents to stimulate cellular differentiation
data(cellular)
fit5 <- overglm(cbind(cells,200-cells) ~ tnf + ifn, family="bb(logit)", data=cellular)
```



```
summary(fit5)

### Example 6: Teratogenic effects of phenytoin and trichloropropene oxide
data(ossification)
model6 <- cbind(fetuses,litter-fetuses) ~ pht + tcpo
fit6 <- overglm(model6, family="rcb(cloglog)", data=ossification)
summary(fit6)

### Example 7: Germination of orobanche seeds
data(orobanche)
model7 <- cbind(germinated,seeds-germinated) ~ specie + extract
fit7 <- overglm(model7, family="rcb(cloglog)", data=orobanche)
summary(fit7)
```

PAC

Pardo-Alonso's Criterion for Generalized Estimating Equations

Description

Computes the Pardo-Alonso's criterion (PAC) for one or more objects of the class *glmgee*.

Usage

```
PAC(..., verbose = TRUE, digits = max(3, getOption("digits") - 2))
```

Arguments

...	one or several objects of the class <i>glmgee</i> .
verbose	an (optional) logical switch indicating if should the report of results be printed. As default, verbose is set to TRUE.
digits	an (optional) integer indicating the number of digits to print. As default, digits is set to $\max(3, \text{getOption}(\text{"digits"}) - 2)$.

Value

A data.frame with the values of the PAC for each *glmgee* object in the input.

References

Pardo M.C., Alonso R. (2019) Working correlation structure selection in GEE analysis. *Statistical Papers* 60:1447–1467.

Vanegas L.H., Rondon L.M., Paula G.A. (2023) Generalized Estimating Equations using the new R package *glmtoolbox*. *The R Journal* 15:105-133.

See Also

[QIC](#), [CIC](#), [RJC](#), [AGPC](#), [SGPC](#), [GHYC](#)

Examples

```
##### Example 1: Effect of ozone-enriched atmosphere on growth of sitka spruces
data(spruces)
mod1 <- size ~ poly(days,4) + treat
fit1 <- glmgee(mod1, id=tree, family=Gamma(log), data=spruces)
fit2 <- update(fit1, corstr="AR-M-dependent")
fit3 <- update(fit1, corstr="Stationary-M-dependent(2)")
fit4 <- update(fit1, corstr="Exchangeable")
PAC(fit1, fit2, fit3, fit4)

##### Example 2: Treatment for severe postnatal depression
data(depression)
mod2 <- depressd ~ visit + group
fit1 <- glmgee(mod2, id=subj, family=binomial(logit), data=depression)
fit2 <- update(fit1, corstr="AR-M-dependent")
fit3 <- update(fit1, corstr="Stationary-M-dependent(2)")
fit4 <- update(fit1, corstr="Exchangeable")
PAC(fit1, fit2, fit3, fit4)

##### Example 3: Treatment for severe postnatal depression (2)
mod3 <- dep ~ visit*group
fit1 <- glmgee(mod3, id=subj, family=gaussian(identity), data=depression)
fit2 <- update(fit1, corstr="AR-M-dependent")
fit3 <- update(fit1, corstr="Exchangeable")
PAC(fit1, fit2, fit3)
```

pipeline

Alaska pipeline

Description

The Alaska pipeline data consists of in-field ultrasonic measurements of defects depths in the Alaska pipeline. The depth of the defects was measured again in the laboratory. These measurements were performed in six batches. The data were analyzed to calibrate the bias of field measurements relative to laboratory measurements. In this analysis, the field measurement is the response variable and the laboratory measurement is the predictor variable.

Usage

```
data(pipeline)
```

Format

A data frame with 107 rows and 2 variables:

Field a numeric vector indicating the number of defects measured in the field.

Lab a numeric vector indicating the number of defects measured in the laboratory.

Source

<https://www.itl.nist.gov/div898/handbook/pmd/section6/pmd621.htm>

References

Weisberg S. (2005). *Applied Linear Regression*, 3rd edition. Wiley, New York.

Examples

```
data(pipeline)
dev.new()
xlab <- "In-laboratory measurements"
ylab <- "In-field measurements"
with(pipeline,plot(Lab,Field,pch=20,xlab=xlab,ylab=ylab))
```

predict.glmgee

Predictions for Generalized Estimating Equations

Description

Produces predictions and optionally estimates standard errors of those predictions from a fitted generalized estimating equation.

Usage

```
## S3 method for class 'glmgee'
predict(
  object,
  ...,
  newdata,
  se.fit = FALSE,
  type = c("link", "response"),
  varest = c("robust", "df-adjusted", "model", "bias-corrected")
)
```

Arguments

object	an object of the class <i>glmgee</i> .
...	further arguments passed to or from other methods.
newdata	an (optional) data frame in which to look for variables with which to predict. If omitted, the fitted linear predictors are used.
se.fit	an (optional) logical switch indicating if standard errors are required. As default, <i>se.fit</i> is set to <code>FALSE</code> .
type	an (optional) character string giving the type of prediction required. The default, "link", is on the scale of the linear predictors, and the alternative, "response", is on the scale of the response variable.

`varest` an (optional) character string indicating the type of estimator which should be used to the variance-covariance matrix of the interest parameters. The available options are: robust sandwich-type estimator ("robust"), degrees-of-freedom-adjusted estimator ("df-adjusted"), bias-corrected estimator ("bias-corrected"), and the model-based or naive estimator ("model"). As default, `varest` is set to "robust".

Value

A matrix with so many rows as `newdata` and one column with the predictions. If `se.fit=TRUE` then a second column with estimates standard errors is included.

Examples

```
##### Example 1: Effect of ozone-enriched atmosphere on growth of sitka spruces
data(spruces)
mod1 <- size ~ poly(days,4) + treat
fit1 <- glmgee(mod1, id=tree, family=Gamma(log), data=spruces, corstr="AR-M-dependent")
newdata1 <- data.frame(days=c(556,556), treat=as.factor(c("normal", "ozone-enriched")))
predict(fit1, newdata=newdata1, type="response", se.fit=TRUE)

##### Example 2: Treatment for severe postnatal depression
data(depression)
mod2 <- depressd ~ visit + group
fit2 <- glmgee(mod2, id=subj, family=binomial(logit), corstr="AR-M-dependent", data=depression)
newdata2 <- data.frame(visit=c(6,6), group=as.factor(c("placebo", "oestrogen")))
predict(fit2, newdata=newdata2, type="response", se.fit=TRUE)

##### Example 3: Treatment for severe postnatal depression (2)
mod3 <- dep ~ visit*group
fit3 <- glmgee(mod3, id=subj, family=gaussian(identity), corstr="AR-M-dependent", data=depression)
newdata3 <- data.frame(visit=c(6,6), group=as.factor(c("placebo", "oestrogen")))
predict(fit3, newdata=newdata3, type="response", se.fit=TRUE)
```

QIC

QIC for Generalized Estimating Equations

Description

Computes the quasi-likelihood under the independence model criterion (QIC) for one or more objects of the class `glmgee`.

Usage

```
QIC(
  ...,
  k = 2,
  u = FALSE,
```

```

  verbose = TRUE,
  digits = max(3, getOption("digits") - 2)
)

```

Arguments

...	one or several objects of the class <i>glmgee</i> .
k	an (optional) non-negative value giving the magnitude of the penalty. As default, k is set to 2.
u	an (optional) logical switch indicating if QIC should be replaced by QICu. As default, u is set to FALSE.
verbose	an (optional) logical switch indicating if should the report of results be printed. As default, verbose is set to TRUE.
digits	an (optional) integer indicating the number of digits to print. As default, digits is set to $\max(3, \text{getOption}("digits") - 2)$.

Value

A data.frame with the values of $-2 \times$ quasi-likelihood, the number of parameters in the linear predictor, and the value of QIC (or QICu if $u=TRUE$) for each *glmgee* object in the input.

References

Pan W. (2001) Akaike's information criterion in generalized estimating equations, *Biometrics* 57:120-125.

Hin L.-Y., Carey V.J., Wang Y.-G. (2007) Criteria for Working–Correlation–Structure Selection in GEE: Assessment via Simulation. *The American Statistician* 61:360–364.

Vanegas L.H., Rondon L.M., Paula G.A. (2023) Generalized Estimating Equations using the new R package *glmtoolbox*. *The R Journal* 15:105-133.

See Also

[CIC](#), [GHYC](#), [RJC](#), [AGPC](#), [SGPC](#)

Examples

```

##### Example 1: Effect of ozone-enriched atmosphere on growth of sitka spruces
data(spruces)
mod1 <- size ~ poly(days,4) + treat
fit1 <- glmgee(mod1, id=tree, family=Gamma(log), data=spruces)
fit2 <- update(fit1, corstr="AR-M-dependent")
fit3 <- update(fit1, corstr="Stationary-M-dependent(2)")
fit4 <- update(fit1, corstr="Exchangeable")
QIC(fit1, fit2, fit3, fit4)

##### Example 2: Treatment for severe postnatal depression
data(depression)
mod2 <- depressd ~ visit + group
fit1 <- glmgee(mod2, id=subj, family=binomial(logit), data=depression)

```

```

fit2 <- update(fit1, corstr="AR-M-dependent")
fit3 <- update(fit1, corstr="Stationary-M-dependent(2)")
fit4 <- update(fit1, corstr="Exchangeable")
QIC(fit1, fit2, fit3, fit4)

##### Example 3: Treatment for severe postnatal depression (2)
mod3 <- dep ~ visit*group
fit1 <- glmgee(mod3, id=subj, family=gaussian(identity), data=depression)
fit2 <- update(fit1, corstr="AR-M-dependent")
fit3 <- update(fit1, corstr="Exchangeable")
QIC(fit1, fit2, fit3)

```

rabbits

Age and Eye Lens Weight of Rabbits in Australia

Description

The dry weight of the eye lens was measured for 71 free-living wild rabbits of known age. Eye lens weight tends to vary much less with environmental conditions than does total body weight, and therefore may be a much better indicator of age.

Usage

```
data(rabbits)
```

Format

A data frame with 71 rows and 2 variables:

age a numeric vector indicating the rabbit age, in days.

wlens a numeric vector indicating the dry weight of eye lens, in milligrams.

References

Dudzinski M.L., Mykytowycz R. (1961) The eye lens as an indicator of age in the wild rabbit in Australia. *CSIRO Wildlife Research*, 6, 156-159.

Ratkowsky D.A. (1983). *Nonlinear Regression Modelling*. Marcel Dekker, New York.

Wei B.C. (1998). *Exponential Family Nonlinear Models*. Springer, Singapore.

Examples

```

data(rabbits)
dev.new()
with(rabbits, plot(age, wlens, xlab="Age (in days)", pch=16, col="blue",
                  ylab="Dry weight of eye lens (in milligrams)"))

```

races

Hill races in Scotland

Description

Each year the Scottish Hill Runners Association publishes a list of hill races in Scotland for the year. These data consist of the record time, distance, and cumulative climb of 35 of those races. The statistical analysis of these data aims to explain the differences between the record time of the races. This is done using their differences in distance and cumulative climb.

Usage

```
data(races)
```

Format

A data frame with 35 rows and 4 variables:

race a character vector giving the names of the races.

distance a numeric vector giving the distance, in miles, of the races.

cclimb a numeric vector giving the cumulative climb, in thousands of feet, of the races.

rtime a numeric vector giving the record time, in minutes, of the races.

References

Agresti A. (2015) *Foundations of Linear and Generalized Linear Models*. John Wiley & Sons, New Jersey.

Examples

```
data(races)
breaks <- with(races, quantile(cclimb, probs=c(0:2)/2))
labels <- c("low", "high")
races2 <- within(races, cli <- cut(cclimb, include.lowest=TRUE, breaks, labels))
dev.new()
with(races2, plot(log(distance), log(rtime), pch=16, col=as.numeric(cli)))
legend("topleft", legend=c("low", "high"), title="Cumulative climb",
      col=c(1:2), pch=16, bty="n")
```

residuals.glmgee *Residuals for Generalized Estimating Equations*

Description

Calculates residuals for a fitted generalized estimating equation.

Usage

```
## S3 method for class 'glmgee'
residuals(
  object,
  ...,
  type = c("mahalanobis", "pearson", "deviance"),
  plot.it = FALSE,
  identify
)
```

Arguments

object	a object of the class <i>glmgee</i> .
...	further arguments passed to or from other methods
type	an (optional) character string giving the type of residuals which should be returned. The available options are: (1) "pearson"; (2) "deviance"; (3) the distance between the observed response vector and the fitted mean vector using a metric based on the product between the cluster size and fitted variance-covariance matrix ("mahalanobis"). As default, type is set to "mahalanobis".
plot.it	an (optional) logical switch indicating if a plot of the residuals is required. As default, plot.it is set to FALSE.
identify	an (optional) integer value indicating the number of individuals/clusters to identify on the plot of residuals. This is only appropriate when plot.it=TRUE.

Value

A vector with the observed residuals type type.

Examples

```
##### Example 1: Effect of ozone-enriched atmosphere on growth of sitka spruces
data(spruces)
mod1 <- size ~ poly(days,4) + treat
fit1 <- glmgee(mod1, id=tree, family=Gamma(log), data=spruces, constr="AR-M-dependent")
### Plot to assess the adequacy of the chosen variance function
residuals(fit1, type="deviance", plot.it=TRUE, col="red", pch=20, col.lab="blue",
          col.axis="blue", col.main="black", family="mono", cex=0.8)
### Plot to identify trees suspicious to be outliers
```



```

residuals(fit1, type="mahalanobis", plot.it=TRUE, col="red", pch=20, col.lab="blue",
          col.axis="blue", col.main="black", family="mono", cex=0.8)

