Package ‘cqrReg’

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Author Jueyu Gao & Linglong Kong
Maintainer Jueyu Gao <jueyu@ualberta.ca>
Description Estimate quantile regression(QR) and composite quantile regression (cqr) and with adaptive lasso penalty using interior point (IP), majorize and minimize(MM), coordinate descent (CD), and alternating direction method of multipliers algorithms(ADMM).
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cqr.admm

Composite Quantile regression (cqr) use Alternating Direction Method of Multipliers (ADMM) algorithm.

Description

Composite quantile regression (cqr) find the estimated coefficient which minimize the absolute error for various quantile level. The problem is well suited to distributed convex optimization and is based on Alternating Direction Method of Multipliers (ADMM) algorithm.

Usage

cqr.admm(X, y, tau, rho, beta, maxit, toler)

Arguments

x the design matrix
y response variable
tau vector of quantile level
rho augmented Lagrangian parameter
beta initial value of estimate coefficient (default naive guess by least square estimation)
maxit maxim iteration (default 200)
toler the tolerance critical for stop the algorithm (default 1e-3)
Value

A list structure is with components

- **beta**: the vector of estimated coefficient
- **b**: intercept

Note

cqr.admm(x,y,tau) work properly only if the least square estimation is good.

References


Examples

```r
set.seed(1)
n=100
p=2
a=rnorm(n*p, mean = 1, sd =1)
x=matrix(a,n,p)
beta=rnorm(p,1,1)
beta=matrix(beta,p,1)
y=x%*%beta+matrix(rnorm(n,0.1,1),n,1)
tau=1:5/6
  # x is 1000*10 matrix, y is 1000*1 vector, beta is 10*1 vector
cqr.admm(x,y,tau)
```

Description

Composite quantile regression (cqr) find the estimated coefficient which minimize the absolute error for various quantile level. The algorithm base on greedy coordinate descent and Edgeworth’s for ordinary $l_1$ regression.

Usage

cqr.cd(X,y,tau,beta,maxit,toler)
Arguments

x the design matrix
y response variable
tau vector of quantile level
beta initial value of estimate coefficient (default naive guess by least square estimation)
maxit maxim iteration (default 200)
toler the tolerance critical for stop the algorithm (default 1e-3)

Value

a list structure is with components

beta the vector of estimated coefficient
b intercept

Note

cqr.cd(x,y,tau) work properly only if the least square estimation is good.

References


Examples

```r
set.seed(1)
n=100
p=2
a=rnorm(n*p, mean = 1, sd =1)
x=matrix(a,n,p)
beta=rnorm(p,1,1)
beta=matrix(beta,p,1)
y=x%*%beta-matrix(rnorm(n,0.1,1),n,1)
tau=1:5/6
# x is 1000*10 matrix, y is 1000*1 vector, beta is 10*1 vector
cqr.cd(x,y,tau)
```
cqr.fit

---

**cqr.fit**

*Composite Quantile Regression (cqr) model fitting*

---

**Description**

Composite quantile regression (cqr) find the estimated coefficient which minimize the absolute error for various quantile level. High level function for estimating parameter by composite quantile regression.

**Usage**

```r
cqr.fit(X,y,tau,beta,method,maxit,toler,rho)
```

**Arguments**

- **X**: the design matrix
- **y**: response variable
- **tau**: vector of quantile level
- **method**: "mm" for majorize and minimize method,"cd" for coordinate descent method, "admm" for Alternating method of multipliers method,"ip" for interior point method
- **rho**: augmented Lagrangian parameter
- **beta**: initial value of estimate coefficient (default naive guess by least square estimation)
- **maxit**: maxim iteration (default 200)
- **toler**: the tolerance critical for stop the algorithm (default 1e-3)

**Value**

A list structure is with components

- **beta**: the vector of estimated coefficient
- **b**: intercept

**Note**

cqr.fit(x,y,tau) work properly only if the least square estimation is good. Interior point method is done by quantreg.
**cqr.fit.lasso**  
*Composite Quantile Regression (cqr) with Adaptive Lasso Penalty (lasso)*

**Description**

Composite quantile regression (cqr) find the estimated coefficient which minimize the absolute error for various quantile level. High level function for estimating and selecting parameter by composite quantile regression with adaptive lasso penalty.

