Package 'ADMM'

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Type Package

Title Algorithms using Alternating Direction Method of Multipliers

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Description Provides algorithms to solve popular optimization problems in statistics such as regression or denoising based on Alternating Direction Method of Multipliers (ADMM).
See Boyd et al (2010) <doi:10.1561/2200000016> for complete introduction to the method.

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R topics documented:

ADMM *ADMM : Algorithms using Alternating Direction Method of Multipliers*

Description

An introduction of Alternating Direction Method of Multipliers (ADMM) method has been a breakthrough in solving complex and non-convex optimization problems in a reasonably stable as well as scalable fashion. Our package aims at providing handy tools for fast computation on well-known problems using the method. For interested users/readers, please visit Prof. Stephen Boyd's website entirely devoted to the topic.

admm.bp *Basis Pursuit*

Description

For an underdetermined system, Basis Pursuit aims to find a sparse solution that solves

$$min_x \|x\|_1 \quad \text{s.t} \quad Ax = b$$

which is a relaxed version of strict non-zero support finding problem. The implementation is borrowed from Stephen Boyd's MATLAB code.

Usage

```
admm.bp(A, b, xinit = NA, rho = 1, alpha = 1, abstol = 1e-04,
  reltol = 0.01, maxiter = 1000)
```

Arguments

A	an $(m \times n)$ regressor matrix
b	a length-m response vector
xinit	a length-n vector for initial value
rho	an augmented Lagrangian parameter
alpha	an overrelaxation parameter in [1,2]
abstol	absolute tolerance stopping criterion
reltol	relative tolerance stopping criterion
maxiter	maximum number of iterations

Value

a named list containing

x a length-n solution vector

history dataframe recording iteration numerics. See the section for more details.

Iteration History

When you run the algorithm, output returns not only the solution, but also the iteration history recording following fields over iterates,

objval object (cost) function value

r_norm norm of primal residual

s_norm norm of dual residual

eps_pri feasibility tolerance for primal feasibility condition

eps_dual feasibility tolerance for dual feasibility condition

In accordance with the paper, iteration stops when both `r_norm` and `s_norm` values become smaller than `eps_pri` and `eps_dual`, respectively.

Examples

```
## generate sample data
n = 30;
m = 10;
A = matrix(rnorm(n*m), nrow=m);

x = matrix(rep(0,n))
x[c(3,6,21),] = rnorm(3)
b = A%*%x

## run example
output = admm.bp(A, b)

## report convergence plot
niter  = length(output$history$s_norm)
par(mfrow=c(1,3))
plot(1:niter, output$history$objval, "b", main="cost function")
plot(1:niter, output$history$r_norm, "b", main="primal residual")
plot(1:niter, output$history$s_norm, "b", main="dual residual")
```

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admm.lad *Least Absolute Deviations*

Description

Least Absolute Deviations (LAD) is an alternative to traditional Least Sqaures by using cost function

$$min_x \|Ax - b\|_1$$

to use ℓ_1 norm instead of square loss for robust estimation of coefficient.

Usage

```
admm.lad(A, b, xinit = NA, rho = 1, alpha = 1, abstol = 1e-04,
  reltol = 0.01, maxiter = 1000)
```

Arguments

`A`	an $(m \times n)$ regressor matrix
`b`	a length-m response vector
`xinit`	a length-n vector for initial value
`rho`	an augmented Lagrangian parameter
`alpha`	an overrelaxation parameter in [1,2]
`abstol`	absolute tolerance stopping criterion
`reltol`	relative tolerance stopping criterion
`maxiter`	maximum number of iterations

Value

a named list containing

x a length-n solution vector

history dataframe recording iteration numerics. See the section for more details.

Iteration History

When you run the algorithm, output returns not only the solution, but also the iteration history recording following fields over iterates,

objval object (cost) function value

r_norm norm of primal residual

s_norm norm of dual residual

eps_pri feasibility tolerance for primal feasibility condition

eps_dual feasibility tolerance for dual feasibility condition

In accordance with the paper, iteration stops when both `r_norm` and `s_norm` values become smaller than `eps_pri` and `eps_dual`, respectively.

Examples

```
## generate data
m = 1000
n = 100
A = matrix(rnorm(m*n),nrow=m)
x = 10*matrix(rnorm(n))
b = A%*%x

## add impulsive noise to 10% of positions
idx = sample(1:m, round(m/10))
b[idx] = b[idx] + 100*rnorm(length(idx))

## run the code
output = admm.lad(A,b)
```

```
## report convergence plot
niter  = length(output$history$s_norm)
par(mfrow=c(1,3))
plot(1:niter, output$history$objval, "b", main="cost function")
plot(1:niter, output$history$r_norm, "b", main="primal residual")
plot(1:niter, output$history$s_norm, "b", main="dual residual")
```

`admm.lasso` *LASSO*

Description

LASSO, or L1-regularized regression, is an optimization problem to solve

$$min_x \frac{1}{2}\|Ax - b\|_2^2 + \lambda\|x\|_1$$

for sparsifying the coefficient vector x. The implementation is borrowed from Stephen Boyd's MATLAB code.