##### Example 2: Treatment for severe postnatal depression
data(depression)
mod2 <- depressd ~ visit + group
fit2 <- glmgee(mod2, id=subj, family=binomial(logit), corstr="AR-M-dependent", data=depression)
### Plot to identify women suspicious to be outliers
residuals(fit2, type="mahalanobis", plot.it=TRUE, col="red", pch=20, col.lab="blue",
          col.axis="blue", col.main="black", family="mono", cex=0.8)

##### Example 3: Treatment for severe postnatal depression (2)
mod3 <- dep ~ visit*group
fit3 <- glmgee(mod3, id=subj, family=gaussian(identity), corstr="AR-M-dependent", data=depression)
### Plot to assess the adequacy of the chosen variance function
residuals(fit3, type="pearson", plot.it=TRUE, col="red", pch=20, col.lab="blue",
          col.axis="blue", col.main="black", family="mono", cex=0.8)
### Plot to identify women suspicious to be outliers
residuals(fit3, type="mahalanobis", plot.it=TRUE, col="red", pch=20, col.lab="blue",
          col.axis="blue", col.main="black", family="mono", cex=0.8)

```

residuals.gnm

Residuals for Generalized Nonlinear Models

Description

Computes residuals for a fitted generalized nonlinear model.

Usage

```

## S3 method for class 'gnm'
residuals(
  object,
  type = c("quantile", "deviance", "pearson"),
  standardized = FALSE,
  plot.it = FALSE,
  identify,
  dispersion = NULL,
  ...
)

```

Arguments

object	a object of the class <i>gnm</i> .
type	an (optional) character string giving the type of residuals which should be returned. The available options are: (1) "quantile", (2) "deviance", and (3) "pearson". As default, type is set to "quantile".

standardized	an (optional) logical switch indicating if the residuals should be standardized by dividing by the square root of $(1 - h)$, where h is a measure of leverage. As default, standardized is set to FALSE.
plot.it	an (optional) logical switch indicating if a plot of the residuals versus the fitted values is required. As default, plot.it is set to FALSE.
identify	an (optional) integer value indicating the number of individuals to identify on the plot of residuals. This is only appropriate when plot.it=TRUE.
dispersion	an (optional) value indicating the dispersion parameter estimate that must be used to calculate residuals.
...	further arguments passed to or from other methods

Value

A vector with the observed residuals type type.

References

- Atkinson A.C. (1985) *Plots, Transformations and Regression*. Oxford University Press, Oxford.
- Davison A.C., Gigli A. (1989) Deviance Residuals and Normal Scores Plots. *Biometrika* 76, 211-221.
- Dunn P.K., Smyth G.K. (1996) Randomized Quantile Residuals. *Journal of Computational and Graphical Statistics* 5, 236-244.
- Pierce D.A., Schafer D.W. (1986) Residuals in Generalized Linear Models. *Journal of the American Statistical Association* 81, 977-986.

Examples

```
##### Example 1: The effects of fertilizers on coastal Bermuda grass
data(Grass)
fit1 <- gnm(Yield ~ b0 + b1/(Nitrogen + a1) + b2/(Phosphorus + a2) + b3/(Potassium + a3),
           family=gaussian(inverse), start=c(b0=0.1,b1=13,b2=1,b3=1,a1=45,a2=15,a3=30), data=Grass)
residuals(fit1, type="quantile", plot.it=TRUE, col="red", pch=20, col.lab="blue",
          col.axis="blue", col.main="black", family="mono", cex=0.8)

##### Example 2: Assay of an Insecticide with a Synergist
data(Melanopus)
fit2 <- gnm(Killed/Exposed ~ b0 + b1*log(Insecticide-a1) + b2*Synergist/(a2 + Synergist),
           family=binomial(logit), weights=Exposed, start=c(b0=-3,b1=1.2,a1=1.7,b2=1.7,a2=2),
           data=Melanopus)
residuals(fit2, type="quantile", plot.it=TRUE, col="red", pch=20, col.lab="blue",
          col.axis="blue", col.main="black", family="mono", cex=0.8)

##### Example 3: Developmental rate of Drosophila melanogaster
data(Drosophila)
fit3 <- gnm(Duration ~ b0 + b1*Temp + b2/(Temp-a), family=Gamma(log),
           start=c(b0=3,b1=-0.25,b2=-210,a=55), weights=Size, data=Drosophila)
residuals(fit3, type="quantile", plot.it=TRUE, col="red", pch=20, col.lab="blue",
          col.axis="blue", col.main="black", family="mono", cex=0.8)
```

```
##### Example 4: Radioimmunological Assay of Cortisol
data(Cortisol)
fit4 <- gnm(Y ~ b0 + (b1-b0)/(1 + exp(b2+ b3*I Dose))^b4, family=Gamma(identity),
            start=c(b0=130,b1=2800,b2=3,b3=3,b4=0.5), data=Cortisol)
residuals(fit4, type="quantile", plot.it=TRUE, col="red", pch=20, col.lab="blue",
           col.axis="blue", col.main="black", family="mono", cex=0.8)

##### Example 5: Age and Eye Lens Weight of Rabbits in Australia
data(rabbits)
fit5 <- gnm(wlens ~ b1 - b2/(age + b3), family=Gamma(log),
            start=c(b1=5.5,b2=130,b3=35), data=rabbits)
residuals(fit5, type="quantile", plot.it=TRUE, col="red", pch=20, col.lab="blue",
           col.axis="blue", col.main="black", family="mono", cex=0.8)

##### Example 6: Calls to a technical support help line
data(calls)
fit6 <- gnm(calls ~ SSlogis(week, Asym, xmid, scal), family=poisson(identity), data=calls)
residuals(fit6, type="quantile", plot.it=TRUE, col="red", pch=20, col.lab="blue",
           col.axis="blue", col.main="black", family="mono", cex=0.8)
```

residuals.overglm *Residuals for alternatives to the Poisson and Binomial Regression Models under the presence of Overdispersion.*

Description

Computes various types of residuals to assess the individual quality of model fit for regression models based on the negative binomial, beta-binomial, and random-clumped binomial distributions, which are alternatives to the Poisson and binomial regression models under the presence of overdispersion.

Usage

```
## S3 method for class 'overglm'
residuals(
  object,
  type = c("quantile", "standardized", "response"),
  plot.it = FALSE,
  identify,
  ...
)
```

Arguments

object an object of class *overglm*.

type an (optional) character string which allows to specify the required type of residuals. The available options are: (1) the difference between the observed response

	and the fitted mean ("response"); (2) the standardized difference between the observed response and the fitted mean ("standardized"); and (3) the randomized quantile residual ("quantile"). By default, type is set to "quantile".
plot.it	an (optional) logical switch indicating if the plot of residuals versus the fitted values is required. As default, plot.it is set to FALSE.
identify	an (optional) positive integer value indicating the number of individuals to identify on the plot of residuals versus the fitted values. This is only appropriate if plot.it=TRUE.
...	further arguments passed to or from other methods. If plot.it=TRUE then ... may be used to include graphical parameters to customize the plot. For example, col, pch, cex, main, sub, xlab, ylab.

Value

A vector with the observed type-type residuals.

References

Dunn P.K., Smyth G.K. (1996) Randomized Quantile Residuals. *Journal of Computational and Graphical Statistics*, 5, 236-244.

Examples

```
##### Example 1: Self diagnosed ear infections in swimmers
data(swimmers)
fit1 <- overglm(infections ~ frequency + location, family="nb1(log)", data=swimmers)
residuals(fit1, type="quantile", plot.it=TRUE, col="red", pch=20, col.lab="blue",
          col.axis="blue", col.main="black", family="mono", cex=0.8)

##### Example 2: Article production by graduate students in biochemistry PhD programs
bioChemists <- pscl::bioChemists
fit2 <- overglm(art ~ fem + kid5 + ment, family="nb1(log)", data = bioChemists)
residuals(fit2, type="quantile", plot.it=TRUE, col="red", pch=20, col.lab="blue",
          col.axis="blue", col.main="black", family="mono", cex=0.8)

##### Example 3: Agents to stimulate cellular differentiation
data(cellular)
fit3 <- overglm(cbind(cells,200-cells) ~ tnf + ifn, family="bb(logit)", data=cellular)
residuals(fit3, type="quantile", plot.it=TRUE, col="red", pch=20, col.lab="blue",
          col.axis="blue", col.main="black", family="mono", cex=0.8)
```

residuals.zeroinflation

Residuals in Regression Models to deal with Zero-Excess in Count Data

Description

Computes various types of residuals to assess the individual quality of model fit in regression models to deal with zero-excess in count data.

Usage

```
## S3 method for class 'zeroinflation'
residuals(
  object,
  type = c("quantile", "standardized", "response"),
  plot.it = FALSE,
  identify,
  ...
)
```

Arguments

<code>object</code>	an object of class <i>zeroinflation</i> .
<code>type</code>	an (optional) character string which allows to specify the required type of residuals. The available options are: (1) the difference between the observed response and the fitted mean ("response"); (2) the standardized difference between the observed response and the fitted mean ("standardized"); (3) the randomized quantile residual ("quantile"). By default, <code>type</code> is set to "quantile".
<code>plot.it</code>	an (optional) logical switch indicating if the plot of residuals versus the fitted values is required. As default, <code>plot.it</code> is set to FALSE.
<code>identify</code>	an (optional) positive integer value indicating the number of individuals to identify on the plot of residuals versus the fitted values. This is only appropriate if <code>plot.it=TRUE</code> .
<code>...</code>	further arguments passed to or from other methods. If <code>plot.it=TRUE</code> then <code>...</code> may be used to include graphical parameters to customize the plot. For example, <code>col</code> , <code>pch</code> , <code>cex</code> , <code>main</code> , <code>sub</code> , <code>xlab</code> , <code>ylab</code> .

Value

A vector with the observed residuals type `type`.

References

Dunn P.K., Smyth G.K. (1996) Randomized Quantile Residuals. *Journal of Computational and Graphical Statistics*, 5, 236-244.

Examples

```
##### Example 1: Self diagnosed ear infections in swimmers
data(swimmers)
fit1 <- zeroalt(infections ~ frequency | location, family="nb1(log)", data=swimmers)
residuals(fit1, type="quantile", plot.it=TRUE, col="red", pch=20, col.lab="blue",
          col.axis="blue", col.main="black", family="mono", cex=0.8)
```

```
##### Example 2: Article production by graduate students in biochemistry PhD programs
bioChemists <- pscl::bioChemists
fit2 <- zeroinf(art ~ fem + kid5 + ment | ment, family="nb1(log)", data = bioChemists)
residuals(fit2, type="quantile", plot.it=TRUE, col="red", pch=20, col.lab="blue",
          col.axis="blue", col.main="black", family="mono", cex=0.8)
```

residuals2

*Residuals for Linear and Generalized Linear Models***Description**

Computes residuals for a fitted linear or generalized linear model.

Usage

```
residuals2(object, type, standardized = FALSE, plot.it = FALSE, identify, ...)
```

Arguments

object	a object of the class <i>lm</i> or <i>glm</i> .
type	an (optional) character string giving the type of residuals which should be returned. The available options for LMs are: (1) externally studentized ("external"); (2) internally studentized ("internal") (default). The available options for GLMs are: (1) "pearson"; (2) "deviance" (default); (3) "quantile".
standardized	an (optional) logical switch indicating if the residuals should be standardized by dividing by the square root of $(1 - h)$, where h is a measure of leverage. As default, standardized is set to FALSE.
plot.it	an (optional) logical switch indicating if a plot of the residuals versus the fitted values is required. As default, plot.it is set to FALSE.
identify	an (optional) integer value indicating the number of individuals to identify on the plot of residuals. This is only appropriate when plot.it=TRUE.
...	further arguments passed to or from other methods

Value

A vector with the observed residuals type type.

References

- Atkinson A.C. (1985) *Plots, Transformations and Regression*. Oxford University Press, Oxford.
- Davison A.C., Gigli A. (1989) Deviance Residuals and Normal Scores Plots. *Biometrika* 76, 211-221.
- Dunn P.K., Smyth G.K. (1996) Randomized Quantile Residuals. *Journal of Computational and Graphical Statistics* 5, 236-244.
- Pierce D.A., Schafer D.W. (1986) Residuals in Generalized Linear Models. *Journal of the American Statistical Association* 81, 977-986.

Examples

```
##### Example 1: Species richness in plots
data(richness)
fit1 <- lm(Species ~ Biomass + pH, data=richness)
residuals2(fit1, type="external", plot.it=TRUE, col="red", pch=20, col.lab="blue",
           col.axis="blue", col.main="black", family="mono", cex=0.8)

##### Example 2: Lesions of Aucuba mosaic virus
data(aucuba)
fit2 <- glm(lesions ~ time, family=poisson, data=aucuba)
residuals2(fit2, type="quantile", plot.it=TRUE, col="red", pch=20, col.lab="blue",
           col.axis="blue", col.main="black", family="mono", cex=0.8)
```

richness	<i>Species richness</i>
----------	-------------------------

Description

In these data the response is species richness represented by a count of the number of plant species on plots with different biomass and three different soil pH levels: low, mid, and high.

Usage

```
data(richness)
```

Format

A data frame with 90 rows and 3 variables:

Biomass a numeric vector giving the value of the biomass in the plots.

pH a factor giving the soil pH level in the plots: "low", "mid", and "high".

Species a numeric vector giving the number of plant species in the plots.

References

Crawley M.J. (2007) *The R Book*. John Wiley & Sons, Chichester.

Examples

