Package ‘huge’

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Type Package

Title High-Dimensional Undirected Graph Estimation

Version 1.2.7

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Depends R (>= 3.0.0), Matrix, lattice, igraph, MASS

Imports grDevices, graphics, methods, stats, utils

Description Provides a general framework for high-dimensional undirected graph estimation. It integrates data preprocessing, neighborhood screening, graph estimation, and model selection techniques into a pipeline. In preprocessing stage, the nonparanormal(npn) transformation is applied to help relax the normality assumption. In the graph estimation stage, the graph structure is estimated by Meinshausen-Buhlmann graph estimation or the graphical lasso, and both methods can be further accelerated by the lossy screening rule preselecting the neighborhood of each variable by correlation thresholding. We target on high-dimensional data analysis usually d >> n, and the computation is memory-optimized using the sparse matrix output. We also provide a computationally efficient approach, correlation thresholding graph estimation. Three regularization/thresholding parameter selection methods are included in this package: (1)stability approach for regularization selection (2) rotation information criterion (3) extended Bayesian information criterion which is only available for the graphical lasso.

License GPL-2

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R topics documented:

`huge-package` *High-Dimensional Undirected Graph Estimation*

Description

A package for high-dimensional undirected graph estimation

Details

Package:	huge
Type:	Package
Version:	1.2.7
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License:	GPL-2
LazyLoad:	yes

The package "huge" provides 8 main functions:
(1) the data generator creates random samples from multivariate normal distributions with different graph structures. Please refer to `huge.generator`.
(2) the nonparanormal (npn) transformation helps relax the normality assumption. Please refer to `huge.npn`.
(3) The correlation thresholding graph estimation. Please refer to `huge`.
(4) The Meinshausen-Buhlmann graph estimation. Please refer to `huge`.
(5) The graphical Lasso algorithm using lossless screening rule. Please refer and `huge`.

**Both (4) and (5) can be furether accelerated by the lossy screening rule preselecting the neighborhood of each node via thresholding sample correlation.
(6) The model selection using the stability approach to regularization selection. Please refer to `huge.select`.
(7) The model selection using the rotation information criterion. Please refer to `huge.select`.
(8) The model selection using the extended Bayesian information criterion. Please refer to `huge.select`.

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References

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See Also

`huge.generator`, `huge.npn`, `huge`, `huge.plot` and `huge.roc` huge *High-dimensional undirected graph estimation*

Description

The main function for high-dimensional undirected graph estimation. Three graph estimation methods, including (1) Meinshausen-Buhlmann graph estimation (mb) (2) graphical lasso (glasso) and (3) correlation thresholding graph estimation (ct), are available for data analysis.

Usage

```
huge(x, lambda = NULL, nlambda = NULL, lambda.min.ratio = NULL, method = "mb",
scr = NULL, scr.num = NULL, cov.output = FALSE, sym = "or", verbose = TRUE)
```

Arguments

`x` There are 2 options: (1) `x` is an `n` by `d` data matrix (2) a `d` by `d` sample covariance matrix. The program automatically identifies the input matrix by checking the symmetry. (`n` is the sample size and `d` is the dimension).

`lambda` A sequence of decresing positive numbers to control the regularization when `method = "mb"` or `"glasso"`, or the thresholding in `method = "ct"`. Typical usage is to leave the input `lambda = NULL` and have the program compute its own `lambda` sequence based on `nlambda` and `lambda.min.ratio`. Users can also specify a sequence to override this. When `method = "mb"` or `"glasso"`, use with care - it is better to supply a decreasing sequence values than a single (small) value.

`nlambda` The number of regularization/thresholding paramters. The default value is `30` for `method = "ct"` and `10` for `method = "mb"` or `"glasso"`.

`lambda.min.ratio`
If `method = "mb"` or `"glasso"`, it is the smallest value for `lambda`, as a fraction of the uppperbound (`MAX`) of the regularization/thresholding parameter which makes all estimates equal to `0`. The program can automatically generate `lambda` as a sequence of length = `nlambda` starting from `MAX` to `lambda.min.ratio*MAX` in log scale. If `method = "ct"`, it is the largest sparsity level for estimated graphs. The program can automatically generate `lambda` as a sequence of length = `nlambda`, which makes the sparsity level of the graph path increases from `0` to `lambda.min.ratio` evenly.The default value is `0.1` when `method = "mb"` or `"glasso"`, and 0.05 `method = "ct"`.

