

Package ‘fastcox’

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Title Lasso and Elastic-Net Penalized Cox's Regression in High Dimensions Models using the Cocktail Algorithm

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Imports Matrix, methods

Description We implement a cocktail algorithm, a good mixture of coordinate decent, the majorization-minimization principle and the strong rule, for computing the solution paths of the elastic net penalized Cox's proportional hazards model. The package is an implementation of Yang, Y. and Zou, H. (2013) DOI: <[doi:10.4310/SII.2013.v6.n2.a1](https://doi.org/10.4310/SII.2013.v6.n2.a1)>.

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fastcox-package

Lasso and elastic-net penalized Cox's regression in high dimensions models using the cocktail algorithm

Description

We introduce a cocktail algorithm, a good mixture of coordinate decent, the majorization-minimization principle and the strong rule, for computing the solution paths of the elastic net penalized Cox's proportional hazards model.

Details

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Author(s)

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References

Yang, Y. and Zou, H. (2013), "A Cocktail Algorithm for Solving The Elastic Net Penalized Cox's Regression in High Dimensions", *Statistics and Its Interface*, 6:2, 167-173.
<https://github.com/emeryyi/fastcox>

Examples

```
data(FHT)
m1<-cocktail(x=FHT$x,y=FHT$y,d=FHT$status,alpha=0.5)
predict(m1,type="nonzero")
plot(m1)
```

cocktail

*Fits the regularization paths for the elastic net penalized Cox's model***Description**

Fits a regularization path for the elastic net penalized Cox's model at a sequence of regularization parameters `lambda`.

Usage

```
cocktail(x,y,d,
         nlambda=100,
         lambda.min=ifelse(nobs<nvars,1e-2,1e-4),
         lambda=NULL,
         alpha=1,
         pf=rep(1,nvars),
         exclude,
         dfmax=nvars+1,
         pmax=min(dfmax*1.2,nvars),
         standardize=TRUE,
         eps=1e-6,
         maxit=3e4)
```

Arguments

<code>x</code>	matrix of predictors, of dimension $N \times p$; each row is an observation vector.
<code>y</code>	a survival time for Cox models. Currently tied failure times are not supported.
<code>d</code>	status with 1 if died and 0 if right censored.
<code>nlambda</code>	the number of <code>lambda</code> values - default is 100.
<code>lambda.min</code>	given as a fraction of <code>lambda.max</code> - the smallest value of <code>lambda</code> for which all coefficients are zero. The default depends on the relationship between N (the number of rows in the matrix of predictors) and p (the number of predictors). If $N > p$, the default is 0.0001 , close to zero. If $N < p$, the default is 0.01 . A very small value of <code>lambda.min</code> will lead to a saturated fit. It takes no effect if there is user-defined <code>lambda</code> sequence.
<code>lambda</code>	a user supplied <code>lambda</code> sequence. Typically, by leaving this option unspecified users can have the program compute its own <code>lambda</code> sequence based on <code>nlambda</code> and <code>lambda.min</code> . Supplying a value of <code>lambda</code> overrides this. It is better to supply a decreasing sequence of <code>lambda</code> values than a single (small) value, if not, the program will sort user-defined <code>lambda</code> sequence in decreasing order automatically.
<code>alpha</code>	The elasticnet mixing parameter, with $0 < \alpha \leq 1$. See details.
<code>pf</code>	separate penalty weights can be applied to each coefficient of β to allow differential shrinkage. Can be 0 for some variables, which implies no shrinkage, and results in that variable always being included in the model. Default is 1 for all variables (and implicitly infinity for variables listed in <code>exclude</code>). See details.

<code>exclude</code>	indices of variables to be excluded from the model. Default is none. Equivalent to an infinite penalty factor.
<code>dfmax</code>	limit the maximum number of variables in the model. Useful for very large p , if a partial path is desired. Default is $p + 1$.
<code>pmax</code>	limit the maximum number of variables ever to be nonzero. For example once β enters the model, no matter how many times it exits or re-enters model through the path, it will be counted only once. Default is $\min(\text{dfmax} * 1.2, p)$.
<code>standardize</code>	logical flag for variable standardization, prior to fitting the model sequence. If TRUE, x matrix is normalized such that sum squares of each column $\sum_{i=1}^N x_{ij}^2 / N = 1$. Note that x is always centered (i.e. $\sum_{i=1}^N x_{ij} = 0$) no matter <code>standardize</code> is TRUE or FALSE. The coefficients are always returned on the original scale. Default is TRUE.
<code>eps</code>	convergence threshold for coordinate majorization descent. Each inner coordinate majorization descent loop continues until the relative change in any coefficient (i.e. $\max_j \beta_j^{\text{new}} - \beta_j^{\text{old}} ^2$) is less than <code>eps</code> . Defaults value is $1e-6$.
<code>maxit</code>	maximum number of outer-loop iterations allowed at fixed lambda value. Default is $1e4$. If models do not converge, consider increasing <code>maxit</code> .

