Package ‘netReg’

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Type Package

Title Network-Regularized Regression Models

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Description netReg fits linear regression models using network-penalization. Graph prior knowledge, in the form of biological networks, is being incorporated into the likelihood of the linear model. The networks describe biological relationships such as co-regulation or dependency of the same transcription factors/metabolites/etc. yielding a part sparse and part smooth solution for coefficient profiles.

URL https://github.com/dirmeier/netReg

BugReports https://github.com/dirmeier/netReg/issues

biocViews Software, StatisticalMethod, Regression, FeatureExtraction, Network, GraphAndNetwork

License GPL-3

Encoding UTF-8

Suggests testthat, knitr, rmarkdown, lintr, lassoshooting

VignetteBuilder knitr

RoxygenNote 6.0.1

SystemRequirements C++11

LinkingTo Rcpp, RcppArmadillo

Imports Rcpp, stats

NeedsCompilation yes

Author Simon Dirmeier [aut, cre]

R topics documented:

netReg-package *netReg*

Description

netReg is a package for generalized linear regression that includes prior graphs in the models objective function.

Details

netReg uses *Armadillo*, *OpenBLAS*, *BLAS* and *LAPACK* for fast matrix computations and *Dlib* for constrained derivate-free optimization.

Author(s)

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References

Friedman J., Hastie T., Hoefling H. and Tibshirani R. (2007), Pathwise coordinate optimization.
The Annals of Applied Statistics

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Bioinformatics

Powell M.J.D. (2009), The BOBYQA algorithm for bound constrained optimization without derivatives.
http://www.damtp.cam.ac.uk/user/na/NA_papers/NA2009_06.pdf

cv.edgenet *Find the optimal shrinkage parameters for edgenet*

Description

Finds the optimal shrinkage parameters using cross-validation for edgenet. We use the BOBYQA algorithm to minimize the sum of squared residuals objective function.

Usage

```
cv.edgenet(X, Y, G.X = NULL, G.Y = NULL, thresh = 1e-05, maxit = 1e+05,
  family = c("gaussian"), epsilon = 0.001, approx.maxit = 10000,
  nfolds = 10, ...)
```

Arguments

`X`	input matrix, of dimension (`n` x `p`) where `n` is the number of observations and `p` is the number of covariables. Each row is an observation vector.
`Y`	output matrix, of dimension (`n` x `q`) where `n` is the number of observations and `q` is the number of response variables Each row is an observation vector.
`G.X`	non-negativ affinity matrix for `n`, of dimensions (`p` x `p`) where `p` is the number of covariables `X`
`G.Y`	non-negativ affinity matrix for `n`, of dimensions (`q` x `q`) where `q` is the number of covariables `Y`
`thresh`	threshold for coordinate descent
`maxit`	maximum number of iterations
`family`	family of response, e.g. gaussian
`epsilon`	the threshold criterion for BOBYQA to stop. Usually 1e-3 is a good choice.
`approx.maxit`	the maximum number of iterations for BOBYQA (if choosen). Usually 1e4 is a good choice.
`nfolds`	the number of folds to be used - default is 10 (minimum 3, maximum nrow(X)).
`...`	additional parameters

Value

An object of class `cv.edgenet`

`call`	the call that produced the object
`lambda`	the estimated (`p` x `q`)-dimensional coefficient matrix B.hat
`psigx`	the estimated (`q` x `1`)-dimensional vector of intercepts
`psigy`	the estimated (`q` x `1`)-dimensional vector of intercepts

Author(s)

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References

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http://www.damtp.cam.ac.uk/user/na/NA_papers/NA2009_06.pdf

Examples

```
X <- matrix(rnorm(100*10), 100, 10)
b <- rnorm(10)
G.X <- matrix(rpois(10*10,1),10)
G.X <- t(G.X) + G.X
diag(G.X) <- 0

# fit a Gaussian model
Y <- X%*%b + rnorm(100)
cv.edge <- cv.edgenet(X=X, Y=Y, G.X=G.X, family="gaussian")
```

`edgenet` *Fit a graph-regularized linear regression model using edge-based regularization.*

Description

Fit a graph-regularized linear regression model using edge-penalization. The coefficients are computed using graph-prior knowledge in the form of one/two affinity matrices. Graph-regularization is an extension to previously introduced regularization techniques, such as the LASSO.

Usage

```
edgenet(X, Y, G.X = NULL, G.Y = NULL, lambda = 1, psigx = 1,
  psigy = 1, thresh = 1e-05, maxit = 1e+05, family = c("gaussian"), ...)
```

Arguments

`X`	input matrix, of dimension (`n` x `p`) where `n` is the number of observations and `p` is the number of covariables. Each row is an observation vector.
`Y`	output matrix, of dimension (`n` x `q`) where `n` is the number of observations and `q` is the number of response variables Each row is an observation vector.
`G.X`	non-negativ affinity matrix for `n`, of dimensions (`p` x `p`) where `p` is the number of covariables `X`
`G.Y`	non-negativ affinity matrix for `n`, of dimensions (`q` x `q`) where `q` is the number of covariables `Y`
`lambda`	shrinkage parameter for LASSO.
`psigx`	shrinkage parameter for graph-regularization of `G.X`
`psigy`	shrinkage parameter for graph-regularization of `G.Y`
`thresh`	threshold for coordinate descent
`maxit`	maximum number of iterations
`family`	family of response, e.g. gaussian
`...`	additional params

Value

An object of class `edgenet`

`coefficients`	the estimated (p x q)-dimensional coefficient matrix B.hat
`intercept`	the estimated (q x 1)-dimensional vector of intercepts
`call`	the call that produced the object
`family`	the family of the response

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References

Friedman J., Hastie T., Hoefling H. and Tibshirani R. (2007), Pathwise coordinate optimization.
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Bioinformatics

Examples

```
X <- matrix(rnorm(100*10), 100, 10)
b <- rnorm(10)
G.X <- matrix(rpois(100,1), 10)
G.X <- t(G.X) + G.X
diag(G.X) <- 0

# fit a Gaussian model
Y <- X%*%b + rnorm(100)
fit <- edgenet(X=X, Y=Y, G.X=G.X, family="gaussian")
```

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predict.gaussian.edgenet

Predict method for gaussian edgenet fits

Description

Predicts the estimated Y.hat values for a newdata design matrix X similar to the other predict methods, e.g. from glm and glmnet

Usage

```
## S3 method for class 'gaussian.edgenet'
predict(object, newdata = NULL, ...)
```

Arguments

`object`	a fitted object of class *gaussian.edgenet*
`newdata`	a new (`m` x `p`)-dimensional design matrix with a variable number of observations `m`, but a constant number of co-variables `p`
`...`	further arguments

Value

A (`m` x `q`)-dimensional matrix

Examples

```
## Not run:
X <- matrix(rnorm(100*10),100,10)
G.X <- matrix(rpois(10*10,1),10)
G.X <- t(G.X) + G.X
diag(G.X) <- 0

Y <- matrix(rnorm(100*10),100,10)
fit <- edgenet(X=X, Y=Y, G.X=G.X, family="gaussian")
pred <- predict(fit, X)

## End(Not run)
```

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