**Usage**

```r
cqr.fit.lasso(X,y,tau,lambda,beta,method,maxit,toler,rho)
```

**Arguments**

- **X**  
  the design matrix

- **y**  
  response variable

- **tau**  
  vector of quantile level

- **method**  
  "mm" for majorize and minimize method,"cd" for coordinate descent method, "admm" for Alternating method of multipliers method

- **lambda**  
  The constant coefficient of penalty function. (default lambda=1)

- **rho**  
  augmented Lagrangian parameter

- **beta**  
  initial value of estimate coefficient (default naive guess by least square estimation)

- **maxit**  
  maxim iteration (default 200)

- **toler**  
  the tolerance critical for stop the algorithm (default 1e-3)

**Value**

A list structure is with components

- **beta**  
  the vector of estimated coefficient

- **b**  
  intercept

**Note**

`cqr.fit.lasso(x,y,tau) work properly only if the least square estimation is good.`
Composite Quantile Regression (cqr) use Interior Point (ip) Method

Description
The function use the interior point method from quantreg to solve the quantile regression problem.

Usage
```r
cqr.ip(X, y, tau)
```

Arguments
- **X**: the design matrix
- **y**: response variable
- **tau**: vector of quantile level

Value
A list structure is with components
- **beta**: the vector of estimated coefficient
- **b**: intercept

Note
Need to install quantreg package from CRAN.

References

Examples
```r
set.seed(1)
n=100
p=2
a=rnorm(n*p, mean = 1, sd =1)
x=matrix(a,n,p)
beta=rnorm(p,1,1)
beta=matrix(beta,p,1)
y=x%*%beta+matrix(rnorm(n,0.1,1),n,1)
tau=1:5/6
# x is 1000*10 matrix, y is 1000*1 vector, beta is 10*1 vector
#you should install quantreg first to run following command
#cqr.ip(x,y,tau)
```
cqr.lasso.admm  

Composite Quantile Regression (cqr) with Adaptive Lasso Penalty (lasso) use Alternating Direction Method of Multipliers (ADMM) algorithm

Description

The adaptive lasso parameter base on the estimated coefficient without penalty function. Composite quantile regression find the estimated coefficient which minimize the absolute error for various quantile level. The problem is well suited to distributed convex optimization and is based on Alternating Direction Method of Multipliers (ADMM) algorithm.

Usage

cqr.lasso.admm(X, y, tau, lambda, rho, beta, maxit)

Arguments

- **X**: the design matrix
- **y**: response variable
- **tau**: vector of quantile level
- **lambda**: The constant coefficient of penalty function. (default lambda=1)
- **rho**: augmented Lagrangian parameter
- **beta**: initial value of estimate coefficient (default naive guess by least square estimation)
- **maxit**: maxim iteration (default 200)

Value

a list structure is with components

- **beta**: the vector of estimated coefficient
- **b**: intercept

Note

cqr.laso.admm(x,y,tau) work properly only if the least square estimation is good.

References


Examples

```r
set.seed(1)
n=100
p=2
a=2*rnorm(n*2*p, mean = 1, sd =1)
x=matrix(a,n,2*p)
b=2*rnorm(p,1,1)
beta=rbind(matrix(b,p,1),matrix(0,p,1))
y=x%*%beta-matrix(rnorm(n,0.1,1),n,1)
```

# x is 1000*20 matrix, y is 1000*1 vector, beta is 20*1 vector with last ten zero value elements.
cqr.lasso.admm(x,y,tau)

---

cqr.lasso.cd

### Composite Quantile Regression (cqr) with Adaptive Lasso Penalty (lasso) use Coordinate Descent (cd) Algorithms

**Description**

The adaptive lasso parameter base on the estimated coefficient without penalty function. Composite quantile regression find the estimated coefficient which minimize the absolute error for various quantile level. The algorithm base on greedy coordinate descent and Edgeworth’s for ordinary \( l_1 \) regression.