`method` Graph estimation methods with 3 options: `"mb"`, `"ct"` and `"glasso"`. The defaulty value is `"mb"`.

`scr` If `scr = TRUE`, the lossy screening rule is applied to preselect the neighborhood before the graph estimation. The default value is `FALSE`. NOT applicable when `method = "ct"`.

`scr.num` The neighborhood size after the lossy screening rule (the number of remaining neighbors per node). ONLY applicable when `scr = TRUE`. The default value is `n-1`. An alternative value is `n/log(n)`. ONLY applicable when `scr = TRUE` and `method = "mb"`.

`cov.output` — If `cov.output = TRUE`, the output will inlcude a path of estimated covariance matrices. ONLY applicable when `method = "glasso"`. Since the estimated covariance matrices are generally not sparse, please use it with care, or it may take much memory under high-dimensional setting. The default value is `FALSE`.

`sym` — Symmetrize the output graphs. If `sym = "and"`, the edge between node `i` and node `j` is selected ONLY when both node `i` and node `j` are selected as neighbors for each other. If `sym = "or"`, the edge is selected when either node `i` or node `j` is selected as the neighbor for each other. The default value is `"or"`. ONLY applicable when `method = "mb"`.

`verbose` — If `verbose = FALSE`, tracing information printing is disabled. The default value is `TRUE`.

Details

The graph structure is estimated by Meinshausen-Buhlmann graph estimation or the graphical lasso, and both methods can be further accelerated via the lossy screening rule by preselecting the neighborhood of each variable by correlation thresholding. We target on high-dimensional data analysis usually d » n, and the computation is memory-optimized using the sparse matrix output. We also provide a highly computationally efficient approaches correlation thresholding graph estimation.

Value

An object with S3 class `"huge"` is returned:

`data` — The `n` by `d` data matrix or `d` by `d` sample covariance matrix from the input

`cov.input` — An indicator of the sample covariance.

`ind.mat` — The `scr.num` by `k` matrix with each column correspondsing to a variable in `ind.group` and contains the indices of the remaining neighbors after the GSS. ONLY applicable when `scr = TRUE` and `approx = FALSE`

`lambda` — The sequence of regularization parameters used in mb or thresholding parameters in ct.

`sym` — The `sym` from the input. ONLY applicable when `method = "mb"`.

`scr` — The `scr` from the input. ONLY applicable when `method = "mb"` or "glasso".

`path` — A list of `k` by `k` adjacency matrices of estimated graphs as a graph path corresponding to `lambda`.

`sparsity` — The sparsity levels of the graph path.

`icov` — A list of `d` by `d` precision matrices as an alternative graph path (numerical path) corresponding to `lambda`. ONLY applicable when method = "glasso"

`cov` — A list of `d` by `d` estimated covariance matrices corresponding to `lambda`. ONLY applicable when `cov.output = TRUE` and method = "glasso"

`method` — The method used in the graph estimation stage.

`df` If `method = "mb"`, it is a `k` by `nlambda` matrix. Each row contains the number of nonzero coefficients along the lasso solution path. If `method = "glasso"`, it is a `nlambda` dimensional vector containing the number of nonzero coefficients along the graph path `icov`.

`loglik` A `nlambda` dimensional vector containing the likelihood scores along the graph path (`icov`). ONLY applicable when `method = "glasso"`. For an estimated inverse convariance Z, the program only calculates log(det(Z)) - trace(SZ) where S is the empirical covariance matrix. For the likelihood for n observations, please multiply by n/2.

Note

This function ONLY estimates the graph path. For more information about the optimal graph selection, please refer to `huge.select`.

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See Also

huge.generator, huge.select, huge.plot, huge.roc, and huge-package.

Examples

```
#generate data
L = huge.generator(n = 50, d = 12, graph = "hub", g = 4)

#graph path estimation using mb
out1 = huge(L$data)
out1
plot(out1)  #Not aligned
plot(out1, align = TRUE) #Aligned
huge.plot(out1$path[[3]])

#graph path estimation using the sample covariance matrix as the input.
#out1 = huge(cor(L$data))
#out1
#plot(out1)  #Not aligned
#plot(out1, align = TRUE) #Aligned
#huge.plot(out1$path[[3]])

#graph path estimation using ct
#out2 = huge(L$data,method = "ct")
#out2
#plot(out2)

#graph path estimation using glasso
#out3 = huge(L$data, method = "glasso")
#out3
#plot(out3)
```

---

huge-internal *Internal huge functions*

Description

Internal huge functions

Details

These are not intended for use by users. Please refer to huge()

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huge.generator *Data generator*

Description

Implements the data generation from multivariate normal distributions with different graph structures, including "random", "hub", "cluster", "band" and "scale-free".

