

Package ‘APML0’

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Type Package

Title Augmented and Penalized Minimization Method L0

Version 0.10

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Description Fit linear, logistic and Cox models regularized with L0, lasso (L1), elastic-net (L1 and L2), or net (L1 and Laplacian) penalty, and their adaptive forms, such as adaptive lasso / elastic-net and net adjusting for signs of linked coefficients. It solves L0 penalty problem by simultaneously selecting regularization parameters and performing hard-thresholding or selecting number of non-zeros. This augmented and penalized minimization method provides an approximation solution to the L0 penalty problem, but runs as fast as L1 regularization problem. The package uses one-step coordinate descent algorithm and runs extremely fast by taking into account the sparsity structure of coefficients. It could deal with very high dimensional data and has superior selection performance.

License GPL (>= 2)

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Description

Fit linear, logistic and Cox models regularized with L0, lasso (L1), elastic-net (L1 and L2), or net (L1 and Laplacian) penalty, and their adaptive forms, such as adaptive lasso / elastic-net and net adjusting for signs of linked coefficients. It solves L0 penalty problem by simultaneously selecting regularization parameters and performing hard-thresholding (or selecting number of non-zeros). This augmented and penalized minimization method provides an approximation solution to the L0 penalty problem, but runs as fast as L1 regularization problem.

The package uses one-step coordinate descent algorithm and runs extremely fast by taking into account the sparsity structure of coefficients. It could deal with very high dimensional data.

Details

Package: APML0
Type: Package
Version: 0.10
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License: GPL (>= 2)

Functions: [APML0](#), [print.APML0](#)

Author(s)

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References

Li, X., Xie, S., Zeng, D., Wang, Y. (2018). *Efficient l0-norm feature selection based on augmented and penalized minimization*. *Statistics in medicine*, 37(3), 473-486.

<https://onlinelibrary.wiley.com/doi/full/10.1002/sim.7526>

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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Friedman, J., Hastie, T., Tibshirani, R. (2010). *Regularization paths for generalized linear models via coordinate descent*, *Journal of Statistical Software*, Vol. 33(1), 1.

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

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]%*%beta
y=rnorm(N,xb)

fiti=APML0(x,y,penalty="Lasso",nlambda=10) # Lasso
fiti2=APML0(x,y,penalty="Lasso",nlambda=10,nfolds=10) # Lasso
# attributes(fiti)

### Logistic model ###
set.seed(1213)
N=100;p=30;p1=5
x=matrix(rnorm(N*p),N,p)
beta=rnorm(p1)
xb=x[,1:p1]%*%beta
y=rbinom(n=N, size=1, prob=1.0/(1.0+exp(-xb)))

fiti=APML0(x,y,family="binomial",penalty="Lasso",nlambda=10) # Lasso
fiti2=APML0(x,y,family="binomial",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]%*%beta
ty=rexp(N, exp(xb))
td=rexp(N, 0.05)
tcens=ifelse(td<ty,1,0) # censoring indicator
y=cbind(time=ty,status=1-tcens)

fiti=APML0(x,y,family="cox",penalty="Lasso",nlambda=10) # Lasso
fiti2=APML0(x,y,family="cox",penalty="Lasso",nlambda=10,nfolds=10) # Lasso
# attributes(fiti)

```

Description

Fit linear, logistic and Cox models regularized with L0, lasso (L1), elastic-net (L1 and L2), or net (L1 and Laplacian) penalty, and their adaptive forms, such as adaptive lasso / elastic-net and net

adjusting for signs of linked coefficients.

It solves L0 penalty problem by simultaneously selecting regularization parameters and performing hard-thresholding (or selecting number of non-zeros). This augmented and penalized minimization method provides an approximation solution to the L0 penalty problem and runs as fast as L1 regularization.

The function uses one-step coordinate descent algorithm and runs extremely fast by taking into account the sparsity structure of coefficients. It could deal with very high dimensional data.

Usage

