# Package 'StepReg'

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Title Stepwise Regression Analysis

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Author Junhui Li,Xiaohuan Lu,Kun Cheng,Wenxin Liu
Maintainer Junhui Li <junhuili@cau.edu.cn></junhuili@cau.edu.cn>
Description Three most common types of stepwise regression including linear regression, logistic regression and cox proportional hazard regression can be performed to select best model with methods of forward selection, backward elimination, bidirectional selection and best subset selection. A widely used selection criteria are available for variable selection.
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2 modelFitStat

# **Description**

Fit Model Statistics with least square or likelihood method to return an information criteria value

# Usage

```
modelFitStat(ic, fit, method = c("LeastSquare", "Likelihood"), cox = FALSE)
```

#### Arguments

ic	Information criteria, including AIC, AICc, BIC, CP, HQ, HQc, Rsq, adjRsq and SBC
fit	Object of linear model or general linear model
method	Method to calculate information criteria value, including 'LeastSquare' and 'Likelihood'
сох	Compute model fit statistics for cox regression or not, where partial likelihood value will be used instead of the ordinary.

## Author(s)

Junhui Li

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Sawa, T. (1978). Information criteria for discriminating among alternative regression models. Econometrica, 46(6), 1273-1291.

Schwarz, G. (1978). Estimating the dimension of a model. Annals of Statistics, 6(2), pags. 15-18.

# **Examples**

```
data(mtcars)
fit <- lm(mpg~wt+qsec+vs+am+gear+carb,data=mtcars)
modelFitStat("AIC",fit,"LeastSquare")</pre>
```

stepwise

Stepwise Linear Model Regression

#### Description

Stepwise linear regression analysis selects model based on information criteria and F or approximate F test with 'forward', 'backward', 'bidirection' and 'score' model selection method.

# Usage

```
stepwise(
  formula,
  data,
  include = NULL,
  selection = c("forward", "backward", "bidirection", "score"),
  select = c("AIC", "AICc", "BIC", "CP", "HQ", "HQc", "Rsq", "adjRsq", "SL", "SBC"),
  sle = 0.15,
  sls = 0.15,
  multivarStat = c("Pillai", "Wilks", "Hotelling-Lawley", "Roy"),
  weights = NULL,
  best = NULL
)
```

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#### **Arguments**

formula Model formulae. The models fitted by the lm functions are specified in a com-

pact symbolic form. The basic structure of a formula is the tilde symbol ( $\sim$ ) and at least one independent (righthand) variable. In most (but not all) situations, a single dependent (lefthand) variable is also needed. Thus we can construct a formula quite simple formula ( $y \sim x$ ). Multiple independent variables by simply separating them with the plus (+) symbol ( $y \sim x1 + x2$ ). Variables in the formula are removed with a minus(-) symbol ( $y \sim x1 - x2$ ). One particularly useful feature is the . operator when modelling with lots of variables ( $y \sim x$ ). The %in% operator indicates that the terms on its left are nested within those on the right. For example  $y \sim x1 + x2$  %in% x1 expands to the formula  $y \sim x1 + x1:x2$ . A model with no intercept can be specified as  $y \sim x - 1$  or  $y \sim x + 0$  or  $y \sim 0 + x$ . Multivariate multiple regression can be specified as cbind(y1,y2)  $\sim x1 + x2$ .

data Data set including dependent and independent variables to be analyzed

include Force vector of effects name to be included in all models.

selection Model selection method including "forward", "backward", "bidirection" and

'score', forward selection starts with no effects in the model and adds effects, backward selection starts with all effects in the model and removes effects, while bidirection regression is similar to the forward method except that effects already in the model do not necessarily stay there, and score method requests specifies the best-subset selection method, which uses the branch-and-bound technique to efficiently search for subsets of model effects that best predict the

response variable.

select Specify the criterion that uses to determine the order in which effects enter and

leave at each step of the specified selection method including "AIC", "AICc", "BIC", "CP", "HQ", "HQC", "R

and "SL".

sle Specify the significance level for entry, default is 0.15

sls Specify the significance level for staying in the model, default is 0.15

multivarStat Statistic for multivariate regression analysis, including Wilks' lamda ("Wilks"),

Pillai Trace ("Pillai"), Hotelling-Lawley's Trace ("Hotelling"), Roy's Largest

Root ("Roy")

weights Numeric vector to provide a weight for each observation in the input data set.

Note that weights should be ranged from 0 to 1, while negative numbers are forcibly converted to 0, and numbers greater than 1 are forcibly converted to 1. If you do not specify a weight vector, each observation has a default weight of

1.

best Control the number of models displayed in the output, default is NULL, which

means all possible model will be displayed.

# Author(s)

Junhui Li

#### References

Alsubaihi, A. A., Leeuw, J. D., and Zeileis, A. (2002). Variable selection in multivariable regression using sas/iml., 07(i12).

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# Examples

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stepwiseCox

Stepwise Cox Proportional Hazards Regression

# **Description**

Stepwise Cox regression analysis selects model based on information criteria and significant test with 'forward', 'backward', 'bidirection' and 'score' variable selection method.