Usage

```
huge.generator(n = 200, d = 50, graph = "random", v = NULL, u = NULL,
g = NULL, prob = NULL, vis = FALSE, verbose = TRUE)
```

Arguments

n	The number of observations (sample size). The default value is 200.
d	The number of variables (dimension). The default value is 50.
graph	The graph structure with 4 options: "random", "hub", "cluster", "band" and "scale-free".
v	The off-diagonal elements of the precision matrix, controlling the magnitude of partial correlations with u. The default value is 0.3.
u	A positive number being added to the diagonal elements of the precision matrix, to control the magnitude of partial correlations. The default value is 0.1.
g	For "cluster" or "hub" graph, g is the number of hubs or clusters in the graph. The default value is about d/20 if d >= 40 and 2 if d < 40. For "band" graph, g is the bandwidth and the default value is 1. NOT applicable to "random" graph.
prob	For "random" graph, it is the probability that a pair of nodes has an edge. The default value is 3/d. For "cluster" graph, it is the probability that a pair of nodes has an edge in each cluster. The default value is 6*g/d if d/g <= 30 and 0.3 if d/g > 30. NOT applicable to "hub" or "band" graphs.
vis	Visualize the adjacency matrix of the true graph structure, the graph pattern, the covariance matrix and the empirical covariance matrix. The default value is FALSE
verbose	If verbose = FALSE, tracing information printing is disabled. The default value is TRUE.

Details

Given the adjacency matrix theta, the graph patterns are generated as below:

(I) "random": Each pair of off-diagonal elements are randomly set theta[i,j]=theta[j,i]=1 for i!=j with probability prob, and 0 other wise. It results in about d*(d-1)*prob/2 edges in the graph.

(II)"hub":The row/columns are evenly partitioned into g disjoint groups. Each group is associated with a "center" row i in that group. Each pair of off-diagonal elements are set theta[i,j]=theta[j,i]=1 for i!=j if j also belongs to the same group as i and 0 otherwise. It results in d - g edges in the graph.

(III)"cluster":The row/columns are evenly partitioned into g disjoint groups. Each pair of off-diagonal elements are set theta[i,j]=theta[j,i]=1 for i!=j with the probability probif both i and j belong to the same group, and 0 other wise. It results in about g*(d/g)*(d/g-1)*prob/2 edges in the graph.

(IV)"band": The off-diagonal elements are set to be theta[i,j]=1 if 1<=|i-j|<=g and 0 other wise. It results in (2d-1-g)*g/2 edges in the graph.

(V) "scale-free": The graph is generated using B-A algorithm. The initial graph has two connected nodes and each new node is connected to only one node in the existing graph with the probability proportional to the degree of the each node in the existing graph. It results in d edges in the graph.

The adjacency matrix theta has all diagonal elements equal to 0. To obtain a positive definite precision matrix, the smallest eigenvalue of theta*v (denoted by e) is computed. Then we set the precision matrix equal to theta*v+(|e|+0.1+u)I. The covariance matrix is then computed to generate multivariate normal data.

Value

An object with S3 class "sim" is returned:

data	The n by d matrix for the generated data
sigma	The covariance matrix for the generated data
omega	The precision matrix for the generated data
sigmahat	The empirical covariance matrix for the generated data
theta	The adjacency matrix of true graph structure (in sparse matrix representation) for the generated data

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See Also

huge and huge-package

Examples

```
## band graph with bandwidth 3
L = huge.generator(graph = "band", g = 3)
plot(L)

## random sparse graph
L = huge.generator(vis = TRUE)

## random dense graph
L = huge.generator(prob = 0.5, vis = TRUE)

## hub graph with 6 hubs
L = huge.generator(graph = "hub", g = 6, vis = TRUE)

## hub graph with 8 clusters
L = huge.generator(graph = "cluster", g = 8, vis = TRUE)

## scale-free graphs
L = huge.generator(graph="scale-free", vis = TRUE)
```

---

huge.npn *Nonparanormal(npn) transformation*

Description

Implements the Gausianization to help relax the assumption of normality.