```
APML0(x, y, family=c("gaussian", "binomial", "cox"), penalty=c("Lasso", "Enet", "Net"),
      Omega=NULL, alpha=1.0, lambda=NULL, nlambda=50, rlambda=NULL, wbeta=rep(1, ncol(x)),
      sgn=rep(1, ncol(x)), nfolds=1, foldid=NULL, ill=TRUE, iL0=TRUE, icutB=FALSE, ncutB=10,
      ifast=TRUE, isd=FALSE, iysd=FALSE, ifastr=TRUE, keep.beta=FALSE,
      thresh=1e-6, maxit=1e+5, threshC=1e-5, maxitC=1e+2, threshP=1e-5)
```

Arguments

x	input matrix. Each row is an observation vector.
y	response variable. For family = "gaussian", y is a continuous vector. For family = "binomial", y is a binary vector with 0 and 1. 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", "binomial" or "cox".
penalty	penalty type. Can choose "Net", "Enet" (elastic net) and "Lasso". For "Net", need to specify Omega; otherwise, "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	adjacency matrix with zero diagonal and non-negative off-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 sequence 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.
wbeta	penalty weights used with L1 penalty (adaptive L1), given by $\sum_{j=1}^q w_j \beta_j $. The wbeta is a vector of non-negative values and works as adaptive L1. No penalty is imposed for those coefficients with zero values in wbeta. Default is 1 for all coefficients. The same weights are also applied to L0.

sgn	sign adjustment used with Laplacian penalty (adaptive Laplacian). The sgn is a vector of 1 or -1. The sgn could be based on an initial estimate of β , and 1 is used for $\beta > 0$ and -1 is for $\beta < 0$. Default is 1 for all coefficients.
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 overrides nfolds.
foldid	an optional vector of values between 1 and nfolds specifying which fold each observation is in.
ill	logical flag for using likelihood-based as the cross-validation criteria. Default is ill = TRUE. For family = "gaussian", set ill = FALSE to use predict mean squared error as the criteria.
il0	logical flag for simultaneously performing L0-norm via performing hard-thresholding or selecting number of non-zeros. Default is il0 = TRUE.
icutB	logical flag for performing hard-thresholding by selecting the number of non-zero coefficients with the default of icutB = FALSE. Alternative way is to apply thresholding on the coefficients by setting icutB = TRUE.
ncutB	the number of thresholds used for icutB = TRUE. Default is ncutB=10. Increasing ncutB may improve the variable selection performance but will increase the computation time.
ifast	logical flag for searching for the best cutoff or the number of non-zero. Default is ifast=TRUE for local searching. Setting ifast=TRUE will search from the smallest cutoff (or number of non-zeros) to the largest but will increase the computation time.
isd	logical flag for outputting standardized coefficients. x is always standardized prior to fitting the model. Default is isd = FALSE, returning β on the original scale.
iysd	logical flag for standardizing y prior to computation, for family = "gaussian". The returning coefficients are always based the original y (unstandardized). Default is isd = FALSE.
ifastr	logical flag for efficient calculation of risk set updates for family = "cox". Default is ifastr = TRUE. Setting ifastr = FALSE may improve the accuracy of calculating the risk set.
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.
thresh	convergence threshold for coordinate descent. Default value is 1E-6.
maxit	Maximum number of iterations for coordinate descent. Default is 10^5.
threshC	convergence threshold for hard-thresholding for family = "binomial". Default value is 1E-5.
maxitC	Maximum number of iterations for hard-thresholding for family = "binomial". Default is 10^2.
threshP	Cutoff when calculating the probability in family = "binomial". The probability is bounded within threshP and 1-threshP. Default value is 1E-5.

Details