**Usage**

```r
cqr.lasso.cd(X,y,tau,lambda,beta,maxit,toler)
```

**Arguments**

- **X** the design matrix
- **y** response variable
- **tau** vector of quantile level
- **lambda** The constant coefficient of penalty function. (default lambda=1)
- **beta** initial value of estimate coefficient (default naive guess by least square estimation)
- **maxit** maxim iteration (default 200)
- **toler** the tolerance critical for stop the algorithm (default 1e-3)

**Value**

a **list** structure is with components

- **beta** the vector of estimated coefficient
- **b** intercept
Note

cqr.lasso.cd(x,y,tau) work properly only if the least square estimation is good.

References


Examples

```r
set.seed(1)
n=100
p=2
a=2*rnorm(n*2*p, mean = 1, sd =1)
x=matrix(a,n,2*p)
beta=2*rnorm(p,1,1)
beta=rbind(matrix(beta,p,1),matrix(0,p,1))
y=x%*%beta-matrix(rnorm(n,0.1,1),n,1)
tau=1:5/6
# x is 1000*20 matrix, y is 1000*1 vector, beta is 20*1 vector with last ten zero value elements.
cqr.lasso.cd(x,y,tau)
```

**cqr.lasso.mm**

Composite Quantile Regression (cqr) with Adaptive Lasso Penalty (lasso) use Majorize and Minimize (mm) Algorithm

Description

The adaptive lasso penalty parameter base on the estimated coefficient without penalty function. Composite quantile regression find the estimated coefficient which minimize the absolute error for various quantile level. The algorithm majorizing the objective function by a quadratic function followed by minimizing that quadratic.

Usage

cqr.lasso.mm(X,y,tau,lambda,beta,maxit, toler)

Arguments

- **X** : the design matrix
- **y** : response variable
- **tau** : vector of quantile level
- **lambda** : The constant coefficient of penalty function. (default lambda=1)
- **beta** : initial value of estimate coefficient (default naive guess by least square estimation)
cqr.mm

maxit maxim iteration (default 200)
toler the tolerance critical for stop the algorithm (default 1e-3)

Value

a list structure is with components

beta the vector of estimated coefficient
b intercept for various quantile level

Note

CQR.lasso.mm(x,y,tau) work properly only if the least square estimation is good.

References


Examples

set.seed(1)
n=100
p=2
a=2*rnorm(n*2*p, mean = 1, sd =1)
x=matrix(a,n,2*p)
b=2*rnorm(p,1,1)
b=cbind(matrix(b,p,1),matrix(0,p,1))
y=x%*%b+matrix(rnorm(n,0.1,1),n,1)
tau=1:5/6
# x is 1000*20 matrix, y is 1000*1 vector, beta is 20*1 vector with last ten zero value elements.
cqr.lasso.mm(x,y,tau)
Arguments

- **x**: the design matrix
- **y**: response variable
- **tau**: vector of quantile level
- **beta**: initial value of estimate coefficient (default naive guess by least square estimation)
- **maxit**: maxim iteration (default 200)
- **toler**: the tolerance critical for stop the algorithm (default 1e-3)

Value

A list structure is with components

- **beta**: the vector of estimated coefficient
- **b**: intercept for various quantile level

Note

cqr.mm(x,y,tau) work properly only if the least square estimation is good.

