# Package 'clrdag'

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Type Package

Description

constraints.

Title Likelihood ratio tests of a large directed acyclic graph
<b>Version</b> 0.19.03
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<b>Depends</b> R (>= 3.5.3)
<b>Imports</b> Rcpp (>= 1.0.1)
LinkingTo Rcpp, RcppArmadillo
Suggests mytnorm
<b>Description</b> The 'clrdag' package provides R functions for constrained likelihood ratio tests of a large directed acyclic graph. Documentation about 'clrdag' is provided by the vignette included in this package and via the paper by Li, Shen, and Pan (2019).
License GPL (>= 2)
BugReports https://github.umn.edu/li000007/clrdag/issues
NeedsCompilation yes
R topics documented:
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clrdag cmleDAG

A function computes the MLE/likelihood ratio of a Gaussian directed acyclic graph with specified

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#### Usage

### **Arguments**

X An n by p data matrix, where n is the number of observations and p is the di-

mension.

A, Lambda Initial estimate. A is a p by p adjacency matrix, Lambda is a p by p dual matrix

in acyclicity condition. A must be a DAG! If A is NULL (default), the initial

estimate is provided automatically (Be careful!).

D A p by p matrix indicating hypothesized edges. For the entries equal to 1, no

sparse penalty is imposed.

tau A positive real number. tau is the threshold parameter in TLP.

mu A positive real number. mu is the sparsity parameter.

rho A positive real number. rho is the ADMM dual parameter.

tol\_abs, tol\_rel

Positive real. The absolute and relative tolerance.

dc\_max\_iter, admm\_max\_iter

Positive integer. The maximum iteration number of DC and ADMM.

test\_path Logical. If TRUE, the path test is used.

trace\_obj Logical. If TRUE, the objective values are printed after each iteration.

### Author(s)

Chunlin Li

#### References

Li, C., Shen, X., and Pan, W. (2019). Likelihood ratio tests of a large directed acyclic graph. Submitted.

#### **Examples**

```
library(mvtnorm)
##
## Example 1: random graph
##
set.seed(2019)
p<-50
n<-1000
## random graph: randomly generate adjacency matrix A, A lower triangular sparsity <- 2/p
A <- matrix(rbinom(p*p,1,sparsity)*sign(runif(p*p,min=-1,max=1)),p,p)
A[upper.tri(A, diag = TRUE)] <- 0
Sigma <- solve(diag(p) - A)</pre>
```

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```
Sigma <- Sigma %*% t(Sigma)</pre>
X <- rmvnorm(n,mean=rep(0,p), sigma=Sigma, method="chol")</pre>
out <- cmleDAG(X=X,tau=0.3,mu=1,rho=1.2,trace_obj=FALSE) # compute the MLE
B <- out$A
B <- ifelse(abs(B)>0.3,1,0)
B == abs(A)
##
## Example 2: hub graph
set.seed(2019)
p<-50
n<-1000
## hub graph: randomly generate adjacency matrix A, A lower triangular
A \leftarrow matrix(0,p,p)
A[,1] <- sign(runif(p,min=-1,max=1))
A[1,1] <- 0
Sigma <- solve(diag(p) - A)</pre>
Sigma <- Sigma %*% t(Sigma)
X \leftarrow rmvnorm(n,mean=rep(0,p), sigma=Sigma, method="chol")
out <- cmleDAG(X=X,tau=0.3,mu=1,rho=1.2,trace_obj=FALSE) \# compute the MLE
B <- out$A
B <- ifelse(abs(B)>0.3,1,0)
B == abs(A)
```

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