

# Package ‘coxphMIC’

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**Type** Package

**Title** Sparse Estimation of Cox Proportional Hazards Models via  
Approximated Information Criterion

**Version** 0.1.0

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**Description** Sparse estimation for Cox PH models is done via

Minimum approximated Information Criterion (MIC) by Su, Wijayasinghe,  
Fan, and Zhang (2016) <DOI:10.1111/biom.12484>. MIC mimics the best  
subset selection using a penalized likelihood approach yet with no need  
of a tuning parameter. The problem is further reformulated with a  
re-parameterization step so that it reduces to one unconstrained non-convex  
yet smooth programming problem, which can be solved efficiently. Furthermore,  
the re-parameterization tactic yields an additional advantage in terms of  
circumventing post-selection inference.

**License** GPL-2

**Depends** R (>= 3.1.0), stats (>= 3.2.5), graphics (>= 3.2.5), utils (>= 3.2.5)

**Imports** survival (>= 2.38), numDeriv (>= 2014.2-1)

**LazyData** TRUE

**RoxygenNote** 6.0.1

**NeedsCompilation** no

**Repository** CRAN

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coxphMIC

*Sparse Estimation for a Cox PH model via Approximated Information Criterion***Description**

Sparse Estimation for a Cox PH model via Approximated Information Criterion

**Usage**

```
coxphMIC(formula = Surv(time, status) ~ ., data, method.beta0 = "MPLE",
beta0 = NULL, theta0 = 1, method = "BIC", lambda0 = 2, a0 = NULL,
scale.x = TRUE, maxit.global = 300, maxit.local = 100,
rounding.digits = 4, zero = sqrt(.Machine$double.eps),
compute.se.gamma = TRUE, compute.se.beta = TRUE, CI.gamma = TRUE,
conf.level = 0.95, details = FALSE)
```

**Arguments**

<code>formula</code>	A formula object, with the response on the left of a <code>~</code> operator, and the terms on the right. The response must be a survival object as returned by the <code>Surv</code> function.
<code>data</code>	A <code>data.frame</code> in which to interpret the variables named in the <code>formula</code> argument.
<code>method.beta0</code>	A method to supply the starting point for beta with choices: "MPLE" and "ridge". By default, the maximum partial likelihood estimator (MPLE) is used with "MPLE". The option "ridge" asks for a ridge estimator with penalty parameter specified by <code>theta0</code> . You may supply a set of values for <code>beta0</code> of your choice. If <code>NULL</code> , then <code>beta0</code> is set as 0.
<code>beta0</code>	User-supplied <code>beta0</code> value, the starting point for optimization.
<code>theta0</code>	Specified the penalty parameter for the ridge estimator when <code>method.beta0="ridge"</code> .
<code>method</code>	Specifies the model selection criterion used. If "AIC", the complexity penalty parameter ( <code>lambda</code> ) equals 2; if "BIC", <code>lambda</code> equals $\ln(n_0)$ , where $n_0$ denotes the number of uncensored events. You may specify the penalty parameter of your choice by setting <code>lambda0</code> .
<code>lambda0</code>	User-supplied penalty parameter for model complexity. If <code>method="AIC"</code> or "BIC", the value of <code>lambda0</code> will be ignored.
<code>a0</code>	The scale (or sharpness) parameter used in the hyperbolic tangent penalty. By default, <code>a0</code> is set as $n_0$ , where $n_0$ is again the number of uncensored events.
<code>scale.x</code>	Logical value: should the predictors X be normalized? Default to TRUE.
<code>maxit.global</code>	Maximum number of iterations allowed for the global optimization algorithm – SANN. Default value is 300.
<code>maxit.local</code>	Maximum number of iterations allowed for the local optimizaiton algorithm – BFGS. Default value is 100.

<code>rounding.digits</code>	Number of digits after the decimal point for rounding-up estimates. Default value is 4.
<code>zero</code>	Tolerance level for convergence. Default is <code>sqrt(.Machine\$double.eps)</code> .
<code>compute.se.gamma</code>	Logical value indicating whether to compute the standard errors for gamma in the reparameterization. Default is TRUE.
<code>compute.se.beta</code>	Logical value indicating whether to compute the standard errors for nonzero beta estimates. Default is TRUE. Note that this result is subject to post-selection inference.
<code>CI.gamma</code>	Logical indicator of whether the confidence interval for gamma is outputted. Default is TRUE.
<code>conf.level</code>	Specifies the confidence level for <code>CI.gamma</code> . Defaulted as 0.95.
<code>details</code>	Logical value: if TRUE, detailed results will be printed out when running <code>coxphMIC</code> .