```
data(richness)
dev.new()
with(richness, plot(Biomass, Species, col=as.numeric(pH), pch=16))
legend("topright", legend=c("low", "mid", "high"), col=c(1:3), pch=16,
      title="pH level", bty="n")
```

rinse

*Dental Clinical Trial***Description**

These data arose from a study in dentistry. In this trial, subjects were generally healthy adult male and female volunteers, ages 18–55, with pre-existing plaque but without advanced periodontal disease. Prior to entry, subjects were screened for a minimum of 20 sound, natural teeth and a minimum mean plaque index of 2.0. Subjects with gross oral pathology or on antibiotic, antibacterial, or anti-inflammatory therapy were excluded from the study. One hundred nine volunteers were randomized in a double-blinded way to one of two novel mouth rinses (A and B) or to a control mouth rinse. Plaque was scored at baseline, at 3 months, and at 6 months by the Turesky modification of the Quigley-Hein index, a continuous measure. Four subjects had missing plaque scores. The main objective of the analysis is to measure the effectiveness of three mouth rinses at inhibiting dental plaque.

Usage

```
data(rinse)
```

Format

A data frame with 315 rows and 7 variables:

subject a character string giving the identifier of the volunteer.

gender a factor indicating the gender of the volunteer: "Female" and "Male".

age a numeric vector indicating the age of the volunteer.

rinse a factor indicating the type of rinse used by the volunteer: "Placebo", "A" and "B".

smoke a factor indicating if the volunteer smoke: "Yes" and "No".

time a numeric vector indicating the time (in months) since the treatment began.

score a numeric vector giving the subject's score of plaque.

References

Hadgu A., Koch G. (1999) Application of generalized estimating equations to a dental randomized clinical trial. *Journal of Biopharmaceutical Statistics* 9:161-178.

Examples

```
data(rinse)
dev.new()
boxplot(score ~ time, data=subset(rinse,rinse=="Placebo"),ylim=c(0,3.5),
        at=c(1:3)-0.2, col="yellow", xaxt="n", boxwex=0.15)
boxplot(score ~ time, data=subset(rinse,rinse=="A"), add=TRUE,
        at=c(1:3), col="gray", xaxt="n", boxwex=0.15)
boxplot(score ~ time, data=subset(rinse,rinse=="B"), add=TRUE,
        at=c(1:3) + 0.2, col="blue", xaxt="n", boxwex=0.15)
```



```
axis(1, at=c(1:3), labels=unique(rinse$time))
legend("bottomleft", legend=c("placebo", "rinse A", "rinse B"),
       title="Treatment", fill=c("yellow", "gray", "blue"), bty="n")
```

RJC

*Rotnitzky–Jewell’s Criterion for Generalized Estimating Equations***Description**

Computes the Rotnitzky–Jewell’s criterion (RJC) for one or more objects of the class `glmgee`.

Usage

```
RJC(..., verbose = TRUE, digits = max(3, getOption("digits") - 2))
```

Arguments

<code>...</code>	one or several objects of the class <i>glmgee</i> .
<code>verbose</code>	an (optional) logical switch indicating if should the report of results be printed. As default, <code>verbose</code> is set to <code>TRUE</code> .
<code>digits</code>	an (optional) integer indicating the number of digits to print. As default, <code>digits</code> is set to <code>max(3, getOption("digits") - 2)</code> .

Value

A data.frame with the values of the RJC for each *glmgee* object in the input.

References

Hin L.-Y., Carey V.J., Wang Y.-G. (2007) Criteria for Working–Correlation–Structure Selection in GEE: Assessment via Simulation. *The American Statistician* 61:360-364.

Vanegas L.H., Rondon L.M., Paula G.A. (2023) Generalized Estimating Equations using the new R package `glmtoolbox`. *The R Journal* 15:105-133.

See Also

[QIC](#), [CIC](#), [GHYC](#), [AGPC](#), [SGPC](#)

Examples

```
##### Example 1: Effect of ozone-enriched atmosphere on growth of sitka spruces
data(spruces)
mod1 <- size ~ poly(days,4) + treat
fit1 <- glmgee(mod1, id=tree, family=Gamma(log), data=spruces)
fit2 <- update(fit1, corstr="AR-M-dependent")
fit3 <- update(fit1, corstr="Stationary-M-dependent(2)")
fit4 <- update(fit1, corstr="Exchangeable")
RJC(fit1, fit2, fit3, fit4)
```

```
##### Example 2: Treatment for severe postnatal depression
data(depression)
mod2 <- depressd ~ visit + group
fit1 <- glmgee(mod2, id=subj, family=binomial(logit), data=depression)
fit2 <- update(fit1, corstr="AR-M-dependent")
fit3 <- update(fit1, corstr="Stationary-M-dependent(2)")
fit4 <- update(fit1, corstr="Exchangeable")
RJC(fit1, fit2, fit3, fit4)

##### Example 3: Treatment for severe postnatal depression (2)
mod3 <- dep ~ visit*group
fit1 <- glmgee(mod3, id=subj, family=gaussian(identity), data=depression)
fit2 <- update(fit1, corstr="AR-M-dependent")
fit3 <- update(fit1, corstr="Exchangeable")
RJC(fit1, fit2, fit3)
```

ROcc

The Receiver Operating Characteristic (ROC) Curve

Description

Computes the exact area under the ROC curve (AUROC), the Gini coefficient, and the Kolmogorov-Smirnov (KS) statistic for a binary classifier. Optionally, this function can plot the ROC curve, that is, the plot of the estimates of Sensitivity versus the estimates of 1-Specificity. This function also computes confidence intervals for AUROC and Gini coefficient using the method proposed by DeLong et al. (1988).

Usage

```
ROcc(
  object,
  plot.it = TRUE,
  verbose = TRUE,
  level = 0.95,
  digits = max(3, getOption("digits") - 2),
  ...
)
```

Arguments

object	a matrix with two columns: the first one is a numeric vector of 1's and 0's indicating whether each row is a "success" or a "failure"; the second one is a numeric vector of values indicating the probability (or propensity score) of each row to be a "success". Optionally, object can be an object of the class glm which is obtained from the fit of a generalized linear model where the distribution of the response variable is assumed to be binomial.
--------	--

<code>plot.it</code>	an (optional) logical switch indicating if the plot of the ROC curve is required or just the data matrix in which it is based. As default, <code>plot.it</code> is set to TRUE.
<code>verbose</code>	an (optional) logical switch indicating if should the report of results be printed. As default, <code>verbose</code> is set to TRUE.
<code>level</code>	an (optional) value indicating the required confidence level. As default, <code>level</code> is set to 0.95.
<code>digits</code>	an (optional) integer value indicating the number of decimal places to be used. As default, <code>digits</code> is set to $\max(3, \text{getOption("digits")} - 2)$.
<code>...</code>	further arguments passed to or from other methods. For example, if <code>plot.it=TRUE</code> then <code>...</code> may to include graphical parameters as <code>col</code> , <code>pch</code> , <code>cex</code> , <code>main</code> , <code>sub</code> , <code>xlab</code> , <code>ylab</code> .

Value

A list which contains the following objects:

`roc` A matrix with the Cutoffs and the associated estimates of Sensitivity and Specificity.

`auroc` The exact area under the ROC curve.

`ci.auroc` Confidence interval for the area under the ROC curve.

`gini` The value of the Gini coefficient computed as $2(\text{auroc}-0.5)$.

`ci.gini` Confidence interval for the Gini coefficient.

`ks` The value of the Kolmogorov-Smirnov statistic computed as the maximum value of $|1-\text{Sensitivity}-\text{Specificity}|$.

References

Cho H., Matthews G.J., Harel O. (2019) Confidence Intervals for the Area Under the Receiver Operating Characteristic Curve in the Presence of Ignorable Missing Data. *International statistical review* 87, 152–177.

DeLong E.R., DeLong D.M., Clarke-Pearson D.L. (1988). Comparing the areas under two or more correlated receiver operating characteristic curves: a nonparametric approach. *Biometrics* 44, 837–845.

Nahm F.S. (2022). Receiver operating characteristic curve: overview and practical use for clinicians. *Korean journal of anesthesiology* 75, 25–36.

Hanley J.A., McNeil B.J. (1982) The Meaning and Use of the Area under a Receiver Operating Characteristic (ROC) Curve. *Radiology* 143, 29–36.

Examples

```
##### Example: Patients with burn injuries
burn1000 <- aplore3::burn1000
burn1000 <- within(burn1000, death2 <- ifelse(death=="Dead",1,0))

### splitting the sample: 70% for the training sample and 30% for the validation sample
train <- sample(1:nrow(burn1000),size=nrow(burn1000)*0.7)
traindata <- burn1000[train,]
```

```
testdata <- burn1000[-train,]

fit <- glm(death ~ age*inh_inj + tbsa*inh_inj, family=binomial("logit"), data=traindata)
probs <- predict(fit, newdata=testdata, type="response")

### ROC curve for the validation sample
ROCC(cbind(testdata[, "death2"], probs), col="red", col.lab="blue", col.axis="black",
      col.main="black", family="mono")
```

Seizures

Seizures

Description

The dataset reports the number of epileptic seizures in each of four two-week intervals, and in a baseline eight-week interval, for Progabide treatment and placebo groups with a total of 59 individuals.

Usage

```
data(Seizures)
```

Format

A data frame with 236 rows and 6 variables:

seizures a numeric vector indicating the number of epileptic seizures.

treatment a factor indicating the applied treatment: "Progabide" and "Placebo".

base a numeric vector indicating the number of epileptic seizures in the baseline eight-week interval.

age a numeric vector indicating the age of the individuals.

time a numeric vector indicating which the two-week interval corresponds to the reported number of epileptic seizures.

id a numeric vector indicating the identifier of each individual.

Source

Thall P.F., Vail S.C. (1990) Some covariance models for longitudinal count data with overdispersion. *Biometrics* 46:657–671.

References

Carey V.J., Wang Y.-G. (2011) Working covariance model selection for generalized estimating equations. *Statistics in Medicine* 30:3117–3124.

Fu L., Hao Y., Wang Y.-G. (2018) Working correlation structure selection in generalized estimating equations. *Computational Statistics & Data Analysis* 33:983–996.

Diggle P.J., Liang K.Y., Zeger S.L. (1994, page 166) *Analysis of Longitudinal Data*. Clarendon Press.

Examples

```
dev.new()
data(Seizures)
boxplot(seizures ~ treatment:time, data=Seizures, ylim=c(0,25), col=c("blue","yellow"))
```

 SGPC

SGPC for Generalized Estimating Equations

Description

Computes the Schwarz-type penalized Gaussian pseudo-likelihood criterion (SGPC) for one or more objects of the class *glmgee*.

Usage

```
SGPC(..., verbose = TRUE, digits = max(3, getOption("digits") - 2))
```

Arguments

...	one or several objects of the class <i>glmgee</i> .
verbose	an (optional) logical switch indicating if should the report of results be printed. As default, verbose is set to TRUE.
digits	an (optional) integer indicating the number of digits to print. As default, digits is set to $\max(3, \text{getOption}(\text{"digits"}) - 2)$.

Value

A data.frame with the values of the gaussian pseudo-likelihood, the number of parameters in the linear predictor plus the number of parameters in the correlation matrix, and the value of SGPC for each *glmgee* object in the input.

References

Carey V.J., Wang Y.-G. (2011) Working covariance model selection for generalized estimating equations. *Statistics in Medicine* 30:3117-3124.

Zhu X., Zhu Z. (2013) Comparison of Criteria to Select Working Correlation Matrix in Generalized Estimating Equations. *Chinese Journal of Applied Probability and Statistics* 29:515-530.

Fu L., Hao Y., Wang Y.-G. (2018) Working correlation structure selection in generalized estimating equations. *Computational Statistics* 33:983-996.

Vanegas L.H., Rondon L.M., Paula G.A. (2023) Generalized Estimating Equations using the new R package *glmtoolbox*. *The R Journal* 15:105-133.

See Also

[QIC](#), [CIC](#), [RJC](#), [GHYC](#), [AGPC](#)

Examples

```
##### Example 1: Effect of ozone-enriched atmosphere on growth of sitka spruces
data(spruces)
mod1 <- size ~ poly(days,4) + treat
fit1 <- glmgee(mod1, id=tree, family=Gamma(log), data=spruces)
fit2 <- update(fit1, corstr="AR-M-dependent")
fit3 <- update(fit1, corstr="Stationary-M-dependent(2)")
fit4 <- update(fit1, corstr="Exchangeable")
SGPC(fit1, fit2, fit3, fit4)

##### Example 2: Treatment for severe postnatal depression
data(depression)
mod2 <- depressd ~ visit + group
fit1 <- glmgee(mod2, id=subj, family=binomial(logit), data=depression)
fit2 <- update(fit1, corstr="AR-M-dependent")
fit3 <- update(fit1, corstr="Stationary-M-dependent(2)")
fit4 <- update(fit1, corstr="Exchangeable")
SGPC(fit1, fit2, fit3, fit4)

##### Example 3: Treatment for severe postnatal depression (2)
mod3 <- dep ~ visit*group
fit1 <- glmgee(mod3, id=subj, family=gaussian(identity), data=depression)
fit2 <- update(fit1, corstr="AR-M-dependent")
fit3 <- update(fit1, corstr="Exchangeable")
SGPC(fit1, fit2, fit3)
```

shelflife

Shelf life of a photographic developer

Description

These data arise from an experiment using accelerated life testing to determine the estimated shelf life of a photographic developer. Maximum density and temperature seem to be reliable indicators of overall developer/film performance.

Usage

```
data(shelflife)
```

Format

A data frame with 21 rows and 3 variables:

Time a numeric vector giving the shelf life, in hours.

Temp a factor giving the temperature, in degrees celsius.

Dmax a numeric vector giving the maximum density.

References

Chapman R.E. (1997) Degradation study of a photographic developer to determine shelf life, *Quality Engineering* 10:1, 137-140.

Examples

```
data(shelflife)
dev.new()
with(shelflife,plot(Dmax, Time, pch=16, col=as.numeric(Temp)))
legend("topright", legend=c("72C", "82C", "92C"), col=c(1:3), pch=16,
      title="Temperature", bty="n")
```

skincancer

Skin cancer in women

Description

The data describe the incidence of nonmelanoma skin cancer among women stratified by age in Minneapolis (St. Paul) and Dallas (Fort Worth).

Usage