Details

The algorithm estimates β based on observed data, through elastic net penalized log partial likelihood of Cox's model.

$$\arg \min(-\text{loglik}(\text{Data}, \beta) + \lambda * P(\beta))$$

It can compute estimates at a fine grid of values of λ s in order to pick up a data-driven optimal λ for fitting a 'best' final model. The penalty is a combination of l1 and l2 penalty:

$$P(\beta) = (1 - \alpha)/2 \|\beta\|_2^2 + \alpha \|\beta\|_1.$$

`alpha=1` is the lasso penalty. For computing speed reason, if models are not converging or running slow, consider increasing `eps`, decreasing `nlambda`, or increasing `lambda.min` before increasing `maxit`.

FAQ:

Question: "I am not sure how are we optimizing alpha. I can get optimal lambda for each value of alpha. But how do I select optimum alpha?"

Answer: `cv.cocktail` only finds the optimal lambda given alpha fixed. So to chose a good alpha you need to fit CV on a grid of alpha, say (0.1, 0.3, 0.6, 0.9, 1) and let `cv.cocktail` choose the optimal lambda for each alpha, then you choose the (alpha, lambda) pair that corresponds to the lowest predicted deviance.

Question: "I understand your are referring to minimizing the quantity `cv.cocktail$cvm`, the mean 'cross-validated error' to optimize alpha and lambda as you did in your implementation. However, I don't know what the equation of this error is and this error is not referred to in your paper either. Do you mind explaining what this is?"

Answer: We first define the log partial-likelihood for the Cox model. Assume $\hat{\beta}^{[k]}$ is the estimate fitted on k -th fold, define the log partial likelihood function as

$$L(\text{Data}, \hat{\beta}^{[k]}) = \sum_{s=1}^S x_{i_s}^T \hat{\beta}^{[k]} - \log \left(\sum_{i \in R_s} \exp(x_i^T \hat{\beta}^{[k]}) \right).$$

Then the log partial-likelihood deviance of the k -th fold is defined as

$$D[Data, k] = -2(L(Data, \hat{\beta}[k])).$$

We now define the measurement we actually use for cross validation: it is the difference between the log partial-likelihood deviance evaluated on the full dataset and that evaluated on the on the dataset with k -th fold excluded. The cross-validated error is defined as

$$CV - ERR[k] = D(Data[full], k) - D(Data[k^{th} \text{ fold excluded}], k).$$

Value

An object with S3 class `cocktail`.

<code>call</code>	the call that produced this object
<code>beta</code>	a $p \times \text{length}(\text{lambda})$ matrix of coefficients, stored as a sparse matrix (<code>dgCMatrix</code> class, the standard class for sparse numeric matrices in the <code>Matrix</code> package.). To convert it into normal type matrix use <code>as.matrix()</code> .
<code>lambda</code>	the actual sequence of lambda values used
<code>df</code>	the number of nonzero coefficients for each value of lambda.
<code>dim</code>	dimension of coefficient matrix (ices)
<code>npasses</code>	total number of iterations (the most inner loop) summed over all lambda values
<code>jerr</code>	error flag, for warnings and errors, 0 if no error.

Author(s)

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References

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<https://github.com/emeryyi/fastcox>

See Also

`plot.cocktail`

Examples

```
data(FHT)
m1<-cocktail(x=FHT$x,y=FHT$y,d=FHT$status,alpha=0.5)
predict(m1,type="nonzero")
plot(m1)
```

 cv.cocktail

Cross-validation for cocktail

Description

Does k-fold cross-validation for cocktail, produces a plot, and returns a value for lambda. This function is modified based on the cv function from the glmnet package.

Usage

```
cv.cocktail(x,y,d,lambda=NULL,nfolds=5,foldid,...)
```

Arguments

x	matrix of predictors, of dimension $N \times p$; each row is an observation vector.
y	a survival time for Cox models. Currently tied failure times are not supported.
d	tensor status with 1 if died and 0 if right censored.
lambda	optional user-supplied lambda sequence; default is NULL, and <code>cocktail</code> chooses its own sequence.
nfolds	number of folds - default is 5. Although nfolds can be as large as the sample size (leave-one-out CV), it is not recommended for large datasets. Smallest value allowable is nfolds=3.
foldid	an optional vector of values between 1 and nfold identifying what fold each observation is in. If supplied, nfold can be missing.
...	other arguments that can be passed to cocktail.