Usage

```
admm.lasso(A, b, lambda = 1, xinit = NA, rho = 1, alpha = 1,
  abstol = 1e-04, reltol = 0.01, maxiter = 1000)
```

Arguments

`A`	an $(m \times n)$ regressor matrix
`b`	a length-m response vector
`lambda`	a regularization parameber
`xinit`	a length-n vector for initial value
`rho`	an augmented Lagrangian parameter
`alpha`	an overrelaxation parameter in [1,2]
`abstol`	absolute tolerance stopping criterion
`reltol`	relative tolerance stopping criterion
`maxiter`	maximum number of iterations

Value

a named list containing

x a length-n solution vector

history dataframe recording iteration numerics. See the section for more details.

Iteration History

When you run the algorithm, output returns not only the solution, but also the iteration history recording following fields over iterates,

objval object (cost) function value

r_norm norm of primal residual

s_norm norm of dual residual

eps_pri feasibility tolerance for primal feasibility condition

eps_dual feasibility tolerance for dual feasibility condition

In accordance with the paper, iteration stops when both `r_norm` and `s_norm` values become smaller than `eps_pri` and `eps_dual`, respectively.

References

Tibshirani R (1996). "Regression Shrinkage and Selection via the Lasso." *Journal of the Royal Statistical Society. Series B (Methodological)*, **58**(1), pp. 267–288. ISSN 00359246, http://www.jstor.org/stable/2346178.

Examples

```
## generate sample data
m = 500
n = 1000
p = 0.1   # percentange of non-zero elements

x0 = matrix(Matrix::rsparsematrix(n,1,p))
A  = matrix(rnorm(m*n),nrow=m)
for (i in 1:ncol(A)){
  A[,i] = A[,i]/sqrt(sum(A[,i]*A[,i]))
}
b = A%*%x0 + sqrt(0.001)*matrix(rnorm(m))

## set regularization lambda value
lambda = 0.1*Matrix::norm(t(A)%*%b, 'I')

## run example
output = admm.lasso(A, b, lambda)

## report convergence plot
niter  = length(output$history$s_norm)
par(mfrow=c(1,3))
plot(1:niter, output$history$objval, "b", main="cost function")
plot(1:niter, output$history$r_norm, "b", main="primal residual")
plot(1:niter, output$history$s_norm, "b", main="dual residual")
```

admm.rpca *Robust Principal Component Analysis*

Description

Given a data matrix M, it finds a decomposition

$$min\ \|L\|_* + \lambda\|S\|_1 \quad \text{s.t.} \quad L + S = M$$

where $\|L\|_*$ represents a nuclear norm for a matrix L and $\|S\|_1 = \sum|S_{i,j}|$, and λ a balancing/regularization parameter. The choice of such norms leads to impose *low-rank* property for L and *sparsity* on S.

Usage

```
admm.rpca(M, lambda = 1/sqrt(max(nrow(M), ncol(M))), mu = 1, tol = 1e-07,
  maxiter = 1000)
```

Arguments

M	an $(m \times n)$ data matrix
lambda	a regularization parameber
mu	an augmented Lagrangian parameter
tol	relative tolerance stopping criterion
maxiter	maximum number of iterations

Value

a named list containing

L an $(m \times n)$ low-rank matrix

S an $(m \times n)$ sparse matrix

history dataframe recording iteration numerics. See the section for more details.

Iteration History

For RPCA implementation, we chose a very simple stopping criterion

$$\|M - (L_k + S_k)\|_F \leq tol * \|M\|_F$$

for each iteration step k. So for this method, we provide a vector of only relative errors,

error relative error computed

References

Candès EJ, Li X, Ma Y and Wright J (2011). "Robust principal component analysis?" *Journal of the ACM*, **58**(3), pp. 1–37. ISSN 00045411, doi: 10.1145/1970392.1970395, http://portal.acm.org/citation.cfm?doid=1970392.1970395.