Usage

```
huge.npn(x, npn.func = "shrinkage", npn.thresh = NULL, verbose = TRUE)
```

Arguments

`x`	The `n` by `d` data matrix representing `n` observations in `d` dimensions
`npn.func`	The transformation function used in the npn transformation. If `npn.func = "truncation"`, the truncated ECDF is applied. If `npn.func = "shrinkage"`, the shrunken ECDF is applied. The default is `"shrinkage"`. If `npn.func = "skeptic"`, the nonparanormal skeptic is applied.
`npn.thresh`	The truncation threshold used in nonparanormal transformation, ONLY applicable when `npn.func = "truncation"`. The default value is `1/(4*(n^0.25)*sqrt(pi*log(n)))`.
`verbose`	If `verbose = FALSE`, tracing information printing is disabled. The default value is `TRUE`.

Details

The nonparanormal extends Gaussian graphical models to semiparametric Gaussian copula models.Motivated by sparse additive models, the nonparanormal method estimates the Gasussian copula by marginally transforming the variables using smooth functions.Computationally, the estimation of a nonparanormal transformation is very efficient and only requires one pass of the data matrix.

Value

`data`	A `d` by `d` nonparanormal correlation matrix if `npn.func = "skeptic"`, and A `n` by `d` data matrix representing `n` observations in `d` transformed dimensions other wise.

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See Also

huge and huge-package.

Examples

```
# generate nonparanormal data
L = huge.generator(graph = "cluster", g = 5)
L$data = L$data^5

# transform the data using the shrunken ECDF
Q = huge.npn(L$data)

# transform the non-Gaussian data using the truncated ECDF
Q = huge.npn(L$data, npn.func = "truncation")

# transform the non-Gaussian data using the truncated ECDF
Q = huge.npn(L$data, npn.func = "skeptic")
```

---

huge.plot *Graph visualization*

Description

Implements the graph visualization using adjacency matrix. It can automatic organize 2D embedding layout.

Usage

```
huge.plot(G, epsflag = FALSE, graph.name = "default", cur.num = 1,
location)
```

Arguments

`G`	The adjaceny matrix corresponding to the graph.
`epsflag`	If `epsflag = TRUE`, save the plot as an eps file in the target directory. The default value is `FALSE`.
`graph.name`	The name of the output eps files. The default value is "default".
`cur.num`	The number of plots saved as eps files. Only applicale when `epsflag = TRUE`. The default value is 1.
`location`	Target directory. The default value is the current working directory.

Details

The user can change `cur.num` to plot several figures and select the best one. The implementation is based on the popular package "igraph".

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See Also

huge and huge-package

Examples

```
## visualize the hub graph
L = huge.generator(graph = "hub")
huge.plot(L$theta)

## visualize the band graph
L = huge.generator(graph = "band",g=5)
huge.plot(L$theta)

## visualize the cluster graph
L = huge.generator(graph = "cluster")
huge.plot(L$theta)

#show working directory
getwd()
#plot 5 graphs and save the plots as eps files in the working directory
huge.plot(L$theta, epsflag = TRUE, cur.num = 5)
```

---

huge.roc *Draw ROC Curve for a graph path*

Description

Draws ROC curve for a graph path according to the true graph structure

Usage

```
huge.roc(path, theta, verbose = TRUE)
```

Arguments

path	A graph path.
theta	The true graph structure.
verbose	If verbose = FALSE, tracing information printing is disabled. The default value is TRUE.

Details

To avoid the horizontal oscillation, false positive rates is automaically sorted in the ascent oder and true positive rates also follow the same order.

Value

An object with S3 class "roc" is returned:

`F1`	The F1 scores along the graph path.
`tp`	The true positive rates along the graph path
`fp`	The false positive rates along the graph paths
`AUC`	Area under the ROC curve

Note

For a lasso regression, the number of nonzero coefficients is at most `n-1`. If `d>>n`, even when regularization parameter is very small, the estimated graph may still be sparse. In this case, the AUC may not be a good choice to evaluate the performance.

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See Also

`huge` and `huge-package`

Examples

```
#generate data
L = huge.generator(d = 200, graph = "cluster", prob = 0.3)
out1 = huge(L$data)

#draw ROC curve
Z1 = huge.roc(out1$path,L$theta)

#Maximum F1 score
max(Z1$F1)
```

---

huge.select — *Model selection for high-dimensional undirected graph estimation*

Description

Implements the regularization parameter selection for high dimensional undirected graph estimation. The optional approaches are rotation information criterion (ric), stability approach to regularization selection (stars) and extended Bayesian information criterion (ebic).