Details

The function runs `cocktail` nfolds+1 times; the first to get the lambda sequence, and then the remainder to compute the fit with each of the folds omitted. The average error and standard deviation over the folds are computed.

Value

an object of class `cv.cocktail` is returned, which is a list with the ingredients of the cross-validation fit.

lambda	the values of lambda used in the fits.
cvm	the mean cross-validated error - a vector of length length(lambda).
cvsd	estimate of standard error of cvm.
cvup	upper curve = cvm+cvsd.
cvlo	lower curve = cvm-cvsd.
nzero	number of non-zero coefficients at each lambda.
name	a text string indicating partial likelihood (for plotting purposes).

`cocktail.fit` a fitted `cocktail` object for the full data.
`lambda.min` The optimal value of `lambda` that gives minimum cross validation error `cvm`.
`lambda.1se` The largest value of `lambda` such that error is within 1 standard error of the minimum.

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References

Yang, Y. and Zou, H. (2013), "A Cocktail Algorithm for Solving The Elastic Net Penalized Cox's Regression in High Dimensions", *Statistics and Its Interface*, 6:2, 167-173.
<https://github.com/emeryyi/fastcox>

Friedman, J., Hastie, T., and Tibshirani, R. (2010), "Regularization paths for generalized linear models via coordinate descent," *Journal of Statistical Software*, 33, 1.
<http://www.jstatsoft.org/v33/i01/>

See Also

[cocktail](#), [plot.cv.cocktail](#).

Examples

```
data(FHT)
cv1<-cv.cocktail(x=FHT$x[,1:10],y=FHT$y,d=FHT$status,alpha=0.5,nfolds=3)
cv1
plot(cv1)
```

FHT

FHT data introduced in Simon et al. (2011).

Description

The FHT data set has $n = 50$ observations and $p = 100$ predictors. The covariance between predictors X_j and $X_{j'}$ has the same correlation 0.5. See details in Simon et al. (2011).

Usage

```
data(FHT)
```

Format

This list object named "FHT" contains the following data:

x a covariate matrix with 50 rows and 100 columns

y the distinct failure times

status the censoring indicator (status = 1 indicates no censoring and status = 0 indicates right censoring)

References

Friedman, J., Hastie, T. and Tibshirani, R. (2008) "Regularization Paths for Generalized Linear Models via Coordinate Descent", <http://www.stanford.edu/~hastie/Papers/glmnet.pdf>
Journal of Statistical Software, Vol. 33(1), 1-22 Feb 2010
<http://www.jstatsoft.org/v33/i01/>

Simon, N., Friedman, J., Hastie, T., Tibshirani, R. (2011) "Regularization Paths for Cox's Proportional Hazards Model via Coordinate Descent", *Journal of Statistical Software*, Vol. 39(5) 1-13
<http://www.jstatsoft.org/v39/i05/>

Examples

```
data(FHT)
```

plot.cocktail	<i>Plot coefficients from a "cocktail" object</i>
---------------	---

Description

Produces a coefficient profile plot of the coefficient paths for a fitted `cocktail` object. This function is modified based on the plot function from the `glmnet` package.

Usage

```
## S3 method for class 'cocktail'
plot(x, xvar = c("norm", "lambda"), color = FALSE, label = FALSE, ...)
```

Arguments

x	fitted <code>cocktail</code> model
xvar	what is on the X-axis. "norm" plots against the L1-norm of the coefficients, "lambda" against the log-lambda sequence.
color	if TRUE, plot the curves with rainbow colors. FALSE is gray colors. Default is FALSE
label	if TRUE, label the curves with variable sequence numbers. Default is FALSE
...	other graphical parameters to plot

Details

A coefficient profile plot is produced.

Author(s)

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References

Yang, Y. and Zou, H. (2013), "A Cocktail Algorithm for Solving The Elastic Net Penalized Cox's Regression in High Dimensions", *Statistics and Its Interface*, 6:2, 167-173.
<https://github.com/emeryyi/fastcox>

Friedman, J., Hastie, T. and Tibshirani, R. (2008) "Regularization Paths for Generalized Linear Models via Coordinate Descent", <http://www.stanford.edu/~hastie/Papers/glmnet.pdf>
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Simon, N., Friedman, J., Hastie, T., Tibshirani, R. (2011) "Regularization Paths for Cox's Proportional Hazards Model via Coordinate Descent", *Journal of Statistical Software*, Vol. 39(5) 1-13
<http://www.jstatsoft.org/v39/i05/>

Examples

```
data(FHT)
m1<-cocktail(x=FHT$x,y=FHT$y,d=FHT$status,alpha=0.5)
par(mfrow=c(1,3))
plot(m1) # plots against the L1-norm of the coefficients
plot(m1,xvar="lambda",label=TRUE) # plots against the log-lambda sequence
plot(m1,color=TRUE)
```

plot.cv.cocktail

plot the cross-validation curve produced by cv.cocktail

Description

Plots the cross-validation curve, and upper and lower standard deviation curves, as a function of the lambda values used. This function is modified based on the plot.cv function from the glmnet package.