```
data(skincancer)
```

Format

A data frame with 16 rows and 4 variables:

cases a numeric vector giving the nonmelanoma skin cancer counts.

city a factor giving the city to which correspond the skin cancer counts: "St.Paul" and "Ft.Worth".

ageC a factor giving the age range to which correspond the skin cancer counts: "15-24", "25-34", "35-44", "45-54", "55-64", "65-74", "75-84" and "85+".

population a numeric vector giving the population of women.

age a numeric vector giving the midpoint of age range.

References

Kleinbaum D., Kupper L., Nizam A., Rosenberg E.S. (2013) *Applied Regression Analysis and other Multivariable Methods, Fifth Edition*, Cengage Learning, Boston.

Examples

```
data(skincancer)
dev.new()
barplot(1000*cases/population ~ city + ageC, beside=TRUE, col=c("yellow","blue"),
        data=skincancer)
legend("topleft", legend=c("St.Paul","Ft.Worth"), title="City",
       fill=c("yellow","blue"), bty="n")
```

 spruces

Effect of ozone-enriched atmosphere on growth of sitka spruces

Description

These data are analyzed primarily to determine how ozone pollution affects tree growth. As ozone pollution is common in urban areas, the impact of increased ozone concentrations on tree growth is of considerable interest. The response variable is tree size, where size is conventionally measured by the product of tree height and stem diameter squared. In the first group, 54 trees were grown under an ozone-enriched atmosphere, ozone exposure at 70 parts per billion. In the second group, 25 trees were grown under normal conditions. The size of each tree was observed 13 times across time, that is, 152, 174, 201, 227, 258, 469, 496, 528, 556, 579, 613, 639 and 674 days since the beginning of the experiment. Hence, the objective is to compare the trees' growth patterns under the two conditions.

Usage

```
data(spruces)
```

Format

A data frame with 1027 rows and 4 variables:

tree a factor giving an unique identifier for each tree.

days a numeric vector giving the number of days since the beginning of the experiment.

size a numeric vector giving an estimate of the volume of the tree trunk.

treat a factor giving the treatment received for each tree: "normal" and "ozone-enriched".

References

Diggle P.J., Heagarty P., Liang K.-Y., Zeger S.L. (2002) *Analysis of Longitudinal Data*. Oxford University Press, Oxford.

Crainiceanu C.M., Ruppert D., Wand M.P. (2005). Bayesian Analysis for Penalized Spline Regression Using WinBUGS. *Journal of Statistical Software* 14(14):1-24.

Examples

```

data(spruces)
dev.new()
boxplot(size ~ days, data=subset(spruces,treat=="normal"), at=c(1:13) - 0.2,
        col="yellow", boxwex=0.3, xaxt="n", xlim=c(0.9,13.1))
boxplot(size ~ days, data=subset(spruces,treat=="ozone-enriched"), add=TRUE,
        at=c(1:13) + 0.2, col="blue", boxwex=0.3, xaxt="n")
axis(1, at=c(1:13), labels=unique(spruces$days))
axis(2, at=seq(0,2000,250), labels=seq(0,2000,250))
legend("topleft", legend=c("normal","ozone-enriched"), fill=c("yellow","blue"),
      title="Atmosphere", bty="n")

```

Steel

*Hardened Steel***Description**

This dataset consists of failure times for hardened steel specimens in a rolling contact fatigue test. Ten independent observations were taken at each of the four contact stress values. Response is the time that each specimen of hardened steel failed.

Usage

```
data(Steel)
```

Format

A data frame with 40 rows and 2 variables:

stress a numeric vector indicating the values of contact stress, in pounds per square inch $\times 10^{-6}$.

life a numeric vector indicating the length of the time until the specimen of the hardened steel failed.

References

McCool J. (1980) Confidence limits for Weibull regression with censored data. *Transactions on Reliability* 29:145-150.

Examples

```

dev.new()
data(Steel)
with(Steel,plot(log(stress), log(life), pch=16, xlab="Log(Stress)", ylab="log(Life)"))

```

stepCriterion	<i>Variable selection in regression models from a chosen criterion</i>
---------------	--

Description

Generic function for selecting variables from a fitted regression model using a chosen criterion.

Usage

```
stepCriterion(model, ...)
```

Arguments

model	a fitted model object.
...	further arguments passed to or from other methods.

Value

A list which includes the descriptions of the linear predictors of the initial and final models as well as the criterion used to compare the candidate models.

stepCriterion.glm	<i>Variable Selection in Generalized Linear Models</i>
-------------------	--

Description

Performs variable selection in generalized linear models using hybrid versions of forward stepwise and backward stepwise.

Usage

```
## S3 method for class 'glm'
stepCriterion(
  model,
  criterion = c("adjr2", "bic", "aic", "p-value", "qicu"),
  test = c("wald", "lr", "score", "gradient"),
  direction = c("forward", "backward"),
  levels = c(0.05, 0.05),
  trace = TRUE,
  scope,
  force.in,
  force.out,
  ...
)
```

Arguments

model	an object of the class <i>glm</i> .
criterion	an (optional) character string indicating the criterion which should be used to compare the candidate models. The available options are: AIC ("aic"), BIC ("bic"), adjusted deviance-based R-squared ("adjr2"), and <i>p</i> -value of the test test ("p-value"). As default, criterion is set to "adjr2".
test	an (optional) character string indicating the statistical test which should be used to compare nested models. The available options are: Wald ("wald"), Rao's score ("score"), likelihood-ratio ("lr") and gradient ("gradient") tests. As default, test is set to "wald".
direction	an (optional) character string indicating the type of procedure which should be used. The available options are: hybrid backward stepwise ("backward") and hybrid forward stepwise ("forward"). As default, direction is set to "forward".
levels	an (optional) two-dimensional vector of values in the interval (0, 1) indicating the levels at which the variables should in and out from the model. This is only appropriate if criterion="p-value". As default, levels is set to $c(0.05, 0.05)$.
trace	an (optional) logical switch indicating if should the stepwise reports be printed. As default, trace is set to TRUE.
scope	an (optional) list, containing components lower and upper, both formula-type objects, indicating the range of models which should be examined in the stepwise search. As default, lower is a model with no predictors and upper is the linear predictor of the model in model.
force.in	an (optional) formula-type object indicating the effects that should be in all models
force.out	an (optional) formula-type object indicating the effects that should be in no models
...	further arguments passed to or from other methods. For example, k, that is, the magnitude of the penalty in the AIC/QICu, which by default is set to 2.

Details

The "hybrid forward stepwise" algorithm starts with the simplest model (which may be chosen at the argument scope, and As default, is a model whose parameters in the linear predictor, except the intercept, if any, are set to 0), and then the candidate models are built by hierarchically including effects in the linear predictor, whose "relevance" and/or "importance" in the model fit is assessed by comparing nested models (that is, by comparing the models with and without the added effect) using a criterion previously specified. If an effect is added to the equation, this strategy may also remove any effect which, according to the previously specified criterion, no longer provides improvement in the model fit. That process continues until no more effects are included or excluded. The "hybrid backward stepwise" algorithm works similarly.

Value

a list list with components including

initial a character string indicating the linear predictor of the "initial model",

direction a character string indicating the type of procedure which was used,
criterion a character string indicating the criterion used to compare the candidate models,
final a character string indicating the linear predictor of the "final model",
final.fit an object of class `glm` with the results of the fit to the data of the "final model",

References

James G., Witten D., Hastie T., Tibshirani R. (2013, page 210) An Introduction to Statistical Learning with Applications in R, Springer, New York.

See Also

[bestSubset](#), [stepCriterion.lm](#), [stepCriterion.overglm](#), [stepCriterion.glmgee](#)

Examples

```
##### Example 1: Fuel consumption of automobiles
Auto <- ISLR::Auto
Auto2 <- within(Auto, origin <- factor(origin))
mod <- mpg ~ cylinders + displacement + acceleration + origin + horsepower*weight
fit1 <- glm(mod, family=inverse.gaussian("log"), data=Auto2)
stepCriterion(fit1, direction="forward", criterion="p-value", test="lr")
stepCriterion(fit1, direction="backward", criterion="bic", force.in=~cylinders)

##### Example 2: Patients with burn injuries
burn1000 <- aplore3::burn1000
burn1000 <- within(burn1000, death <- factor(death, levels=c("Dead","Alive")))
upper <- ~ age + gender + race + tbsa + inh_inj + flame + age*inh_inj + tbsa*inh_inj
fit2 <- glm(death ~ age + gender + race + tbsa + inh_inj, family=binomial("logit"), data=burn1000)
stepCriterion(fit2, direction="backward", criterion="bic", scope=list(upper=upper),force.in=~tbsa)
stepCriterion(fit2, direction="forward", criterion="p-value", test="score")

##### Example 3: Skin cancer in women
data(skincancer)
upper <- cases ~ city + age + city*age
fit3 <- glm(upper, family=poisson("log"), offset=log(population), data=skincancer)
stepCriterion(fit3, direction="backward", criterion="aic", scope=list(lower=~ 1,upper=upper))
stepCriterion(fit3, direction="forward", criterion="p-value", test="lr")
```

Description

Performs variable selection in generalized estimating equations using hybrid versions of forward stepwise and backward stepwise.

Usage

```
## S3 method for class 'glmgee'
stepCriterion(
  model,
  criterion = c("p-value", "qic", "qicu", "agpc", "sgpc"),
  test = c("wald", "score"),
  direction = c("forward", "backward"),
  levels = c(0.05, 0.05),
  trace = TRUE,
  scope,
  digits = max(3, getOption("digits") - 2),
  varest = c("robust", "df-adjusted", "model", "bias-corrected"),
  force.in,
  force.out,
  ...
)
```

Arguments

model	an object of the class <code>glmgee</code> which is obtained from the fit of a generalized estimating equation.
criterion	an (optional) character string indicating the criterion which should be used to compare the candidate models. The available options are: QIC (" <code>qic</code> "), QICu (" <code>qicu</code> "), Akaike-type penalized gaussian pseudo-likelihood criterion (" <code>agpc</code> "), Schwarz-type penalized gaussian pseudo-likelihood criterion (" <code>sgpc</code> ") and p -value of the test test (" <code>p-value</code> "). By default, <code>criterion</code> is set to " <code>p-value</code> ".
test	an (optional) character string indicating the statistical test which should be used to compare nested models. The available options are: Wald (" <code>wald</code> ") and generalized score (" <code>score</code> ") tests. As default, <code>test</code> is set to " <code>wald</code> ".
direction	an (optional) character string indicating the type of procedure which should be used. The available options are: hybrid backward stepwise (" <code>backward</code> ") and hybrid forward stepwise (" <code>forward</code> "). As default, <code>direction</code> is set to " <code>forward</code> ".
levels	an (optional) two-dimensional vector of values in the interval $(0, 1)$ indicating the levels at which the variables should in and out from the model. This is only appropriate if <code>criterion="p-value"</code> . By default, <code>levels</code> is set to <code>c(0.05, 0.05)</code> .
trace	an (optional) logical switch indicating if should the stepwise reports be printed. By default, <code>trace</code> is set to <code>TRUE</code> .
scope	an (optional) list, containing components <code>lower</code> and <code>upper</code> , both formula-type objects, indicating the range of models which should be examined in the stepwise search. As default, <code>lower</code> is a model with no predictors and <code>upper</code> is the linear predictor of the model in <code>model</code> .

digits	an (optional) integer indicating the number of digits which should be used to print the most of the criteria to compare the candidate models. As default, digits is set to $\max(3, \text{getOption}(\text{"digits"}) - 2)$.
varest	an (optional) character string indicating the type of estimator which should be used to the variance-covariance matrix of the interest parameters in the Wald-type test. The available options are: robust sandwich-type estimator ("robust"), degrees-of-freedom-adjusted estimator ("df-adjusted"), bias-corrected estimator ("bias-corrected"), and the model-based or naive estimator ("model"). As default, varest is set to "robust".
force.in	an (optional) formula-type object indicating the effects that should be in all models
force.out	an (optional) formula-type object indicating the effects that should be in no models
...	further arguments passed to or from other methods. For example, k, that is, the magnitude of the penalty in the AGPC, which by default is set to 2.

Value

A list which contains the following objects:

`initial` a character string indicating the linear predictor of the "initial model".

`direction` a character string indicating the type of procedure which was used.

`criterion` a character string indicating the criterion used to compare the candidate models.

`final` a character string indicating the linear predictor of the "final model".

`final.fit` an object of class `glmgee` with the results of the fit to the data of the "final model".

References

James G., Witten D., Hastie T., Tibshirani R. (2013, page 210) *An Introduction to Statistical Learning with Applications in R*. Springer, New York.

Jianwen X., Jiamao Z., Liya F. (2019) Variable selection in generalized estimating equations via empirical likelihood and Gaussian pseudo-likelihood. *Communications in Statistics - Simulation and Computation* 48:1239-1250.

Vanegas L.H., Rondon L.M., Paula G.A. (2023) Generalized Estimating Equations using the new R package `glmtoolbox`. *The R Journal* 15:105-133.

See Also

[stepCriterion.lm](#), [stepCriterion.glm](#), [stepCriterion.overglm](#)

Examples

```
##### Example 1: Effect of ozone-enriched atmosphere on growth of sitka spruces
data(spruces)
mod <- size ~ poly(days,4)*treat
fit1 <- glmgee(mod, id=tree, family=Gamma(log), data=spruces, corstr="AR-M-dependent")
stepCriterion(fit1, criterion="p-value", direction="forward", scope=list(upper=mod),force.in=~treat)
```