References


Examples

```r
set.seed(1)
n=100
p=2
a=rnorm(n*p, mean = 1, sd =1)
x=matrix(a,n,p)
betar=rnorm(p,1,1)
betamatrix(betar,p,1)
y=x%*%betamatrix(rnorm(n,0.1,1),n,1)
tau=1:5/6
# x is 1000*10 matrix, y is 1000*1 vector, beta is 10*1 vector
cqr.mm(x,y,tau)
```
Composite Quantile Regression (cqr) use Alternating Direction Method of Multipliers (ADMM) algorithm core computational part

Description
Composite quantile regression (cqr) find the estimated coefficient which minimize the absolute error for various quantile level. The problem is well suited to distributed convex optimization and is based on Alternating Direction Method of Multipliers (ADMM) algorithm.

Composite Quantile Regression (cqr) use Coordinate Descent (cd) Algorithms core computational part

Description
Composite quantile regression (cqr) find the estimated coefficient which minimize the absolute error for various quantile level. The algorithm base on greedy coordinate descent and Edgeworth’s for ordinary $l_1$ regression.

Composite Quantile Regression (cqr) use Majorize and Minimize (mm) Algorithm core computational part

Description
Composite quantile regression find the estimated coefficient which minimize the absolute error for various quantile level. The algorithm majorizing the objective function by a quadratic function followed by minimizing that quadratic.

Composite Quantile Regression (cqr) with Adaptive Lasso Penalty (lasso) use Alternating Direction Method of Multipliers (ADMM) algorithm core computational part

Description
The adaptive lasso parameter base on the estimated coefficient without penalty function. Composite quantile regression find the estimated coefficient which minimize the absolute error for various quantile level. The problem is well suited to distributed convex optimization and is based on Alternating Direction Method of Multipliers (ADMM) algorithm.
CQRPCDCPP

*Composite Quantile Regression (cqr) with Adaptive Lasso Penalty (lasso) use Coordinate Descent (cd) Algorithms core computational part*

### Description

The adaptive lasso parameter base on the estimated coefficient without penalty function. Composite quantile regression find the estimated coefficient which minimize the absolute error for various quantile level. The algorithm base on greedy coordinate descent and Edgeworth’s for ordinary $l_1$ regression.

CQRPMMCPP

*Composite Quantile Regression (cqr) with Adaptive Lasso Penalty (lasso) use Majorize and Minimize (mm) Algorithm core computational part*

### Description

The adaptive lasso penalty parameter base on the estimated coefficient without penalty function. Composite quantile regression find the estimated coefficient which minimize the absolute error for various quantile level. The algorithm majorizing the objective function by a quadratic function followed by minimizing that quadratic.

QR.admm

*Quantile Regression (QR) use Alternating Direction Method of Multipliers (ADMM) algorithm*

### Description

The problem is well suited to distributed convex optimization and is based on Alternating Direction Method of Multipliers (ADMM) algorithm.

### Usage

```r
QR.admm(X,y,tau,rho,beta, maxit, toler)
```
Arguments

- **x**: the design matrix
- **y**: response variable
- **tau**: quantile level
- **rho**: augmented Lagrangian parameter
- **beta**: initial value of estimate coefficient (default naive guess by least square estimation)
- **maxit**: maxim iteration (default 200)
- **toler**: the tolerance critical for stop the algorithm (default 1e-3)

Value

A list structure is with components

- **beta**: the vector of estimated coefficient
- **b**: intercept

Note

QR.admm(x,y,tau) work properly only if the least square estimation is good.

References


Examples

```r
set.seed(1)
n=100
p=2
a=rnorm(n*p, mean = 1, sd = 1)
x=matrix(a,n,p)
beta=rnorm(p,1,1)
beta=matrix(beta,p,1)
y=x%*%beta-matrix(rnorm(n,0.1,1),n,1)
# x is 1000*10 matrix, y is 1000*1 vector, beta is 10*1 vector
QR.admm(x,y,0.1)
```
Quantile Regression (QR) use Coordinate Descent (cd) Algorithms

Description
The algorithm base on greedy coordinate descent and Edgeworth’s for ordinary $l_1$ regression.