One-step coordinate descent algorithm is applied for each λ . Cross-validation is used for tuning parameters. For $iL0 = \text{TRUE}$, we further perform hard-thresholding (for $icutB = \text{TRUE}$) to the coefficients or select the number of non-zero coefficients (for $icutB = \text{FALSE}$), which is obtained from regularized model at each λ . This is motivated by formulating L_0 variable selection in an augmented form, which shows significant improvement over the commonly used regularized methods without this technique. Details could be found in our publication.

x is always standardized prior to fitting the model and the estimate is returned on the original scale for $isd = \text{FALSE}$.

Each one element of $wbeta$ corresponds to each variable in x . Setting the value in $wbeta$ will not impose any penalty on that variable.

For $family = "cox"$, $ifastr = \text{TRUE}$ adopts an efficient way to update risk set and sometimes the algorithm ends before all $nlambda$ values of λ have been evaluated. To evaluate small values of λ , use $ifast = \text{FALSE}$. The two methods only affect the efficiency of algorithm, not the estimates.

$ifast = \text{TRUE}$ seems to perform well.

Value

An object with S3 class "APML0".

<code>a</code>	the intercept for $family = "gaussian"$.
<code>Beta</code>	a sparse Matrix of coefficients, stored in class "dgCMatrix". For $family = "binomial"$, the first coefficient is the intercept.
<code>Beta0</code>	coefficients after additionally performing L_0 -norm for $iL0 = \text{TRUE}$. For $family = "binomial"$, the first coefficient is the intercept.
<code>fit</code>	a data.frame containing λ 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.
<code>fit0</code>	a data.frame containing λ , cvm and $nzero$ based on $iL0 = \text{TRUE}$. cvm in <code>fit0</code> may be different from cvm in <code>fit</code> , because the constraint on the number of non-zeros is imposed in the cross-validation. The maximum number of non-zeros is based on the full dataset not the one used in the cross-validation.
<code>lambda.min</code>	value of λ that gives minimum cvm .
<code>lambda.opt</code>	value of λ based on $iL0 = \text{TRUE}$.
<code>penalty</code>	penalty type.
<code>adaptive</code>	logical flags for adaptive version (see above).
<code>flag</code>	convergence flag (for internal debugging). $flag = 0$ means converged.

Warning

It may terminate and return NULL.

Author(s)

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References

- Li, X., Xie, S., Zeng, D., Wang, Y. (2018). *Efficient l0-norm feature selection based on augmented and penalized minimization*. *Statistics in medicine*, 37(3), 473-486.
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- 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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<http://www.jstatsoft.org/v33/i01/>

See Also

[APML0](#), [print.APML0](#)

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]%*%beta
y=rnorm(N,xb)

fiti=APML0(x,y,penalty="Lasso",nlambda=10) # Lasso
fiti2=APML0(x,y,penalty="Lasso",nlambda=10,nfolds=10) # Lasso
# attributes(fiti)

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set.seed(1213)
N=100;p=30;p1=5
x=matrix(rnorm(N*p),N,p)
beta=rnorm(p1)
xb=x[,1:p1]%*%beta
y=rbinom(n=N, size=1, prob=1.0/(1.0+exp(-xb)))

fiti=APML0(x,y,family="binomial",penalty="Lasso",nlambda=10) # Lasso
fiti2=APML0(x,y,family="binomial",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]%%beta
ty=rexp(N, exp(xb))
td=rexp(N, 0.05)
tcens=ifelse(td<ty,1,0) # censoring indicator
y=cbind(time=ty,status=1-tcens)

fiti=APML0(x,y,family="cox",penalty="Lasso",nlambda=10) # Lasso
fiti2=APML0(x,y,family="cox",penalty="Lasso",nlambda=10,nfolds=10) # Lasso
# attributes(fiti)

```

```
print.APML0
```

```
Print a APML0 Object
```

Description

Print a summary of results along the path of lambda.

Usage

```
## S3 method for class 'APML0'
print(x, digits = 4, ...)
```

Arguments

x	fitted APML0 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 APML0 object.

Value

The data frame above is silently returned

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See Also

[APML0](#)

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]%*%beta
y=rnorm(N,xb)

fiti2=APML0(x,y,penalty="Lasso",nlambda=10,nfolds=10) # Lasso
fiti2
```

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