```
##### Example 2: Treatment for severe postnatal depression
data(depression)
mod <- depressd ~ visit*group
fit2 <- glmgee(mod, id=subj, family=binomial(probit), corstr="AR-M-dependent", data=depression)
stepCriterion(fit2, criterion="agpc", direction="forward", scope=list(upper=mod),force.in=~group)

##### Example 3: Treatment for severe postnatal depression (2)
mod <- dep ~ visit*group
fit2 <- glmgee(mod, id=subj, family=gaussian(identity), corstr="AR-M-dependent", data=depression)
stepCriterion(fit2, criterion="sgpc", direction="forward", scope=list(upper=mod),force.in=~group)
```

stepCriterion.lm

Variable Selection in Normal Linear Models

Description

Performs variable selection in normal linear models using a hybrid versions of forward stepwise and backward stepwise.

Usage

```
## S3 method for class 'lm'
stepCriterion(
  model,
  criterion = c("bic", "aic", "adjr2", "prdr2", "cp", "p-value"),
  direction = c("forward", "backward"),
  levels = c(0.05, 0.05),
  trace = TRUE,
  scope,
  force.in,
  force.out,
  ...
)
```

Arguments

model	an object of the class <i>lm</i> .
criterion	an (optional) character string indicating the criterion which should be used to compare the candidate models. The available options are: AIC ("aic"), BIC ("bic"), adjusted R-squared ("adjr2"), predicted R-squared ("prdr2"), Mallows' CP ("cp") and <i>p</i> -value of the F test ("p-value"). As default, criterion is set to "bic".
direction	an (optional) character string indicating the type of procedure which should be used. The available options are: hybrid backward stepwise ("backward") and hybrid forward stepwise ("forward"). As default, direction is set to "forward".

levels	an (optional) two-dimensional vector of values in the interval (0, 1) indicating the levels at which the variables should in and out from the model. This is only appropriate if <code>criterion="p-value"</code> . As default, <code>levels</code> is set to <code>c(0.05, 0.05)</code> .
trace	an (optional) logical switch indicating if should the stepwise reports be printed. As default, <code>trace</code> is set to <code>TRUE</code> .
scope	an (optional) list containing components <code>lower</code> and <code>upper</code> , both formula-type objects, indicating the range of models which should be examined in the stepwise search. As default, <code>lower</code> is a model with no predictors and <code>upper</code> is the linear predictor of the model in <code>model</code> .
force.in	an (optional) formula-type object indicating the effects that should be in all models
force.out	an (optional) formula-type object indicating the effects that should be in no models
...	further arguments passed to or from other methods. For example, <code>k</code> , that is, the magnitude of the penalty in the AIC/QICu, which by default is set to 2.

Details

The "hybrid forward stepwise" algorithm starts with the simplest model (which may be chosen at the argument `scope`, and As default, is a model whose parameters in the linear predictor, except the intercept, if any, are set to 0), and then the candidate models are built by hierarchically including effects in the linear predictor, whose "relevance" and/or "importance" in the model fit is assessed by comparing nested models (that is, by comparing the models with and without the added effect) using a criterion previously specified. If an effect is added to the equation, this strategy may also remove any effect which, according to the previously specified criteria, no longer provides an improvement in the model fit. That process continues until no more effects are included or excluded. The "hybrid backward stepwise" algorithm works similarly.

Value

a list list with components including

<code>initial</code>	a character string indicating the linear predictor of the "initial model",
<code>direction</code>	a character string indicating the type of procedure which was used,
<code>criterion</code>	a character string indicating the criterion used to compare the candidate models,
<code>final</code>	a character string indicating the linear predictor of the "final model",
<code>final.fit</code>	an object of class <code>lm</code> with the results of the fit to the data of the "final model",

References

James G., Witten D., Hastie T., Tibshirani R. (2013, page 210) An Introduction to Statistical Learning with Applications in R, Springer, New York.

See Also

[stepCriterion.glm](#), [stepCriterion.overglm](#), [stepCriterion.glmgee](#)
[stepCriterion.glm](#), [stepCriterion.overglm](#), [stepCriterion.glmgee](#)

Examples

```
##### Example 1: New York air quality measurements
fit1 <- lm(log(Ozone) ~ Solar.R + Temp + Wind, data=airquality)
scope=list(lower=~1, upper=~Solar.R*Temp*Wind)
stepCriterion(fit1, direction="forward", criterion="adjr2", scope=scope)
stepCriterion(fit1, direction="forward", criterion="bic", scope=scope)
stepCriterion(fit1, direction="forward", criterion="p-value", scope=scope)

##### Example 2: Fuel consumption of automobiles
fit2 <- lm(mpg ~ log(hp) + log(wt) + qsec, data=mtcars)
scope=list(lower=~1, upper=~log(hp)*log(wt)*qsec)
stepCriterion(fit2, direction="backward", criterion="bic", scope=scope)
stepCriterion(fit2, direction="forward", criterion="cp", scope=scope)
stepCriterion(fit2, direction="backward", criterion="prdr2", scope=scope)

##### Example 3: Credit card balance
Credit <- ISLR::Credit
fit3 <- lm(Balance ~ Cards + Age + Rating + Income + Student + Limit, data=Credit)
stepCriterion(fit3, direction="forward", criterion="prdr2")
stepCriterion(fit3, direction="forward", criterion="cp")
stepCriterion(fit3, direction="forward", criterion="p-value")
```

stepCriterion.overglm *Variable selection for alternatives to the Poisson and Binomial Regression Models under the presence of Overdispersion*

Description

Performs variable selection using hybrid versions of forward stepwise and backward stepwise by comparing hierarchically build candidate models using a criterion previously specified such as AIC, BIC or p -value of the significance tests.

Usage

```
## S3 method for class 'overglm'
stepCriterion(
  model,
  criterion = c("bic", "aic", "p-value"),
  test = c("wald", "score", "lr", "gradient"),
  direction = c("forward", "backward"),
  levels = c(0.05, 0.05),
  trace = TRUE,
```

```

    scope,
    force.in,
    force.out,
    ...
  )

```

Arguments

model	an object of the class <i>overglm</i> .
criterion	an (optional) character string which allows to specify the criterion which should be used to compare the candidate models. The available options are: AIC ("aic"), BIC ("bic"), and <i>p</i> -value of the test-type test ("p-value"). As default, criterion is set to "bic".
test	an (optional) character string which allows to specify the statistical test which should be used to compare nested models. The available options are: Wald ("wald"), Rao's score ("score"), likelihood-ratio ("lr") and gradient ("gradient") tests. As default, test is set to "wald".
direction	an (optional) character string which allows to specify the type of procedure which should be used. The available options are: hybrid backward stepwise ("backward") and hybrid forward stepwise ("forward"). As default, direction is set to "forward".
levels	an (optional) two-dimensional vector of values in the interval (0, 1) indicating the levels at which the variables should in and out from the model. This is only appropriate if criterion="p-value". By default, levels is set to $c(0.05, 0.05)$.
trace	an (optional) logical switch indicating if should the stepwise reports be printed. By default, trace is set to TRUE.
scope	an (optional) list, containing components lower and upper, both formula-type objects, indicating the range of models which should be examined in the stepwise search. As default, lower is a model with no predictors and upper is the linear predictor of the model in model.
force.in	an (optional) formula-type object indicating the effects that should be in all models
force.out	an (optional) formula-type object indicating the effects that should be in no models
...	further arguments passed to or from other methods. For example, k, that is, the magnitude of the penalty in the AIC, which by default is set to 2.

Value

A list which contains the following objects:

initial	a character string indicating the linear predictor of the "initial model",
direction	a character string indicating the type of procedure which was used,
criterion	a character string indicating the criterion used to compare the candidate models,

`final` a character string indicating the linear predictor of the "final model",

`final.fit` an object of class `overglm` with the results of the fit to the data of the "final model",

References

James G., Witten D., Hastie T., Tibshirani R. (2013, page 210) An Introduction to Statistical Learning with Applications in R. Springer, New York.

See Also

[stepCriterion.lm](#), [stepCriterion.glm](#), [stepCriterion.glmgee](#)

Examples

```
##### Example 1: Self diagnosed ear infections in swimmers
data(swimmers)
fit1 <- overglm(infections ~ age + gender + frequency + location, family="nb1(log)", data=swimmers)

stepCriterion(fit1, criterion="p-value", direction="forward", test="lr")

stepCriterion(fit1, criterion="bic", direction="backward", test="score", force.in=~location)

##### Example 2: Article production by graduate students in biochemistry PhD programs
bioChemists <- pscl::bioChemists
fit2 <- overglm(art ~ fem + mar + kid5 + phd + ment, family="nb1(log)", data = bioChemists)

stepCriterion(fit2, criterion="p-value", direction="forward", test="lr")

stepCriterion(fit2, criterion="bic", direction="backward", test="score", force.in=~fem)

##### Example 3: Agents to stimulate cellular differentiation
data(cellular)
fit3 <- overglm(cbind(cells,200-cells) ~ tnf + ifn + tnf*ifn, family="bb(logit)", data=cellular)

stepCriterion(fit3, criterion="p-value", direction="backward", test="lr")

stepCriterion(fit3, criterion="bic", direction="forward", test="score")
```

swimmers

Self diagnosed ear infections in swimmers

Description

A pilot surf/health study was conducted by NSW Water Board in 1990 on 287 recruits. The objective of the study was to determine whether beach swimmers run an increased risk of contracting ear infections than non-beach swimmers.

Usage

```
data(swimmers)
```

Format

A data frame with 287 rows and 5 variables:

frequency a factor giving the recruit's perception of whether he or she is a frequent swimmer: "frequent" and "occasional".

location a factor giving the recruit's usually chosen swimming location: "beach" and "non-beach".

age a factor giving the recruit's age range: "15-19", "20-24" and "25-29".

gender a factor giving the recruit's gender: "male" and "female".

infections a numeric vector giving the number of self diagnosed ear infections that were reported by the recruit.

References

Hand D.J., Daly F., Lunn A.D., McConway K.J., Ostrowsky E. (1994) *A Handbook of Small Data Sets*, Chapman and Hall, London.

Vanegas L.H., Rondon L.M. (2020) A data transformation to deal with constant under/over-dispersion in binomial and poisson regression models. *Journal of Statistical Computation and Simulation* 90:1811-1833.

Examples

```
data(swimmers)
dev.new()
boxplot(infections ~ frequency, data=subset(swimmers,location=="non-beach"),
        at=c(1:2) - 0.2, col="yellow", boxwex=0.25, xaxt="n")
boxplot(infections ~ frequency, data=subset(swimmers,location=="beach"), add=TRUE,
        at=c(1:2) + 0.2, col="blue", boxwex=0.25, xaxt="n")
axis(1, at=c(1:2), labels=levels(swimmers$frequency))
legend("topleft", title="Location", legend=c("non-beach", "beach"),
       fill=c("yellow", "blue"), bty="n")
```

Trajan

Roots Produced by the Columnar Apple Cultivar Trajan.

Description

The data arose from a horticultural experiment to study the number of roots produced by 270 micro-propagated shoots of the columnar apple cultivar Trajan. During the rooting period, all shoots were maintained under identical conditions. However, the shoots themselves were cultured on media containing different concentrations of the cytokinin 6-benzylaminopurine (BAP), in growth cabinets with an 8 or 16 hour photoperiod. The objective is to assess the effect of both the photoperiod and BAP concentration levels on the number of roots produced.

Usage

```
data(Trajan)
```

Format

A data frame with 270 rows and 4 variables:

roots a numeric vector indicating the number of roots produced.

shoot a numeric vector indicating the number of micropropogated shoots.

photoperiod a factor indicating the photoperiod, in hours: 8 or 16.

bap a numeric vector indicating the concentrations of the cytokinin 6-benzylaminopurine: 2.2, 4.4, 8.8 or 17.6.

References

Ridout M., Demétrio C.G., Hinde J. (1998). Models for count data with many zeros. In *Proceedings of the XIXth international biometric conference*, 179–192.

Ridout M., Hinde J., Demétrio C.G. (2001). A score test for testing a zero-inflated Poisson regression model against zero-inflated negative binomial alternatives. *Biometrics* 57:219-223.

Garay A.M., Hashimoto E.M., Ortega E.M.M., Lachos V. (2011). On estimation and influence diagnostics for zero-inflated negative binomial regression models. *Computational Statistics & Data Analysis* 55:1304-1318.

Examples

```
data(Trajan)
dev.new()
boxplot(roots ~ bap, data=subset(Trajan,photoperiod=="8"), at=c(1:4) - 0.15,
        col="blue", boxwex=0.2, xaxt="n", ylim=c(-0.5,17))
boxplot(roots ~ bap, data=subset(Trajan,photoperiod=="16"), add=TRUE,
        at=c(1:4) + 0.15, col="yellow", boxwex=0.2, xaxt="n")
axis(1, at=c(1:4), labels=levels(Trajan$bap))
legend("topright", legend=c("8","16"), title="Photoperiod", bty="n",
       fill=c("blue","yellow"))
```

Description

These data arose from a study conducted in the Department of Internal Medicine at Utrecht University Hospital, in the Netherlands. In this study, 98 HIV-infected men were followed for up to two years. Urinary cultures were obtained during the first visit and every six months thereafter. Also, cultures were obtained between regular scheduled visits when signs and symptoms of urinary tract infections (UTI) occurred, or when patients had a fever of unknown origin. CD4+ cell counts were also measured. A CD4+ count is a blood test to determine how well the immune system works in people diagnosed with HIV. In general, a decreasing CD4+ count indicates HIV progression.

Usage