Usage
QR.cd(X,y,tau,beta,maxit,toler)

Arguments
X the design matrix
y response variable
tau quantile level
beta initial value of estimate coefficient (default naive guess by least square estimation)
maxit maxim iteration (default 200)
toler the tolerance critical for stop the algorithm (default 1e-3)

Value
a list structure is with components
beta the vector of estimated coefficient
b intercept

Note
QR.cd(x,y,tau) work properly only if the least square estimation is good.

References

Examples
set.seed(1)
n=100
p=2
a=rnorm(n*p, mean = 1, sd =1)
x=matrix(a,n,p)
beta=rnorm(p,1,1)
beta=matrix(beta,p,1)
y = x %*% beta - matrix(rnorm(n, 0.1, 1), n, 1)
# x is 1000*10 matrix, y is 1000*1 vector, beta is 10*1 vector
QR.cd(x, y, 0.1)

---

<table>
<thead>
<tr>
<th>QR.ip</th>
<th>Quantile Regression (QR) use Interior Point (ip) Method</th>
</tr>
</thead>
</table>

**Description**

The function uses the interior point method from quantreg to solve the quantile regression problem.

**Usage**

```r
QR.ip(X, y, tau)
```

**Arguments**

- `X`: the design matrix
- `y`: response variable
- `tau`: quantile level

**Value**

A list structure is with components:

- `beta`: the vector of estimated coefficient
- `b`: intercept

**Note**

Need to install quantreg package from CRAN.

**References**


**Examples**

```r
set.seed(1)
n = 100
p = 2
a = rnorm(n * p, mean = 1, sd = 1)
x = matrix(a, n, p)
beta = rnorm(p, 1, 1)
beta = matrix(beta, p, 1)
y = x %*% beta - matrix(rnorm(n, 0.1, 1), n, 1)
```
QR.lasso.admm

Quantile Regression (QR) with Adaptive Lasso Penalty (lasso) use Alternating Direction Method of Multipliers (ADMM) algorithm

Description

The adaptive lasso parameter base on the estimated coefficient without penalty function. The problem is well suited to distributed convex optimization and is based on Alternating Direction Method of Multipliers (ADMM) algorithm.

Usage

QR.lasso.admm(X,y,tau,lambda,rho,beta,maxit)

Arguments

x the design matrix
y response variable
tau quantile level
lambda The constant coefficient of penalty function. (default lambda=1)
rho augmented Lagrangian parameter
beta initial value of estimate coefficient (default naive guess by least square estimation)
maxit maxim iteration (default 200)

Value

a list structure is with components
beta the vector of estimated coefficient
b intercept

Note

QR.lasso.admm(x,y,tau) work properly only if the least square estimation is good.

References


Examples

```r
set.seed(1)
n=100
p=2
a=2*rnorm(n*2*p, mean = 1, sd =1)
x=matrix(a,n,2*p)
beta=2*rnorm(p,1,1)
b=cbind(matrix(beta,p,1),matrix(0,p,1))
y=x%*%beta+matrix(rnorm(n,0.1,1),n,1)
```

# x is 1000*20 matrix, y is 1000*1 vector, beta is 20*1 vector with last ten zero value elements.
QR.lasso.admm(x,y,0.1)

QR.lasso.cd

Quantile Regression (QR) with Adaptive Lasso Penalty (lasso) use Coordinate Descent (cd) Algorithms

Description

The adaptive lasso parameter base on the estimated coefficient without penalty function. The algorithm base on greedy coordinate descent and Edgeworth’s for ordinary $l_1$ regression. As explored by Tong Tong Wu and Kenneth Lange.