## Details

The main idea of MIC involves approximation of the  $\ell_0$  norm with a continuous or smooth unit dent function. This method bridges the best subset selection and regularization by borrowing strength from both. It mimics the best subset selection using a penalized likelihood approach yet with no need of a tuning parameter.

The problem is further reformulated with a reparameterization step by relating `beta` to `gamma`. There are two benefits of doing so: first, it reduces the optimization to one unconstrained nonconvex yet smooth programming problem, which can be solved efficiently as in computing the maximum partial likelihood estimator (MPLE); furthermore, the reparameterization tactic yields an additional advantage in terms of circumventing post-selection inference. Significance testing on `beta` can be done through `gamma`.

To solve the smooth yet nonconvex optimization, a simulated annealing (`method="SANN"` option in `optim`) global optimization algorithm is first applied. The resultant estimator is then used as the starting point for another local optimization algorithm. The quasi-Newton BFGS method (`method="BFGS"` in `optim`) is used.

In its current version, some appropriate data preparation might be needed. For example, nominal variables (especially character-valued ones) needed to be coded with dummy variables; missing values would cause errors too and hence need prehandling too.

## Value

A list containing the following component is returned.

**opt.global** Results from the preliminary run of a global optimization procedure (SANN as default).

**opt.local** Results from the second run of a local optimization procedure (BFGS as default).

**min.Q** Value of the minimized objective function.

**gamma** Estimated gamma;

**beta** Estimated beta;

**VCOV.gamma** The estimated variance-covariance matrix for the gamma estimate;

- se.gamma** Standard errors for the gamma estimate;
- se.beta** Standard errors for the beta estimate (post-selection);
- BIC** The BIC value for the *selected* model;
- result** A summary table of the fitting results.
- call** the matched call.

## References

- Abdolyousefi, R. N. and Su, X. (2016). **coxphMIC**: An R package for sparse estimation of Cox PH Models via approximated information criterion. Tentatively accepted, *The R Journal*.
- Su, X. (2015). Variable selection via subtle uprooting. *Journal of Computational and Graphical Statistics*, **24**(4): 1092–1113. URL <http://www.tandfonline.com/doi/pdf/10.1080/10618600.2014.955176>
- Su, X., Wijayasinghe, C. S., Fan, J., and Zhang, Y. (2015). Sparse estimation of Cox proportional hazards models via approximated information criteria. *Biometrics*, **72**(3): 751–759. URL <http://onlinelibrary.wiley.com/doi/10.1111/biom.12484/epdf>

## See Also

[coxph](#)

## Examples

```
# PREPARE THE PBC DATA
library(survival); data(pbc);
dat <- pbc; dim(dat);
dat$status <- ifelse(pbc$status==2, 1, 0)
# HANDLE CATEGORICAL VARIABLES
dat$sex <- ifelse(pbc$sex=="f", 1, 0)
# LISTWISE DELETION USED TO HANDLE MISSING VALUES
dat <- stats::na.omit(dat);
dim(dat); utils::head(dat)

fit.mic <- coxphMIC(formula=Surv(time, status)~.-id, data=dat, method="BIC", scale.x=TRUE)
names(fit.mic)
print(fit.mic)
plot(fit.mic)
```

LoglikPen

*Compute the penalized log partial likelihood for a Cox PH model with MIC penalty*

## Description

Compute the penalized log partial likelihood for a Cox PH model with MIC penalty

**Usage**

```
LoglikPen(beta, time, status, X, lambda, a)
```

**Arguments**

beta	A p-dimensional vector containing the regression coefficients in the CoxPH model.
time	The observed survival time.
status	The status indicator: 1 for event and 0 for censoring.
X	An $n$ by $p$ design matrix.
lambda	The penalty parameter equals either 2 in AIC or $\ln(n_0)$ in BIC (by default), where $n_0$ is the number of uncensored survival times observed in the data. You can also specify it to a specific value of your own choice.
a	The scale parameter in the hyperbolic tangent function of the MIC penalty. By default, $a = n_0$ , i.e., the number of uncensored survival times observed in the data.