```
data(uti)
```

Format

A data frame with 98 rows and 3 variables:

episodes a numeric vector indicating the number of episodes, that is, the number of times each patient had urinary tract infections (UTI).

time a numeric vector indicating the time to follow up, in months.

cd4 a numeric vector indicating the immune status of the patient as measured by the CD4+ cell counts.

References

Hoepelman A.I.M., Van Buren M., Van den Broek J., Borleffs J.C.C. (1992) Bacteriuria in men infected with HIV-1 is related to their immune status (CD4+ cell count). *AIDS* 6:179-184.

Morel J.G., Nagaraj N.K. (2012) *Overdispersion Models in SAS*. SAS Institute Inc., Cary, North Carolina, USA.

van den Broek J. (1995) A Score Test for Zero Inflation in a Poisson Distribution. *Biometrics* 51:738–743.

Examples

```
data(uti)
dev.new()
uti2 <- within(uti, cd4C <- cut(log(cd4), 4, labels=c("low", "mid-low", "mid-high", "high")))
out <- aggregate(cbind(episodes, time) ~ cd4C, sum, data=uti2)
barplot(12*episodes/time ~ cd4C, beside=TRUE, data=out, col="red",
        xlab="CD4+ cell count", ylab="Number of UTIs per year")
```

vcov.glmgee

Estimate of the variance-covariance matrix in GEEs

Description

Computes the type-type estimate of the variance-covariance matrix from an object of the class glmgee.

Usage

```
## S3 method for class 'glmgee'
vcov(
  object,
  ...,
  type = c("robust", "df-adjusted", "model", "bias-corrected", "jackknife")
)
```

Arguments

object	An object of the class <i>glmgee</i> .
...	further arguments passed to or from other methods.
type	an (optional) character string indicating the type of estimator which should be used. The available options are: robust sandwich-type estimator ("robust"), degrees-of-freedom-adjusted estimator ("df-adjusted"), bias-corrected estimator ("bias-corrected"), and the model-based or naive estimator ("model"). As default, type is set to "robust".

Value

A matrix with the type-type estimate of the variance-covariance matrix.

References

Mancl L.A., DeRouen T.A. (2001) A Covariance Estimator for GEE with Improved Small-Sample Properties. *Biometrics* 57:126-134.

Vanegas L.H., Rondon L.M., Paula G.A. (2023) Generalized Estimating Equations using the new R package glmtoolbox. *The R Journal* 15:105-133.

Examples

```
##### Example 1: Effect of ozone-enriched atmosphere on growth of sitka spruces
data(spruces)
mod <- size ~ poly(days,4) + treat
fit1 <- glmgee(mod, id=tree, family=Gamma(log), data=spruces, corstr="Exchangeable")
vcov(fit1)
vcov(fit1,type="bias-corrected")

##### Example 2: Treatment for severe postnatal depression
data(depression)
mod <- depressd ~ visit + group
fit3 <- glmgee(mod, id=subj, family=binomial(logit), corstr="AR-M-dependent", data=depression)
vcov(fit3)
vcov(fit3,type="bias-corrected")

##### Example 3: Treatment for severe postnatal depression (2)
mod <- dep ~ visit*group
fit2 <- glmgee(mod, id=subj, family=gaussian(identity), corstr="AR-M-dependent", data=depression)
vcov(fit2)
vcov(fit2,type="bias-corrected")
```

vdtest	<i>Test for Varying Dispersion Parameter</i>
--------	--

Description

Generic function for testing for varying dispersion parameter from a fitted model.

Usage

```
vdtest(model, ...)
```

Arguments

model	a fitted model object.
...	further arguments passed to or from other methods.

Value

A list which includes the main attributes of the test as, for example, value of the statistic and p -value.

vdtest.glm	<i>Test for Varying Dispersion Parameter in Generalized Linear Models</i>
------------	---

Description

Performs Rao's score test for varying dispersion parameter in weighted and unweighted generalized linear models in which the response distribution is assumed to be Gaussian, Gamma, or inverse Gaussian.

Usage

```
## S3 method for class 'glm'
vdtest(model, varformula, verbose = TRUE, ...)
```

Arguments

model	an object of the class <i>glm</i> where the distribution of the response variable is assumed to be gaussian, Gamma or inverse.gaussian.
varformula	an (optional) formula expression of the form $\sim z_1 + z_2 + \dots + z_q$ describing only the potential explanatory variables for the dispersion. As default, the same explanatory variables are taken as in the model for the mean.
verbose	an (optional) logical switch indicating if should the report of results be printed. As default, verbose is set to TRUE.
...	further arguments passed to or from other methods.

Details

From the generalized linear model with varying dispersion in which $\log(\phi) = \gamma_0 + \gamma_1 z_1 + \gamma_2 z_2 + \dots + \gamma_q z_q$, where ϕ is the dispersion parameter of the distribution used to describe the response variable, the Rao's score test (denoted here as S) to assess the hypothesis $H_0 : \gamma = 0$ versus $H_1 : \gamma \neq 0$ is computed, where $\gamma = (\gamma_1, \dots, \gamma_q)$. The corresponding p -value is computed from the chi-squared distribution with q degrees of freedom, that is, $p\text{-value} = \text{Prob}[\chi_q^2 > S]$. If the object model corresponds to an unweighted generalized linear model, this test assesses assumptions of constant variance and constant coefficient of variation on models in which the response distribution is assumed to be Gaussian and Gamma, respectively.

Value

a list list with components including

statistic	value of the Rao's score test (S),
df	number of degrees of freedom (q),
p.value	p -value of the test,
vars	names of explanatory variables for the dispersion parameter,

References

Wei B.-C., Shi, J.-Q., Fung W.-K., Hu Y.-Q. (1998) Testing for Varying Dispersion in Exponential Family Nonlinear Models. *Annals of the Institute of Statistical Mathematics* 50, 277–294.

See Also

[vdtest.lm](#), [vdtest.gnm](#)

Examples

```
##### Example 1: Fuel consumption of automobiles
Auto <- ISLR::Auto
fit1 <- glm(mpg ~ weight*horsepower, family=inverse.gaussian("log"), data=Auto)
vdtest(fit1)
vdtest(fit1,varformula= ~ weight + horsepower)
vdtest(fit1,varformula= ~ log(weight) + log(horsepower))

##### Example 2: Hill races in Scotland
data(races)
fit2 <- glm(rtime ~ log(distance) + cclimb, family=Gamma("log"), data=races)
vdtest(fit2)
vdtest(fit2,varformula= ~ distance + cclimb)
vdtest(fit2,varformula= ~ log(distance) + log(cclimb))

##### Example 3: Mammal brain and body weights
data(brains)
```

```
fit3 <- glm(BrainWt ~ log(BodyWt), family=Gamma("log"), data=brains)
vdtest(fit3)
vdtest(fit3,varformula= ~ BodyWt)
```

vdtest.gnm	<i>Test for Varying Dispersion Parameter in Generalized Nonlinear Models</i>
------------	--

Description

Performs Rao's score test for varying dispersion parameter in weighted and unweighted generalized nonlinear models in which the response distribution is assumed to be Gaussian, Gamma, or inverse Gaussian.

Usage

```
## S3 method for class 'gnm'
vdtest(model, varformula, verbose = TRUE, ...)
```

Arguments

model	an object of the class <i>gnm</i> where the distribution of the response variable is assumed to be <i>gaussian</i> , <i>Gamma</i> or <i>inverse.gaussian</i> .
varformula	an (optional) formula expression of the form $\sim z_1 + z_2 + \dots + z_q$ describing only the potential explanatory variables for the dispersion. As default, the same explanatory variables are taken as in the model for the mean.
verbose	an (optional) logical switch indicating if should the report of results be printed. As default, <i>verbose</i> is set to <i>TRUE</i> .
...	further arguments passed to or from other methods.

Details

From the generalized nonlinear model with varying dispersion in which $\log(\phi) = \gamma_0 + \gamma_1 z_1 + \gamma_2 z_2 + \dots + \gamma_q z_q$, where ϕ is the dispersion parameter of the distribution used to describe the response variable, the Rao's score test (denoted here as S) to assess the hypothesis $H_0 : \gamma = 0$ versus $H_1 : \gamma \neq 0$ is computed, where $\gamma = (\gamma_1, \dots, \gamma_q)$. The corresponding p -value is computed from the chi-squared distribution with q degrees of freedom, that is, $p\text{-value} = \text{Prob}[\chi_q^2 > S]$. If the object *model* corresponds to an unweighted generalized linear model, this test assesses assumptions of constant variance and constant coefficient of variation on models in which the response distribution is assumed to be Gaussian and Gamma, respectively.

Value

a list list with components including

statistic value of the Rao's score test (S),

df number of degrees of freedom (q),

p.value p -value of the test,

vars names of explanatory variables for the dispersion parameter,

References

Wei B.-C., Shi, J.-Q., Fung W.-K., Hu Y.-Q. (1998) Testing for Varying Dispersion in Exponential Family Nonlinear Models. *Annals of the Institute of Statistical Mathematics* 50, 277–294.

See Also

[vdtest.lm](#), [vdtest.glm](#)

Examples

```
##### Example 1: The effects of fertilizers on coastal Bermuda grass
data(Grass)
fit1 <- gnm(Yield ~ b0 + b1/(Nitrogen + a1) + b2/(Phosphorus + a2) + b3/(Potassium + a3),
           family=gaussian(inverse), start=c(b0=0.1,b1=13,b2=1,b3=1,a1=45,a2=15,a3=30), data=Grass)
vdtest(fit1)
vdtest(fit1,varformula = ~ Nitrogen + Phosphorus + Potassium)

##### Example 2: Developmental rate of Drosophila melanogaster
data(Drosophila)
fit2 <- gnm(Duration ~ b0 + b1*Temp + b2/(Temp-a), family=Gamma(log),
           start=c(b0=3,b1=-0.25,b2=-210,a=55), weights=Size, data=Drosophila)
vdtest(fit2)
vdtest(fit2,varformula = ~ Temp)
vdtest(fit2,varformula = ~ log(Temp))

##### Example 3: Radioimmunological Assay of Cortisol
data(Cortisol)
fit3 <- gnm(Y ~ b0 + (b1-b0)/(1 + exp(b2+ b3*ldDose))^b4, family=Gamma(identity),
           start=c(b0=130,b1=2800,b2=3,b3=3,b4=0.5), data=Cortisol)
vdtest(fit3)
vdtest(fit3,varformula = ~ ldDose)
vdtest(fit3,varformula = ~ exp(ldDose))

##### Example 4: Age and Eye Lens Weight of Rabbits in Australia
data(rabbits)
fit4 <- gnm(wlens ~ b1 - b2/(age + b3), family=Gamma(log),
           start=c(b1=5.5,b2=130,b3=35), data=rabbits)
vdtest(fit4)
vdtest(fit4,varformula = ~ age)
vdtest(fit4,varformula = ~ log(age))
```

vdtest.lm

*Test for Varying Dispersion Parameter in Normal Linear Models***Description**

Performs Rao's score test for varying dispersion parameter in weighted and unweighted normal linear models.

Usage

```
## S3 method for class 'lm'
vdtest(model, varformula, verbose = TRUE, ...)
```

Arguments

model	an object of the class <i>lm</i> .
varformula	an (optional) formula expression of the form $\sim z_1 + z_2 + \dots + z_q$ indicating the potential explanatory variables for the dispersion parameter. As default, the same explanatory variables are taken as in the model for the mean.
verbose	an (optional) logical switch indicating if should the report of results be printed. As default, verbose is set to TRUE.
...	further arguments passed to or from other methods.

Details

From the heteroskedastic normal linear model in which $\log(\sigma^2) = \gamma_0 + \gamma_1 z_1 + \gamma_2 z_2 + \dots + \gamma_q z_q$, where σ^2 is the dispersion parameter of the distribution of the random errors, the Rao's score test (denoted here as S) to assess the hypothesis $H_0 : \gamma = 0$ versus $H_1 : \gamma \neq 0$ is computed, where $\gamma = (\gamma_1, \dots, \gamma_q)$. The corresponding p -value is computed from the chi-squared distribution with q degrees of freedom, that is, $p\text{-value} = \text{Prob}[\chi_q^2 > S]$. If the object `model` corresponds to an unweighted normal linear model, then the test assess the assumption of constant variance, which coincides with the non-studentized Breusch-Pagan test against heteroskedasticity.

Value

a list list with components including

statistic	value of the Rao's score test (S),
df	number of degrees of freedom (q),
p.value	p -value of the test,
vars	names of explanatory variables for the dispersion parameter,

References

- Breusch T.S., Pagan A.R. (1979) A simple test for heteroscedasticity and random coefficient variation. *Econometrica* 47, 1287–1294.
- Cook R.D., Weisberg S. (1983) Diagnostics for heteroscedasticity in regression. *Biometrika* 70, 1–10.

See Also

[vdtest.glm](#)

Examples

```
##### Example 1: Fuel consumption of automobiles
fit1 <- lm(mpg ~ log(hp) + log(wt), data=mtcars)
vdtest(fit1)
vdtest(fit1,varformula = ~ hp + wt)
vdtest(fit1,varformula = ~ hp + wt + hp*wt)

##### Example 2: Species richness in plots
data(richness)
fit2 <- lm(Species ~ Biomass + pH, data=richness)
vdtest(fit2)

### The test conclusions change when the outlying observations are excluded
fit2a <- lm(Species ~ Biomass + pH, data=richness, subset=-c(1,3,18,20))
vdtest(fit2a)

##### Example 3: Gas consumption in a home before and after insulation
whiteside <- MASS::whiteside
fit3 <- lm(Gas ~ Temp + Insul + Temp*Insul, data=whiteside)
vdtest(fit3)

### The test conclusions change when the outlying observations are excluded
fit3a <- lm(Gas ~ Temp + Insul + Temp*Insul, data=whiteside, subset=-c(8,9,36,46,55))
vdtest(fit3a)
```

Description

Produces an object of the class `wglmgee` in which the main results of a Weighted Generalized Estimating Equation (WGEE) fitted to the data are stored.

Usage