Usage

QR.lasso.cd(X,y,tau,lambda,beta,maxit,toler)

Arguments

- **X** the design matrix
- **y** response variable
- **tau** quantile level
- **lambda** The constant coefficient of penalty function. (default lambda=1)
- **beta** initial value of estimate coefficient (default naive guess by least square estimation)
- **maxit** maxim iteration (default 200)
- **toler** the tolerance critical for stop the algorithm (default 1e-3)

Value

A list structure is with components

- **beta** the vector of estimated coefficient
- **b** intercept

Note

QR.lasso.cd(x,y,tau) work properly only if the least square estimation is good.
References


Examples

```r
set.seed(1)
n=100
p=2
a=2*rnorm(n*2*p, mean = 1, sd =1)
x=matrix(a,n,2*p)
beta=2*rnorm(p,1,1)
beta=rbind(matrix(beta,1),matrix(0,p,1))
y=x%*%beta-matrix(rnorm(n,0.1,1),n,1)
# x is 1000*20 matrix, y is 1000*1 vector, beta is 20*1 vector with last ten zero value elements.
QR.lasso.cd(x,y,0.1)
```

---

**QR.lasso.ip**

Quantile Regression (QR) with Adaptive Lasso Penalty (lasso) use Interior Point (ip) Method

Description

The function use the interior point method from quantreg to solve the quantile regression problem.

Usage

```r
QR.lasso.ip(X,y,tau,lambda)
```

Arguments

- `X` the design matrix
- `y` response variable
- `tau` quantile level
- `lambda` The constant coefficient of penalty function. (default lambda=1)

Value

A list structure is with components

- `beta` the vector of estimated coefficient
- `b` intercept
- `lambda` The constant coefficient of penalty function. (default lambda=1)
Note

Need to install quantreg package from CRAN.

References


Examples

```r
set.seed(1)
n=100
p=2
a=2*rnorm(n*2*p, mean = 1, sd =1)
x=matrix(a,n,2*p)
beta=2*rnorm(p,1,1)
beta=rbind(matrix(beta,p,1),matrix(0,p,1))
y=x%*%beta-matrix(rnorm(n,0.1,1),n,1)
```

Examples

```r
# x is 1000*20 matrix, y is 1000*1 vector, beta is 20*1 vector with last ten zero value elements.
# you should install Rmosek first to run following command
#QR.lasso.ip(x,y,0.1)
```

QR.lasso.mm

Quantile Regression (QR) with Adaptive Lasso Penalty (lasso) use Majorize and Minimize (mm) algorithm

Description

The adaptive lasso parameter base on the estimated coefficient without penalty function. The algorithm majorizing the objective function by a quadratic function followed by minimizing that quadratic.

Usage

```r
QR.lasso.mm(X,y,tau,lambda,beta,maxit,toler)
```

Arguments

<table>
<thead>
<tr>
<th>Argument</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>X</td>
<td>the design matrix.</td>
</tr>
<tr>
<td>y</td>
<td>response variable.</td>
</tr>
<tr>
<td>tau</td>
<td>quantile level.</td>
</tr>
<tr>
<td>lambda</td>
<td>The constant coefficient of penalty function. (default lambda=1)</td>
</tr>
<tr>
<td>beta</td>
<td>initial value of estimate coefficient.(default naive guess by least square estimation)</td>
</tr>
<tr>
<td>maxit</td>
<td>maxim iteration. (default 200)</td>
</tr>
<tr>
<td>toler</td>
<td>the tolerance critical for stop the algorithm. (default 1e-3)</td>
</tr>
</tbody>
</table>
Value

a list structure is with components

beta the vector of estimated coefficient
b intercept

Note

QR.lasso.mm(x,y,tau) work properly only if the least square estimation is good.

