Package 'ADMMnet'

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Type Package

Title Regularized Model with Selecting the Number of Non-Zeros

Version 0.1.1

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Description Fit linear and cox models regularized with net (L1 and Laplacian), elastic-net (L1 and L2) or lasso (L1) penalty, and their adaptive forms, such as adaptive lasso and net adjusting for signs of linked coefficients. In addition, it treats the number of non-zero coefficients as another tuning parameter and simultaneously selects with the regularization parameter. The package uses one-step coordinate descent algorithm and runs extremely fast by taking into account the sparsity structure of coefficients.

License GPL (>= 2)

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ADMMnet-package *Regularized Model with Selecting the Number of Non-Zeros*

Description

This package fits linear and cox models regularized with net (L1 and Laplacian), elastic-net (L1 and L2) or lasso (L1) penalty, and their adaptive forms, such as adaptive lasso and net adjusting for signs of linked coefficients. In addition, it treats the number of non-zero coefficients as another tuning parameter and simultaneously selects with the regularization parameter `lambda`. This is motivated by formulating L0 variable selection in ADMM form. By selecting the regularization parameter and the number of non-zeros, it shows significant improvement over the commonly used regularized methods, which depend on the regularization parameter only.

The package uses one-step coordinate descent algorithm and runs extremely fast by taking into account the sparsity structure of coefficients.

Details

Package:	ADMMnet
Type:	Package
Version:	0.1
Date:	2015-12-10
License:	GPL (>= 2)

Functions: `ADMMnet`, `print.ADMMnet`

Author(s)

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References

Boyd, S., Parikh, N., Chu, E., Peleato, B., & Eckstein, J. (2011). *Distributed optimization and statistical learning via the alternating direction method of multipliers. Foundations and Trends in Machine Learning, 3(1), 1-122.*
http://dl.acm.org/citation.cfm?id=2185816
Friedman, J., Hastie, T. and Tibshirani, R. (2010). *Regularization paths for generalized linear models via coordinate descent, Journal of Statistical Software, Vol. 33(1), 1.*
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Li, C., and Li, H. (2010). *Variable selection and regression analysis for graph-structured covariates with an application to genomics. The annals of applied statistics, 4(3), 1498.*
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Sun, H., Lin, W., Feng, R., and Li, H. (2014) *Network-regularized high-dimensional cox regression for analysis of genomic data, Statistica Sinica.*

http://www3.stat.sinica.edu.tw/statistica/j24n3/j24n319/j24n319.html

Examples

```
###  Linear model  ###
set.seed(1213)
N=100;p=30;p1=5
x=matrix(rnorm(N*p),N,p)
beta=rnorm(p1)
xb=x[,1:p1]
y=rnorm(N,xb)

fiti=ADMMnet(x,y,penalty="Lasso",nlambda=10,nfolds=10) # Lasso
# attributes(fiti)


###  Cox model  ###
set.seed(1213)
N=100;p=30;p1=5
x=matrix(rnorm(N*p),N,p)
beta=rnorm(p1)
xb=x[,1:p1]
ty=rexp(N,exp(xb))
tcens=rbinom(n=N,prob=.3,size=1)  # censoring indicator
y=cbind(time=ty,status=1-tcens)

fiti=ADMMnet(x,y,family="cox",penalty="Lasso",nlambda=10,nfolds=10) # Lasso
# attributes(fiti)
```

`ADMMnet` *Fit a Model with Various Regularization Forms*

Description

Fit a linear or cox model regularized with net (L1 and Laplacian), elastic-net (L1 and L2) or lasso (L1) penalty, and their adaptive forms, such as adaptive lasso and net adjusting for signs of linked coefficients. In addition, it treats the number of non-zero coefficients as another tuning parameter and simultaneously selects with the regularization parameter `lambda`. The package uses one-step coordinate descent algorithm and runs extremely fast by taking into account the sparsity structure of coefficients.

Usage

```
ADMMnet(x, y, family = c("gaussian", "cox"), penalty = c("Lasso", "Enet", "Net"),
  Omega = NULL, alpha = 1.0, lambda = NULL, nlambda = 50, rlambda = NULL,
  nfolds = 1, foldid = NULL, inzero = TRUE, adaptive = c(FALSE, TRUE), aini = NULL,
  isd = FALSE, keep.beta = FALSE, ifast = TRUE, thresh = 1e-07, maxit = 1e+05)
```