```
wglmgee(
  formula,
  level = c("observations", "clusters"),
  family = gaussian(),
  weights,
  id,
  data,
  subset,
  corstr,
  corr,
  start = NULL,
  scale.fix = FALSE,
  scale.value = 1,
  toler = 1e-05,
  maxit = 50,
  trace = FALSE,
  ...
)
```

Arguments

formula	an Formula expression of the form $\text{response} \sim x_1 + x_2 + \dots \mid z_1 + z_2 + \dots$, whose first part is a symbolic description of the linear predictor of the GEE model to be fitted to the data, whereas the second part is a symbolic description of the linear predictor of the logistic model to be used to calculate the missingness probabilities under the MAR assumption. Then, those probabilities are used to computed the weights to be included in the parameter estimation algorithm.
level	an (optional) character string which allows to specify the weighted GEE method. The available options are: "observations" and "clusters" for Observation- and Cluster-specified Weighted GEE, respectively. As default, <i>level</i> is set to "observations".
family	an (optional) family object, that is, a list of functions and expressions for defining link and variance functions. Families (and links) supported are the same supported by <code>glm</code> using its <code>family</code> argument, that is, <code>gaussian</code> , <code>binomial</code> , <code>poisson</code> , <code>Gamma</code> , <code>inverse.gaussian</code> , and <code>quasi</code> . The family <code>negative.binomial</code> in the library MASS are also available. As default, the argument <code>family</code> is set to <code>gaussian(identity)</code> .
weights	an (optional) vector of positive "prior weights" to be used in the fitting process. The length of <code>weights</code> should be the same as the total number of observations.
id	a vector which identifies the subjects or clusters. The length of <code>id</code> should be the same as the number of observations.
data	an (optional) data frame in which to look for variables involved in the formula expression, as well as for variables specified in the arguments <code>id</code> and <code>weights</code> . The data are assumed to be sorted by <code>id</code> and time.

subset	an (optional) vector specifying a subset of observations to be used in the fitting process.
corstr	an (optional) character string which allows to specify the working-correlation structure. The available options are: "Independence", "Unstructured", "Stationary-M-dependent(m)", "Non-Stationary-M-dependent(m)", "AR-M-dependent(m)", "Exchangeable" and "User-defined", where m represents the lag of the dependence. As default, corstr is set to "Independence".
corr	an (optional) square matrix of the same dimension of the maximum cluster size containing the user specified correlation. This is only appropriate if corstr is specified to be "User-defined".
start	an (optional) vector of starting values for the parameters in the linear predictor.
scale.fix	an (optional) logical variable. If TRUE, the scale parameter is fixed at the value of scale.value. As default, scale.fix is set to FALSE.
scale.value	an (optional) numeric value at which the scale parameter should be fixed. This is only appropriate if scale.fix=TRUE. As default, scale.value is set to 1.
toler	an (optional) positive value which represents the <i>convergence tolerance</i> . The convergence is reached when the maximum of the absolute relative differences between the values of the parameters in the linear predictor in consecutive iterations of the fitting algorithm is lower than toler. As default, toler is set to 0.00001.
maxit	an (optional) integer value which represents the maximum number of iterations allowed for the fitting algorithm. As default, maxit is set to 50.
trace	an (optional) logical variable. If TRUE, output is produced for each iteration of the estimating algorithm.
...	further arguments passed to or from other methods.

Details

The values of the multivariate response variable measured on n subjects or clusters, denoted by $y_i = (y_{i1}, \dots, y_{in_i})^\top$ for $i = 1, \dots, n$, are assumed to be realizations of independent random vectors denoted by $Y_i = (Y_{i1}, \dots, Y_{in_i})^\top$ for $i = 1, \dots, n$. The random variables associated to the i -th subject or cluster, Y_{ij} for $j = 1, \dots, n_i$, are assumed to satisfy $\mu_{ij} = E(Y_{ij})$, $\text{Var}(Y_{ij}) = \frac{\phi}{\omega_{ij}} V(\mu_{ij})$ and $\text{Corr}(Y_{ij}, Y_{ik}) = r_{jk}(\rho)$, where $\phi > 0$ is the dispersion parameter, $V(\mu_{ij})$ is the variance function, $\omega_{ij} > 0$ is a known weight, and $\rho = (\rho_1, \dots, \rho_q)^\top$ is a parameter vector. In addition, μ_{ij} is assumed to be dependent on the regressors vector x_{ij} by $g(\mu_{ij}) = z_{ij} + x_{ij}^\top \beta$, where $g(\cdot)$ is the link function, z_{ij} is a known *offset* and $\beta = (\beta_1, \dots, \beta_p)^\top$ is a vector of regression parameters. The probabilities $Pr[T_{ij} = 1 | T_{i,j-1} = 1, x_{i1}, \dots, x_{ij}, Y_{i1}, \dots, Y_{i,j-1}]$ are estimated by using a logistic model whose covariates are given by z_1, \dots, z_r . Then, those probabilities are used to compute the weights to be included in the parameter estimation algorithm.

A set of standard extractor functions for fitted model objects is available for objects of class *wglmgee*, including methods to the generic functions such as `print`, `summary`, `model.matrix`, `estequa`, `coef`, `vcov`, `fitted`, `confint` and `predict`. The input data are assumed to be ordered in time within each cluster.

Value

an object of class *wglmgee* in which the main results of the weighted GEE model fitted to the data are stored, i.e., a list with components including

coefficients	a vector with the estimates of β_1, \dots, β_p ,
fitted.values	a vector with the estimates of μ_{ij} for $i = 1, \dots, n$ and $j = 1, \dots, n_i$,
start	a vector with the starting values used,
iter	a numeric constant with the number of iterations,
prior.weights	a vector with the values of ω_{ij} for $i = 1, \dots, n$ and $j = 1, \dots, n_i$,
offset	a vector with the values of z_{ij} for $i = 1, \dots, n$ and $j = 1, \dots, n_i$,
terms	an object containing the terms objects,
estfun	a vector with the estimating equations evaluated at the parameter estimates and the observed data,
formula	the formula,
levels	the levels of the categorical regressors,
contrasts	an object containing the contrasts corresponding to levels,
converged	a logical indicating successful convergence,
model	the full model frame,
y	a vector with the values of y_{ij} for $i = 1, \dots, n$ and $j = 1, \dots, n_i$,
family	an object containing the family object used,
linear.predictors	a vector with the estimates of $g(\mu_{ij})$ for $i = 1, \dots, n$ and $j = 1, \dots, n_i$,
R	a matrix with the (robust) estimate of the variance-covariance,
corr	a matrix with the estimate of the working-correlation,
corstr	a character string specifying the working-correlation structure,
level	a character string specifying the weighted GEE method,
id	a vector which identifies the subjects or clusters,
sizes	a vector with the values of n_i for $i = 1, \dots, n$,

call `wglmgee` the original function call,

References

Fitzmaurice G.M., Laird N.M., Ware J.H. (2011). *Applied Longitudinal Analysis*. 2nd ed. John Wiley & Sons.

Preisser J.S., Lohman K.K., Rathouz P.J. (2002). Performance of Weighted Estimating Equations for Longitudinal Binary Data with Drop-Outs Missing at Random. *Statistics in Medicine* 21:3035–3054.

Robins J.M., Rotnitzky A., Zhao L.P. (1995) Analysis of Semiparametric Regression Models for Repeated Outcomes in the Presence of Missing Data. *Journal of the American Statistical Association* 90:122–129.

Vanegas L.H., Rondon L.M., Paula G.A. (2023) Generalized Estimating Equations using the new R package `glmtoolbox`. *The R Journal* 15:105-133.

See Also

[glmgee](#), [gnmgee](#)

Examples

```
##### Example: Amenorrhea rates over time
data(amenorrhea)
amenorrhea2 <- within(amenorrhea,{
  Ctime <- factor(Time)
  Ctime <- relevel(Ctime,ref="1")
  ylag1 <- c(0,amenorrhea[-length(ID)])
  ylag1 <- ifelse(Time==0,0,ylag1)})

mod <- amenorrhea ~ poly(Time,2) + Dose | Ctime + Dose + ylag1

### Observation-specified Weighted GEE
fit1 <- wglmgee(mod, family=binomial, data=amenorrhea2, id=ID,
  corstr="AR-M-dependent(1)", level="observations")
summary(fit1)

### Cluster-specified Weighted GEE
fit2 <- wglmgee(mod, family=binomial, data=amenorrhea2, id=ID,
  corstr="Exchangeable", level="clusters")
summary(fit2)
```

 zero.excess

Test for zero-excess in Count Regression Models

Description

Allows to assess if the observed number of zeros is significantly higher than expected according to the fitted count regression model (poisson or negative binomial).

Usage

```
zero.excess(
  object,
  alternative = c("excess", "lack", "both"),
  method = c("boot", "naive"),
  rep = 100,
  verbose = TRUE
)
```

Arguments

object	an object of the class <code>glm</code> , for poisson regression models, or an object of the class <code>overglm</code> , for negative binomial regression models.
alternative	an (optional) character string indicating the alternative hypothesis. There are three options: excess of zeros ("excess"), lack of zeros ("lack"), and both ("both"). As a default, type is set to "excess".
method	an (optional) character string indicating the method to calculate the mean and variance of the difference between observed and estimated expected number of zeros. There are two options: parametric bootstrapping ("boot") and naive ("naive"). As a default, type is set to "boot".
rep	an (optional) positive integer which allows to specify the number of replicates which should be used by the parametric bootstrapping. As a default, rep is set to 100.
verbose	an (optional) logical switch indicating if should the report of results be printed. As a default, verbose is set to TRUE.

Details

According to the formulated count regression model, we have that $Y_i \sim P(y; \mu_i, \phi)$ for $i = 1, \dots, n$ are independent variables. Consequently, the expected number of zeros can be estimated by $P(0; \hat{\mu}_i, \hat{\phi})$ for $i = 1, \dots, n$, where $\hat{\mu}_i$ and $\hat{\phi}$ represent the estimates of μ_i and ϕ , respectively, obtained from the fitted model. Thus, the statistical test can be defined as the standardized difference between the observed and (estimated) expected number of zeros. The standard normal distribution tends to be the distribution of that statistic when the sample size, n , tends to infinity. In He, Zhang, Ye, and Tang (2019), the above approach is called a naive test since it ignores the sampling variation associated with the estimated model parameters. To correct this, parametric bootstrapping is used to estimate the mean and variance of the difference between the (estimated) expected and observed number of zeros.

Value

A matrix with 1 row and the following columns:

Observed	the observed number of zeros,
Expected	the expected number of zeros,
z-value	the value of the statistical test,
p.value	the p-value of the statistical test.

References

He Hua, Zhang Hui, Ye Peng, Tang Wan (2019) A test of inflated zeros for Poisson regression models, *Statistical Methods in Medical Research* 28, 1157-1169.

See Also

[overglm](#), [zeroinf](#)

Examples

```
##### Example 1: Self diagnosed ear infections in swimmers
data(swimmers)
fit1 <- glm(infections ~ frequency + location, family=poisson, data=swimmers)
zero.excess(fit1,rep=50)
fit2 <- overglm(infections ~ frequency + location, family="nb1", data=swimmers)
zero.excess(fit2,rep=50)

##### Example 2: Article production by graduate students in biochemistry PhD programs
bioChemists <- pscl::bioChemists
fit1 <- glm(art ~ fem + kid5 + ment, family=poisson, data=bioChemists)
zero.excess(fit1,rep=50)
fit2 <- overglm(art ~ fem + kid5 + ment, family="nb1", data=bioChemists)
zero.excess(fit2,rep=50)
##### Example 3: Roots Produced by the Columar Apple Cultivar Trajan
data(Trajan)
fit1 <- glm(roots ~ photoperiod, family=poisson, data=Trajan)
zero.excess(fit1,rep=50)
fit2 <- overglm(roots ~ photoperiod, family="nbf", data=Trajan)
zero.excess(fit2,rep=50)
```

Description

Allows to fit a zero-altered (Poisson or negative binomial) regression model to deal with zero-excess in count data.

Usage