References


Examples

set.seed(1)
n=100
p=2
a=2*runorm(n*2*p, mean = 1, sd =1)
x=matrix(a,n,2*p)
beta=2*runorm(p,1,1)
beta=rbind(matrix(beta,p,1),matrix(0,p,1))
y=x%*%beta-matrix(rnorm(n,0.1,1),n,1)
# x is 1000*20 matrix, y is 1000*1 vector, beta is 20*1 vector with last ten zero value elements.
QR.lasso.mm(x,y,0.1)

QR.mm

Quantile Regression (QR) use Majorize and Minimize (mm) algorithm

Description

The algorithm majorizing the objective function by a quadratic function followed by minimizing that quadratic.

Usage

QR.mm(X,y,tau,beta,maxit,toler)

Arguments

X the design matrix
y response variable
tau quantile level
beta initial value of estimate coefficient (default naive guess by least square estimation)
maxit maxim iteration (default 200)
toler the tolerance critical for stop the algorithm (default 1e-3)
Value

A list structure is with components

- `beta`: the vector of estimated coefficient
- `b`: intercept

Note

QR.mm(x,y,tau) work properly only if the least square estimation is good.

References

David R. Hunter and Kenneth Lange. Quantile Regression via an MM Algorithm, *Journal of Computational and Graphical Statistics*, 9, Number 1, Page 60–77

Examples

```r
set.seed(1)
n=100
p=2
a=rnorm(n*p, mean = 1, sd =1)
x=matrix(a,n,p)
beta=rnorm(p,1,1)
beta=matrix(beta,p,1)
y=x%*%beta+matrix(rnorm(n,0.1,1),n,1)
# x is 1000*10 matrix, y is 1000*1 vector, beta is 10*1 vector
QR.mm(x,y,0.1)
```

---

QRSRMMCPP

Quantile Regression (QR) use Alternating Direction Method of Multipliers (ADMM) algorithm core computational part

Description

The problem is well suited to distributed convex optimization and is based on Alternating Direction Method of Multipliers (ADMM) algorithm .

---

QRSRCDCPP

Quantile Regression (QR) use Coordinate Descent (cd) Algorithms core computational part

Description

The algorithm base on greedy coordinate descent and Edgeworth’s for ordinary $\ell_1$ regression.

Quantile Regression (qr) model fitting

Description

High level function for estimating parameters by quantile regression

Usage

```r
crfit(X, y, tau, beta, method, maxit, toler, rho)
```

Arguments

- **X**: the design matrix
- **y**: response variable
- **tau**: quantile level
- **method**: "mm" for majorize and minimize method,"cd" for coordinate descent method, "admm" for Alternating method of multipliers method,"ip" for interior point method
- **rho**: augmented Lagrangian parameter
- **beta**: initial value of estimated coefficient (default naive guess by least square estimation)
- **maxit**: maximum iteration (default 200)
- **toler**: the tolerance critical for stop the algorithm (default 1e-3)

Value

A list structure is with components

- **beta**: the vector of estimated coefficient
- **b**: intercept

Note

`crfit(x,y,tau)` work properly only if the least square estimation is good. Interior point method is done by quantreg.
qrfit.lasso

Quantile Regression (qr) with Adaptive Lasso Penalty (lasso)

Description

High level function for estimating and selecting parameter by quantile regression with adaptive lasso penalty.

Usage

qrfit.lasso(X, y, tau, lambda, beta, method, maxit, toler, rho)

Arguments

X
the design matrix

y
response variable

tau
quantile level

method
"mm" for majorize and minimize method,"cd" for coordinate descent method, "admm" for Alternating method of multipliers method,"ip" for interior point method

lambda
The constant coefficient of penalty function. (default lambda=1)

rho
augmented Lagrangian parameter

beta
initial value of estimate coefficient (default naive guess by least square estimation)

maxit
maxim iteration (default 200)

toler
the tolerance critical for stop the algorithm (default 1e-3)

Value

a list structure is with components

beta
the vector of estimated coefficient

b
intercept

Note

qrfit.lasso(x, y, tau) work properly only if the least square estimation is good. Interior point method is done by quantreg.
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