## Usage

```
stepwiseCox(
  formula,
  data,
  include = NULL,
  selection = c("forward", "backward", "bidirection", "score"),
  select = c("SL", "AIC", "AICc", "SBC", "HQ", "HQc", "IC(3/2)", "IC(1)"),
  sle = 0.15,
  sls = 0.15,
  method = c("efron", "breslow", "exact"),
  weights = NULL,
  best = NULL
)
```

# **Arguments**

formula

Model formulae. The models fitted by the coxph functions are specified in a compact symbolic form. The basic structure of a formula is the tilde symbol (~) and at least one independent (righthand) variable. In most (but not all) situations, a single dependent (lefthand) variable is also needed. Thus we can construct a formula quite simple formula (y ~ x). Multiple independent variables by simply separating them with the plus (+) symbol (y ~ x1 + x2). Variables in the formula are removed with a minus(-) symbol (y ~ x1 - x2). One particularly useful feature is the . operator when modelling with lots of variables (y ~ .). The %in% operator indicates that the terms on its left are nested within those on the right. For example y ~ x1 + x2 %in% x1 expands to the formula y ~ x1 + x1:x2.

data

Data set including dependent and independent variables to be analyzed

include

Force the effects vector listed in the data to be included in all models. The selection methods are performed on the other effects in the data set

selection

Model selection method including "forward", "backward", "bidirection" and 'score', forward selection starts with no effects in the model and adds effects, backward selection starts with all effects in the model and removes effects, while bidirection regression is similar to the forward method except that effects already in the model do not necessarily stay there, and score method requests best subset selection.

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select Specify the criterion that uses to determine the order in which effects enter and

leave at each step of the specified selection method including AIC, AICc, SBC,

IC(1), IC(3/2), HQ, HQc and Significant Levels(SL)

sle Specify the significance level for entry, default is 0.15

sls Specify the significance level for staying in the model, default is 0.15

method Specify the method for tie handling. If there are no tied death times all the meth-

ods are equivalent. Nearly all Cox regression programs use the Breslow method by default, but not this one. The Efron approximation is used as the default here, it is more accurate when dealing with tied death times, and is as efficient computationally. The "exact partial likelihood is equivalent to a conditional logistic model, and is appropriate when the times are a small set of discrete values.

weights Numeric vector to provide a weight for each observation in the input data set.

Note that weights should be ranged from 0 to 1, while negative numbers are forcibly converted to 0, and numbers greater than 1 are forcibly converted to 1. If you do not specify a weight vector, each observation has a default weight of

1.

best Control the number of models displayed in the output, default is NULL which

means all possible model will be displayed

#### Author(s)

Junhui Li

#### References

Alsubaihi, A. A., Leeuw, J. D., and Zeileis, A. (2002). Variable selection in multivariable regression using sas/iml., 07(i12).

Darlington, R. B. (1968). Multiple regression in psychological research and practice. Psychological Bulletin, 69(3), 161.

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Schwarz, G. (1978). Estimating the dimension of a model. Annals of Statistics, 6(2), pags. 15-18.

#### **Examples**

```
lung <- survival::lung
my.data <- na.omit(lung)
my.data$status1 <- ifelse(my.data$status==2,1,0)
data <- my.data
formula = Surv(time, status1) ~ . - status

stepwiseCox(formula,
data,
include=NULL,
selection=c("bidirection"),
select="HQ",
method=c("efron"),
sle=0.15,
sls=0.15,
weights=NULL,
best=NULL)</pre>
```

stepwiseLogit

Stepwise Logistic Regression

# **Description**

Stepwise logistic regression analysis selects model based on information criteria and Wald or Score test with 'forward', 'backward', 'bidirection' and 'score' model selection method.

## Usage

```
stepwiseLogit(
  formula,
  data,
  include = NULL,
  selection = c("forward", "backward", "bidirection", "score"),
  select = c("SL", "AIC", "AICc", "SBC", "HQ", "HQc", "IC(3/2)", "IC(1)"),
  sle = 0.15,
```

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```
sls = 0.15,
sigMethod = c("Rao", "LRT"),
weights = NULL,
best = NULL
)
```

#### **Arguments**

formula

Model formulae. The models fitted by the glm functions are specified in a compact symbolic form. The basic structure of a formula is the tilde symbol (~) and at least one independent (righthand) variable. In most (but not all) situations, a single dependent (lefthand) variable is also needed. Thus we can construct a formula quite simple formula (y ~ x). Multiple independent variables by simply separating them with the plus (+) symbol (y ~ x1 + x2). Variables in the formula are removed with a minus(-) symbol (y ~ x1 - x2). One particularly useful feature is the . operator when modelling with lots of variables (y ~ .). The %in% operator indicates that the terms on its left are nested within those on the right. For example y ~ x1 + x2 %in% x1 expands to the formula y ~ x1 + x1:x2. A model with no intercept can be specified as y ~ x - 1 or y ~ x + 0 or y ~ 0 + x.

data

Data set including dependent and independent variables to be analyzed

include

Force the effects vector listed in the data to be included in all models. The selection methods are performed on the other effects in the data set

selection

Model selection method including "forward", "backward", "bidirection" and 'score', forward selection starts with no effects in the model and adds effects, backward selection starts with all effects in the model and removes effects, while bidirection regression is similar to the forward method except that effects already in the model do not necessarily stay there, and score method requests best subset selection.

select

Specify the criterion that uses to determine the order in which effects enter and leave at each step of the specified selection method including AIC, AICc, SBC, IC(1), IC(3/2), HQ, HQc and Significant Levels(SL)

sle

Specify the significance level for entry, default is 0.15

sls

Specify the significance level for staying in the model, default is 0.15

sigMethod

Specify the method of significant test for variable to be entered in the model. "Rao" and "LRT" cab be chosen for Rao's efficient score test and likelihood ratio test.

weights

Numeric vector to provide a weights for each observation in the input data set. Note that weights should be ranged from 0 to 1, while negative numbers are forcibly converted to 0, and numbers greater than 1 are forcibly converted to 1. If you do not specify a weights vector, each observation has a default weights of 1.

best

Control the number of models displayed in the output, default is NULL which means all possible model will be displayed

### Author(s)

Junhui Li

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