```
zeroalt(
  formula,
  data,
  offset,
  subset,
  na.action = na.omit(),
  weights,
  family = "poi(log)",
  zero.link = c("logit", "probit", "cloglog", "cauchit", "log"),
  reltol = 1e-13,
  start = list(counts = NULL, zeros = NULL),
  ...
)
```

Arguments

formula	a Formula expression of the form $\text{response} \sim x_1 + x_2 + \dots \mid z_1 + z_2 + \dots$, which is a symbolic description of the linear predictors of the models to be fitted to μ and π , respectively. See Formula documentation. If a formula of the form $\text{response} \sim x_1 + x_2 + \dots$ is supplied, the same regressors are employed in both components. This is equivalent to $\text{response} \sim x_1 + x_2 + \dots \mid x_1 + x_2 + \dots$.
data	an (optional) data frame in which to look for variables involved in the formula expression, as well as for variables specified in the arguments <code>weights</code> and <code>subset</code> .
offset	this can be used to specify an <i>a priori</i> known component to be included in the linear predictor during fitting. This should be <code>NULL</code> or a numeric vector of length equal to the number of cases.
subset	an (optional) vector specifying a subset of observations to be used in the fitting process.
na.action	a function which indicates what should happen when the data contain NAs. By default <code>na.action</code> is set to <code>na.omit()</code> .
weights	an (optional) vector of positive "prior weights" to be used in the fitting process. The length of <code>weights</code> should be the same as the number of observations. As default, <code>weights</code> is set to a vector of 1s.
family	an (optional) character string that allows you to specify the distribution to describe the response variable, as well as the link function to be used in the model for μ . The following distributions are supported: (zero-altered) negative binomial I ("nb1"), (zero-altered) negative binomial II ("nb2"), (zero-altered) negative binomial ("nbf"), and (zero-altered) poisson ("poi"). Link functions are the

	same as those available in Poisson models via glm . See family documentation. As default, <code>family</code> is set to be Poisson with log link.
<code>zero.link</code>	an (optional) character string which allows to specify the link function to be used in the model for π . Link functions available are the same than those available in binomial models via glm . See family documentation. As default, <code>zero.link</code> is set to "logit".
<code>reltol</code>	an (optional) positive value which represents the <i>relative convergence tolerance</i> for the BFGS method in optim . As default, <code>reltol</code> is set to 1e-13.
<code>start</code>	an (optional) list with two components named "counts" and "zeros", which allows to specify the starting values to be used in the iterative process to obtain the estimates of the parameters in the linear predictors of the models for μ and π , respectively.
<code>...</code>	further arguments passed to or from other methods.

Details

The zero-altered count distributions, also called *hurdle models*, may be obtained as the mixture between a zero-truncated count distribution and the Bernoulli distribution. Indeed, if Y is a count random variable such that $Y|\nu = 1$ is 0 with probability 1 and $Y|\nu = 0 \sim ZTP(\mu)$, where $\nu \sim \text{Bernoulli}(\pi)$, then Y is distributed according to the Zero-Altered Poisson distribution, denoted here as $ZAP(\mu, \pi)$.

Similarly, if Y is a count random variable such that $Y|\nu = 1$ is 0 with probability 1 and $Y|\nu = 0 \sim ZTNB(\mu, \phi, \tau)$, where $\nu \sim \text{Bernoulli}(\pi)$, then Y is distributed according to the Zero-Altered Negative Binomial distribution, denoted here as $ZANB(\mu, \phi, \tau, \pi)$. The Zero-Altered Negative Binomial I (μ, ϕ, π) and Zero-Altered Negative Binomial II (μ, ϕ, π) distributions are special cases of $ZANB$ when $\tau = 0$ and $\tau = -1$, respectively.

The "counts" model may be expressed as $g(\mu_i) = x_i^\top \beta$ for $i = 1, \dots, n$, where $g(\cdot)$ is the link function specified at the argument `family`. Similarly, the "zeros" model may be expressed as $h(\pi_i) = z_i^\top \gamma$ for $i = 1, \dots, n$, where $h(\cdot)$ is the link function specified at the argument `zero.link`. Parameter estimation is performed using the maximum likelihood method. The parameter vector γ is estimated by applying the routine [glm.fit](#), where a binary-response model (1 or "success" if `response=0` and 0 or "fail" if `response>0`) is fitted. Then, the rest of the model parameters are estimated by maximizing the log-likelihood function based on the zero-truncated count distribution through the BFGS method available in the routine [optim](#). The accuracy and speed of the BFGS method are increased because the call to the routine [optim](#) is performed using the analytical instead of the numerical derivatives. The variance-covariance matrix estimate is obtained as being minus the inverse of the (analytical) hessian matrix evaluated at the parameter estimates and the observed data. A set of standard extractor functions for fitted model objects is available for objects of class *zeroinflation*, including methods to the generic functions such as [print](#), [summary](#), [model.matrix](#), [estequa](#), [coef](#), [vcov](#), [logLik](#), [fitted](#), [confint](#), [AIC](#), [BIC](#) and [predict](#). In addition, the model fitted to the data may be assessed using functions such as [anova.zeroinflation](#), [residuals.zeroinflation](#), [df-beta.zeroinflation](#), [cooks.distance.zeroinflation](#) and [envelope.zeroinflation](#).

Value

An object of class *zeroinflation* in which the main results of the model fitted to the data are stored, i.e., a list with components including

coefficients	a list with elements "counts" and "zeros" containing the parameter estimates from the respective models,
fitted.values	a list with elements "counts" and "zeros" containing the estimates of μ_1, \dots, μ_n and π_1, \dots, π_n , respectively,
start	a vector containing the starting values for all parameters in the model,
prior.weights	a vector containing the case weights used,
offset	a list with elements "counts" and "zeros" containing the offset vectors, if any, from the respective models,
terms	a list with elements "counts", "zeros" and "full" containing the terms objects for the respective models,
loglik	the value of the log-likelihood function evaluated at the parameter estimates and the observed data,
estfun	a list with elements "counts" and "zeros" containing the estimating functions evaluated at the parameter estimates and the observed data for the respective models,
formula	the formula,
levels	the levels of the categorical regressors,
contrasts	a list with elements "counts" and "zeros" containing the contrasts corresponding to levels from the respective models,
converged	a logical indicating successful convergence,
model	the full model frame,
y	the response count vector,
family	a list with elements "counts" and "zeros" containing the family objects used in the respective models,
linear.predictors	a list with elements "counts" and "zeros" containing the estimates of $g(\mu_1), \dots, g(\mu_n)$ and $h(\pi_1), \dots, h(\pi_n)$, respectively,
R	a matrix with the Cholesky decomposition of the inverse of the variance-covariance matrix of all parameters in the model,
call	the original function call.

References

Cameron A.C., Trivedi P.K. (1998) *Regression Analysis of Count Data*. New York: Cambridge University Press.

Mullahy J. (1986) Specification and Testing of Some Modified Count Data Models. *Journal of Econometrics* 33, 341–365.

See Also

[overglm](#), [zeroinf](#)

Examples

```
##### Example 1: Roots Produced by the Columnar Apple Cultivar Trajan
data(Trajan)
fit1 <- zeroalt(roots ~ photoperiod, family="nbf(log)", zero.link="logit", data=Trajan)
summary(fit1)
```

```
##### Example 2: Self diagnosed ear infections in swimmers
data(swimmers)
fit2 <- zeroalt(infections ~ frequency | location, family="nb1(log)", data=swimmers)
summary(fit2)
```

```
##### Example 3: Article production by graduate students in biochemistry PhD programs
bioChemists <- pscl::bioChemists
fit3 <- zeroalt(art ~ fem + kid5 + ment, family="nb1(log)", data = bioChemists)
summary(fit3)
```

zeroinf

Zero-Inflated Regression Models to deal with Zero-Excess in Count Data

Description

Allows to fit a zero-inflated (Poisson or negative binomial) regression model to deal with zero-excess in count data.

Usage

```
zeroinf(
  formula,
  data,
  offset,
  subset,
  na.action = na.omit(),
  weights,
  family = "poi(log)",
  zero.link = c("logit", "probit", "cloglog", "cauchit", "log"),
```

```

    reltol = 1e-13,
    start = list(counts = NULL, zeros = NULL),
    ...
)

```

Arguments

formula	a Formula expression of the form <code>response ~ x1 + x2 + ... z1 + z2 + ...</code> , which is a symbolic description of the linear predictors of the models to be fitted to μ and π , respectively. See Formula documentation. If a formula of the form <code>response ~ x1 + x2 + ...</code> is supplied, then the same regressors are employed in both components. This is equivalent to <code>response ~ x1 + x2 + ... x1 + x2 + ...</code> .
data	an (optional) data frame in which to look for variables involved in the formula expression, as well as for variables specified in the arguments <code>weights</code> and <code>subset</code> .
offset	this can be used to specify an <i>a priori</i> known component to be included in the linear predictor during fitting. This should be <code>NULL</code> or a numeric vector of length equal to the number of cases.
subset	an (optional) vector specifying a subset of observations to be used in the fitting process.
na.action	a function which indicates what should happen when the data contain NAs. By default <code>na.action</code> is set to <code>na.omit()</code> .
weights	an (optional) vector of positive "prior weights" to be used in the fitting process. The length of <code>weights</code> should be the same as the number of observations. As default, <code>weights</code> is set to a vector of 1s.
family	an (optional) character string that allows you to specify the distribution to describe the response variable, as well as the link function to be used in the model for μ . The following distributions are supported: (zero-inflated) negative binomial I (" <code>nb1</code> "), (zero-inflated) negative binomial II (" <code>nb2</code> "), (zero-inflated) negative binomial (" <code>nbf</code> "), and (zero-inflated) poisson (" <code>poi</code> "). Link functions are the same as those available in Poisson models via glm . See family documentation. As default, <code>family</code> is set to be Poisson with log link.
zero.link	an (optional) character string which allows to specify the link function to be used in the model for π . Link functions available are the same than those available in binomial models via glm . See family documentation. As default, <code>zero.link</code> is set to " <code>logit</code> ".
reltol	an (optional) positive value which represents the <i>relative convergence tolerance</i> for the BFGS method in optim . As default, <code>reltol</code> is set to <code>1e-13</code> .
start	an (optional) list with two components named " <code>counts</code> " and " <code>zeros</code> ", which allows to specify the starting values to be used in the iterative process to obtain the estimates of the parameters in the linear predictors to the models for μ and π , respectively.
...	further arguments passed to or from other methods.

Details

The zero-inflated count distributions may be obtained as the mixture between a count distribution and the Bernoulli distribution. Indeed, if Y is a count random variable such that $Y|\nu = 1$ is 0 with probability 1 and $Y|\nu = 0 \sim \text{Poisson}(\mu)$, where $\nu \sim \text{Bernoulli}(\pi)$, then Y is distributed according to the Zero-Inflated Poisson distribution, denoted here as $\text{ZIP}(\mu, \pi)$.

Similarly, if Y is a count random variable such that $Y|\nu = 1$ is 0 with probability 1 and $Y|\nu = 0 \sim \text{NB}(\mu, \phi, \tau)$, where $\nu \sim \text{Bernoulli}(\pi)$, then Y is distributed according to the Zero-Inflated Negative Binomial distribution, denoted here as $\text{ZINB}(\mu, \phi, \tau, \pi)$. The Zero-Inflated Negative Binomial I (μ, ϕ, π) and Zero-Inflated Negative Binomial II (μ, ϕ, π) distributions are special cases of ZINB when $\tau = 0$ and $\tau = -1$, respectively.

The "counts" model may be expressed as $g(\mu_i) = x_i^\top \beta$ for $i = 1, \dots, n$, where $g(\cdot)$ is the link function specified at the argument family. Similarly, the "zeros" model may be expressed as $h(\pi_i) = z_i^\top \gamma$ for $i = 1, \dots, n$, where $h(\cdot)$ is the link function specified at the argument zero. link. Parameter estimation is performed using the maximum likelihood method. The model parameters are estimated by maximizing the log-likelihood function through the BFGS method available in the routine `optim`. Analytical derivatives are used instead of numerical derivatives to increase BFGS method accuracy and speed. The variance-covariance matrix estimate is obtained as being minus the inverse of the (analytical) hessian matrix evaluated at the parameter estimates and the observed data.

A set of standard extractor functions for fitted model objects is available for objects of class `zeroinflation`, including methods for generic functions such as `print`, `summary`, `model.matrix`, `estequa`, `coef`, `vcov`, `logLik`, `fitted`, `confint`, `AIC`, `BIC` and `predict`. In addition, the model fitted to the data may be assessed using functions such as `anova.zeroinflation`, `residuals.zeroinflation`, `dfbeta.zeroinflation`, `cooks.distance.zeroinflation` and `envelope.zeroinflation`.

Value

An object of class `zeroinflation` in which the main results of the model fitted to the data are stored, i.e., a list with components including

<code>coefficients</code>	a list with elements "counts" and "zeros" containing the parameter estimates from the respective models,
<code>fitted.values</code>	a list with elements "counts" and "zeros" containing the estimates of μ_1, \dots, μ_n and π_1, \dots, π_n , respectively,
<code>start</code>	a vector containing the starting values for all parameters in the model,
<code>prior.weights</code>	a vector containing the case weights used,
<code>offset</code>	a list with elements "counts" and "zeros" containing the offset vectors, if any, from the respective models,
<code>terms</code>	a list with elements "counts", "zeros" and "full" containing the terms objects for the respective models,
<code>loglik</code>	the value of the log-likelihood function evaluated at the parameter estimates and

	the observed data,
estfun	a list with elements "counts" and "zeros" containing the estimating functions evaluated at the parameter estimates and the observed data for the respective models,
formula	the formula,
levels	the levels of the categorical regressors,
contrasts	a list with elements "counts" and "zeros" containing the contrasts corresponding to levels from the respective models,
converged	a logical indicating successful convergence,
model	the full model frame,
y	the response count vector,
family	a list with elements "counts" and "zeros" containing the family objects used in the respective models,
linear.predictors	a list with elements "counts" and "zeros" containing the estimates of $g(\mu_1), \dots, g(\mu_n)$ and $h(\pi_1), \dots, h(\pi_n)$, respectively,
R	a matrix with the Cholesky decomposition of the inverse of the variance-covariance matrix of all parameters in the model,
call	the original function call.

References

- Cameron A.C., Trivedi P.K. 1998. *Regression Analysis of Count Data*. New York: Cambridge University Press.
- Lambert D. 1992. Zero-Inflated Poisson Regression, with an Application to Defects in Manufacturing. *Technometrics* 34, 1-14.
- Garay A.M., Hashimoto E.M., Ortega E.M.M., Lachos V. (2011) On estimation and influence diagnostics for zero-inflated negative binomial regression models. *Computational Statistics & Data Analysis* 55, 1304-1318.

See Also

[overglm](#), [zeroalt](#)

Examples

```
##### Example 1: Roots Produced by the Columnar Apple Cultivar Trajan
data(Trajan)
fit1 <- zeroinf(roots ~ photoperiod, family="nbf(log)", zero.link="logit", data=Trajan)
```

```
summary(fit1)

##### Example 2: Self diagnosed ear infections in swimmers
data(swimmers)
fit2 <- zeroinf(infections ~ frequency | location, family="nb1(log)", data=swimmers)
summary(fit2)

##### Example 3: Article production by graduate students in biochemistry PhD programs
bioChemists <- pscl::bioChemists
fit3 <- zeroinf(art ~ fem + kid5 + ment | ment, family="nb1(log)", data = bioChemists)
summary(fit3)
```

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