Arguments

x	input matrix. Each row is an observation vector.
y	response variable. For family = "gaussian", y is a continuous vector. For family = "cox", y is a two-column matrix with columns named 'time' and 'status'. 'status' is a binary variable, with '1' indicating event, and '0' indicating right censored.
family	type of outcome. Can be "gaussian" or "cox".
penalty	penalty type. Can choose "Net", "Enet" (elastic net) and "Lasso". For "Net", need to specify Omega; otherwises, "Enet" is performed. For penalty = "Net", the penalty is defined as $$\lambda * \alpha * ||\beta||_1 + (1-\alpha)/2 * (\beta^T L \beta),$$ where L is a Laplacian matrix calculated from Omega.
Omega	correlation/adjacency matrix with zero diagonal, used for penalty = "Net" to calculate Laplacian matrix.
alpha	ratio between L1 and Laplacian for "Net", or between L1 and L2 for "Enet". Default is alpha = 1.0, i.e. lasso.
lambda	a user supplied decreasing sequence. If lambda = NULL, a sequency of lambda is generated based on nlambda and rlambda. Supplying a value of lambda overrides this.
nlambda	number of lambda values. Default is 50.
rlambda	fraction of lambda.max to determine the smallest value for lambda. The default is rlambda = 0.0001 when the number of observations is larger than or equal to the number of variables; otherwise, rlambda = 0.01.
nfolds	number of folds. With nfolds = 1 and foldid = NULL by default, cross-validation is not performed. For cross-validation, smallest value allowable is nfolds = 3. Specifying foldid overrisdes nfolds.
foldid	an optional vector of values between 1 and nfolds specifying which fold each observation is in.
inzero	logical flag for simultaneously selecting the number of non-zero coefficients with lambda. Default is inzero = TRUE.
adaptive	logical flags for adaptive version. Default is adaptive = c(FALSE,TRUE). The first element is for adaptive on β in L1 and the second for adjusting for signs of linked coefficients in Laplacian matrix.
aini	a user supplied initial estimate of β. It is a list including wbeta for adaptive L1 and sgn for adjusting Laplacian matrix. wbeta is the absolute value of inverse initial estimates. If aini = NULL but adaptive is required, aini is generated from regularized model with penatly = "Enet" and alpha = 0.0, i.e. a ridge regression.
isd	logical flag for outputing standardized coefficients. x is always standardized prior to fitting the model. Default is isd = FALSE, returning β on the original scale.

keep.beta	logical flag for returning estimates for all lambda values. For keep.beta = FALSE, only return the estimate with the minimum cross-validation value.
ifast	logical flag for efficient calculation of risk set updates for family = "cox". Default is ifast = TRUE.
thresh	convergence threshold for coordinate descent. Default value is 1E-7.
maxit	Maximum number of iterations for coordinate descent. Default is 10^5.

Details

One-step coordinate descent algorithm is applied for each lambda. For family = "cox", ifast = TRUE adopts an efficient way to update risk set and sometimes the algorithm ends before all nlambda values of lambda have been evaluated. To evaluate small values of lambda, use ifast = FALSE. The two methods only affect the efficiency of algorithm, not the estimates.

x is always standardized prior to fitting the model and the estimate is returned on the original scale. For family = "gaussian", y is centered by removing its mean, so there is no intercept output.

Cross-validation is used for tuning parameters. For inzero = TRUE, we further select the number of non-zero coefficients obtained from regularized model at each lambda. This is motivated by formulating L0 variable selection in ADMM form, which shows significant improvement over the commonly used regularized methods without this technique.

Value

An object with S3 class "ADMMnet".

Beta	a sparse Matrix of coefficients, stored in class "dgCMatrix".
Beta0	coefficients after additionally tuning the number of non-zeros, for inzero = TRUE.
fit	a data.frame containing lambda and the number of non-zero coefficients nzero. With cross-validation, additional results are reported, such as average cross-validation partial likelihood cvm and its standard error cvse, and index with '*' indicating the minimum cvm. For family = "gaussian", rsq is also reported.
fit0	a data.frame containing lambda, cvm and nzero based on inzero = TRUE.
lambda.min	value of lambda that gives minimum cvm.
lambda.opt	value of lambda based on inzero = TRUE.
penalty	penalty type.
adaptive	logical flags for adaptive version (see above).
flag	convergence flag (for internal debugging). flag = 0 means converged.

Warning

It may terminate and return NULL.

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References

Boyd, S., Parikh, N., Chu, E., Peleato, B., & Eckstein, J. (2011). *Distributed optimization and statistical learning via the alternating direction method of multipliers. Foundations and Trends in Machine Learning, 3(1), 1-122.*
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See Also

print.ADMMnet

Examples

```
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set.seed(1213)
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x=matrix(rnorm(N*p),N,p)
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y=rnorm(N,xb)

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# attributes(fiti)


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N=100;p=30;p1=5
x=matrix(rnorm(N*p),N,p)
beta=rnorm(p1)
xb=x[,1:p1]
ty=rexp(N,exp(xb))
tcens=rbinom(n=N,prob=.3,size=1)  # censoring indicator
y=cbind(time=ty,status=1-tcens)

fiti=ADMMnet(x,y,family="cox",penalty="Lasso",nlambda=10,nfolds=10) # Lasso
# attributes(fiti)
```

print.ADMMnet *Print a ADMMnet Object*

Description

Print a summary of results along the path of lambda.

Usage

```
## S3 method for class 'ADMMnet'
print(x, digits = 4, ...)
```

Arguments

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

Details

The performed model is printed, followed by fit and fit0 (if any) from a fitted ADMMnet object.

Value

The data frame above is silently returned

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See Also

ADMMnet

Examples

```
###  Linear model  ###
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N=100;p=30;p1=5
x=matrix(rnorm(N*p),N,p)
beta=rnorm(p1)
xb=x[,1:p1]
y=rnorm(N,xb)

fiti=ADMMnet(x,y,penalty="Lasso",nlambda=10,nfolds=10) # Lasso
fiti
```

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