Usage

```
## S3 method for class 'cv.cocktail'
plot(x, sign.lambda, ...)
```

Arguments

`x` fitted `cv.cocktail` object
`sign.lambda` either plot against $\log(\lambda)$ (default) or its negative if `sign.lambda=-1`.
... other graphical parameters to plot

Details

A plot is produced.

Author(s)

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References

Yang, Y. and Zou, H. (2013), "A Cocktail Algorithm for Solving The Elastic Net Penalized Cox's Regression in High Dimensions", *Statistics and Its Interface*, 6:2, 167-173.
<https://github.com/emeryyi/fastcox>

Friedman, J., Hastie, T., and Tibshirani, R. (2010), "Regularization paths for generalized linear models via coordinate descent," *Journal of Statistical Software*, 33, 1.
<http://www.jstatsoft.org/v33/i01/>

See Also

[cv.cocktail](#).

`predict.cocktail` *make predictions from a "cocktail" object.*

Description

Similar to other predict methods, this functions predicts fitted values, link function and more from a fitted `cocktail` object. This function is modified based on the predict function from the `glmnet` package.

Usage

```
## S3 method for class 'cocktail'  
predict(object,newx,s=NULL,type=c("link","response","coefficients","nonzero"),...)
```

Arguments

object	fitted <code>cocktail</code> model object.
newx	matrix of new values for x at which predictions are to be made. Must be a matrix. This argument is not used for <code>type=c("coefficients", "nonzero")</code>
s	value(s) of the penalty parameter lambda at which predictions are required. Default is the entire sequence used to create the model.
type	type of prediction required. <ul style="list-style-type: none"> • Type "link" gives the linear predictors for Cox's model. • Type "response" gives the fitted relative-risk for Cox's model. • Type "coefficients" computes the coefficients at the requested values for s. • Type "nonzero" returns a list of the indices of the nonzero coefficients for each value of s.
...	Not used. Other arguments to predict.

Details

s is the new vector at which predictions are requested. If s is not in the lambda sequence used for fitting the model, the predict function will use linear interpolation to make predictions. The new values are interpolated using a fraction of predicted values from both left and right lambda indices.

Value

The object returned depends on type.

Author(s)

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References

Yang, Y. and Zou, H. (2013), "A Cocktail Algorithm for Solving The Elastic Net Penalized Cox's Regression in High Dimensions", *Statistics and Its Interface*, 6:2, 167-173.
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Friedman, J., Hastie, T. and Tibshirani, R. (2008) "Regularization Paths for Generalized Linear Models via Coordinate Descent", <http://www.stanford.edu/~hastie/Papers/glmnet.pdf>
Journal of Statistical Software, Vol. 33(1), 1-22 Feb 2010
<http://www.jstatsoft.org/v33/i01/>

Simon, N., Friedman, J., Hastie, T., Tibshirani, R. (2011) "Regularization Paths for Cox's Proportional Hazards Model via Coordinate Descent", *Journal of Statistical Software*, Vol. 39(5) 1-13
<http://www.jstatsoft.org/v39/i05/>

See Also

[coef](#) method

Examples

```
data(FHT)
m1<-cocktail(x=FHT$x,y=FHT$y,d=FHT$status,alpha=0.5)
predict(m1,type="nonzero")
predict(m1,newx=FHT$x[1:5,],type="response")
```

print.cocktail	<i>print a cocktail object</i>
----------------	--------------------------------

Description

Print a summary of the cocktail path at each step along the path. This function is modified based on the print function from the glmnet package.

Usage

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

Arguments

x	fitted cocktail object
digits	significant digits in printout
...	additional print arguments

Details

The call that produced the [cocktail](#) object is printed, followed by a two-column matrix with columns Df and Lambda. The Df column is the number of nonzero coefficients.

Value

a two-column matrix, the first columns is the number of nonzero coefficients and the second column is Lambda.

Author(s)

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References

Yang, Y. and Zou, H. (2013), "A Cocktail Algorithm for Solving The Elastic Net Penalized Cox's Regression in High Dimensions", *Statistics and Its Interface*, 6:2, 167-173.

<https://github.com/emeryyi/fastcox>

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<http://www.jstatsoft.org/v33/i01/>

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<http://www.jstatsoft.org/v39/i05/>

Examples

```
data(FHT)
m1<-cocktail(x=FHT$x,y=FHT$y,d=FHT$status,alpha=0.5)
print(m1)
```

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