Examples

```
## generate data matrix from standard normal
X = matrix(rnorm(100*50),nrow=50)

## try different regularization values
out1 = admm.rpca(X, lambda=0.01)
out2 = admm.rpca(X, lambda=0.1)
out3 = admm.rpca(X, lambda=1)

## visualize sparsity
par(mfrow=c(1,3))
image(out1$S, main="lambda=0.01")
image(out2$S, main="lambda=0.1")
image(out3$S, main="lambda=1")
```

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admm.spca *Sparse PCA*

Description

Sparse Principal Component Analysis aims at finding a sparse vector by solving

$$max_x \; x^T \Sigma x \quad \text{s.t.} \quad \|x\|_2 \leq 1, \; \|x\|_0 \leq K$$

where $\|x\|_0$ is the number of non-zero elements in a vector x. A convex relaxation of this problem was proposed to solve the following problem,

$$max_X \; < \Sigma, X > \; \text{s.t.} \quad Tr(X) = 1, \; \|X\|_0 \leq K^2, \; X \geq 0, \; \text{rank}(X) = 1$$

where $X = xx^T$ is a $(p \times p)$ matrix that is outer product of a vector x by itself, and $X \geq 0$ means the matrix X is positive semidefinite. With the rank condition dropped, it can be restated as

$$max_X \; < \Sigma, X > -\rho \|X\|_1 \quad \text{s.t.} \quad Tr(X) = 1, X \geq 0.$$

After acquiring each principal component vector, an iterative step based on Schur complement deflation method is applied to regress out the impact of previously-computed projection vectors. It should be noted that those sparse basis may *not be orthonormal*.

Usage

```
admm.spca(Sigma, numpc, mu = 1, rho = 1, abstol = 1e-04, reltol = 0.01,
  maxiter = 1000)
```

Arguments

Sigma	a $(p \times p)$ (sample) covariance matrix.
numpc	number of principal components to be extracted.
mu	an augmented Lagrangian parameter.

`rho`	a regularization parameter for sparsity.
`abstol`	absolute tolerance stopping criterion.
`reltol`	relative tolerance stopping criterion.
`maxiter`	maximum number of iterations.

Value

a named list containing

basis a $(p \times numpc)$ matrix whose columns are sparse principal components.

history a length-`numpc` list of dataframes recording iteration numerics. See the section for more details.

Iteration History

For SPCA implementation, main computation is sequentially performed for each projection vector. The `history` field is a list of length `numpc`, where each element is a data frame containing iteration history recording following fields over iterates,

r_norm norm of primal residual

s_norm norm of dual residual

eps_pri feasibility tolerance for primal feasibility condition

eps_dual feasibility tolerance for dual feasibility condition

In accordance with the paper, iteration stops when both `r_norm` and `s_norm` values become smaller than `eps_pri` and `eps_dual`, respectively.

References

Ma S (2013). "Alternating Direction Method of Multipliers for Sparse Principal Component Analysis." *Journal of the Operations Research Society of China*, **1**(2), pp. 253–274. ISSN 2194-668X, 2194-6698, doi: 10.1007/s4030501300169, http://link.springer.com/10.1007/s40305-013-0016-9.

Examples

```
## generate a random matrix and compute its sample covariance
X    = matrix(rnorm(1000*5),nrow=1000)
covX = cov(X)

## compute 3 sparse basis
output = admm.spca(covX, 3)
```

admm.tv *Total Variation Minimization*

Description

1-dimensional total variation minimization - also known as signal denoising - is to solve the following

$$min_x \frac{1}{2}\|x-b\|_2^2 + \lambda \sum_i |x_{i+1} - x_i|$$

for a given signal b. The implementation is borrowed from Stephen Boyd's MATLAB code.

Usage

```
admm.tv(b, lambda = 1, xinit = NA, rho = 1, alpha = 1, abstol = 1e-04,
  reltol = 0.01, maxiter = 1000)
```

Arguments

b	a length-m response vector
lambda	regularization parameter
xinit	a length$m$ vector for initial value
rho	an augmented Lagrangian parameter
alpha	an overrelaxation parameter in $[1, 2]$
abstol	absolute tolerance stopping criterion
reltol	relative tolerance stopping criterion
maxiter	maximum number of iterations

Value

a named list containing

x a length-m solution vector

history dataframe recording iteration numerics. See the section for more details.

Iteration History

When you run the algorithm, output returns not only the solution, but also the iteration history recording following fields over iterates,

objval object (cost) function value

r_norm norm of primal residual

s_norm norm of dual residual

eps_pri feasibility tolerance for primal feasibility condition

eps_dual feasibility tolerance for dual feasibility condition

In accordance with the paper, iteration stops when both `r_norm` and `s_norm` values become smaller than `eps_pri` and `eps_dual`, respectively.

Examples

```
## generate sample data
x1 = as.vector(sin(1:100)+0.1*rnorm(100))
x2 = as.vector(cos(1:100)+0.1*rnorm(100)+5)
x3 = as.vector(sin(1:100)+0.1*rnorm(100)+2.5)
xsignal = c(x1,x2,x3)

## run example
output  = admm.tv(xsignal)

## visualize
par(mfrow=c(1,2))
plot(1:300,xsignal,"l",main="original signal")
plot(1:300,output$x,"l",main="denoised signal")
```

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