**Value**

The value of the penalized log partial likelihood function evaluated at beta.

**References**

- Abdolyousefi, R. N. and Su, X. (2016). **coxphMIC**: An R package for sparse estimation of Cox PH Models via approximated information criterion. Tentatively accepted, *The R Journal*.
- Su, X. (2015). Variable selection via subtle uprooting. *Journal of Computational and Graphical Statistics*, **24**(4): 1092–1113. URL <http://www.tandfonline.com/doi/pdf/10.1080/10618600.2014.955176>
- Su, X., Wijayasinghe, C. S., Fan, J., and Zhang, Y. (2015). Sparse estimation of Cox proportional hazards models via approximated information criteria. *Biometrics*, **72**(3): 751–759. URL <http://onlinelibrary.wiley.com/doi/10.1111/biom.12484/epdf>

**See Also**

[coxph](#)

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plot.coxpathMIC

*The Generic plot Function for Object of coxpathMIC Class*

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**Description**

The Generic plot Function for Object of coxpathMIC Class

## Usage

```
## S3 method for class 'coxphMIC'
plot(x, conf.level = 0.95, horizontal = TRUE,
      mar = rep(4.5, 4), ...)
```

## Arguments

<code>x</code>	an object of <code>coxphMIC</code> class.
<code>conf.level</code>	confidence level used for error bar plots. Default is 0.95.
<code>horizontal</code>	Logical indicator of horizontal alignment. Default is TRUE.
<code>mar</code>	margin in terms of the number of lines to be specified on the four sides of the plot
<code>...</code>	further arguments passed to or from other methods.

## Details

The (generic) plot method for an `coxphMIC` object. It plots MIC estimates of gamma and beta. For 0 beta estimates, their corresponding SE are reset to 0 to make the plot.

## Value

Error bar plots for estimated gamma and beta at a given confidence level.

## References

- Abdolyousefi, R. N. and Su, X. (2016). **coxphMIC**: An R package for sparse estimation of Cox PH Models via approximated information criterion. Tentatively accepted, *The R Journal*.
- Su, X. (2015). Variable selection via subtle uprooting. *Journal of Computational and Graphical Statistics*, **24**(4): 1092–1113. URL <http://www.tandfonline.com/doi/pdf/10.1080/10618600.2014.955176>
- Su, X., Wijayasinghe, C. S., Fan, J., and Zhang, Y. (2015). Sparse estimation of Cox proportional hazards models via approximated information criteria. *Biometrics*, **72**(3): 751–759. URL <http://onlinelibrary.wiley.com/doi/10.1111/biom.12484/epdf>

## See Also

[coxphMIC](#)

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print.coxphMIC*The Generic print Function for Object of coxphMIC Class*

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**Description**

The Generic print Function for Object of coxphMIC Class

**Usage**

```
## S3 method for class 'coxphMIC'  
print(x, digits = max(3L, getOption("digits") - 3L), ...)
```

**Arguments**

x	an object of coxphMIC class.
digits	the minimal number of significant digits. See <a href="#">print.default</a> .
...	further arguments passed to or from other methods.

**Details**

The (generic) print method for an coxphMIC object. The results include info on the estimated gamma and beta. Depending on the options, significance testing and confidence intervals are also provided.

**Value**

The table of estimated regression coefficients beta and the reparameterized gamma.

**References**

- Abdolyousefi, R. N. and Su, X. (2016). **coxphMIC**: An R package for sparse estimation of Cox PH Models via approximated information criterion. Tentatively accepted, *The R Journal*.
- Su, X. (2015). Variable selection via subtle uprooting. *Journal of Computational and Graphical Statistics*, **24**(4): 1092–1113. URL <http://www.tandfonline.com/doi/pdf/10.1080/10618600.2014.955176>
- Su, X., Wijayasinghe, C. S., Fan, J., and Zhang, Y. (2015). Sparse estimation of Cox proportional hazards models via approximated information criteria. *Biometrics*, **72**(3): 751–759. URL <http://onlinelibrary.wiley.com/doi/10.1111/biom.12484/epdf>

**See Also**

[coxphMIC](#)

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