Usage

```
huge.select(est, criterion = NULL, ebic.gamma = 0.5, stars.thresh = 0.1,
stars.subsample.ratio = NULL, rep.num = 20, verbose = TRUE)
```

Arguments

`est`	An object with S3 class `"huge"`
`criterion`	Model selection criterion. `"ric"` and `"stars"` are available for all 3 graph estimation methods. `ebic` is only applicable when `est$method = "glasso"` in `huge()`. The default value is `"ric"`.
`ebic.gamma`	The tuning parameter for ebic. The default value is 0.5. Only applicable when `est$method = "glasso"` and `criterion = "ebic"`.
`stars.thresh`	The variability threshold in stars. The default value is `0.1`. An alternative value is `0.05`. Only applicable when `criterion = "stars"`.
`stars.subsample.ratio`	The subsampling ratio. The default value is `10*sqrt(n)/n` when `n>144` and `0.8` when `n<=144`, where `n` is the sample size. Only applicable when `criterion = "stars"`.
`rep.num`	The number of subsamplings when `criterion = "stars"` or rotations when `criterion = "ric"`. The default value is `20`. NOT applicable when `criterion = "ebic"`
`verbose`	If `verbose = FALSE`, tracing information printing is disabled. The default value is `TRUE`.

Details

Stability approach to regularization selection (stars) is a natural way to select optimal regularization parameter for all three estimation methods. It selects the optimal graph by variability of subsamplings and tends to overselect edges in Gaussian graphical models. Besides selecting the regularization parameters, stars can also provide an additional estimated graph by merging the corresponding subsampled graphs using the frequency counts. The subsampling procedure in stars may NOT be very efficient, we also provide the recent developed highly efficient, rotation information criterion approach (ric). Instead of tuning over a grid by cross-validation or subsampling, we directly estimate the optimal regularization paramter based on random Rotations. However, ric usually has very good empirical performances but suffers from underselections sometimes. Therefore, we suggest if user are sensitive of false negative rates, they should either consider increasing `r.num` or applying the stars to model selection. Extended Bayesian information criterion (ebic) is another competive approach, but the `ebic.gamma` can only be tuned by experience.

Value

An object with S3 class "select" is returned:

`refit`	The optimal graph selected from the graph path
`opt.icov`	The optimal precision matrix from the path only applicable when `method = "glasso"`
`opt.cov`	The optimal covariance matrix from the path only applicable when `method = "glasso"` and `est$cov` is avaiable.
`merge`	The graph path estimated by merging the subsampling paths. Only applicable when the input `criterion = "stars"`.
`variability`	The variability along the subsampling paths. Only applicable when the input `criterion = "stars"`.
`ebic.scores`	Extended BIC scores for regularization parameter selection. Only applicable when `criterion = "ebic"`.
`opt.index`	The index of the selected regularization parameter. NOT applicable when the input `criterion = "ric"`
`opt.lambda`	The selected regularization/thresholding parameter.
`opt.sparsity`	The sparsity level of `"refit"`.

and anything else inluded in the input `est`

Note

The model selection is NOT available when the data input is the sample covaraince matrix.

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11. N. Meinshausen and P. Buhlmann. High-dimensional Graphs and Variable Selection with the Lasso. *The Annals of Statistics*, 2006.

See Also

huge and huge-package.

Examples

```
#generate data
L = huge.generator(d = 20, graph="hub")
out.mb = huge(L$data)
out.ct = huge(L$data, method = "ct")
out.glasso = huge(L$data, method = "glasso")

#model selection using ric
out.select = huge.select(out.mb)
plot(out.select)

#model selection using stars
#out.select = huge.select(out.ct, criterion = "stars", stars.thresh = 0.05,rep.num=10)
#plot(out.select)

#model selection using ebic
out.select = huge.select(out.glasso,criterion = "ebic")
plot(out.select)
```

plot.huge *Plot function for S3 class "huge"*

Description

Plot sparsity level information and 3 typical sparse graphs from the graph path

Usage

```
## S3 method for class 'huge'
plot(x, align = FALSE, ...)
```

Arguments

`x`	An object with S3 class `"huge"`
`align`	If `align = FALSE`, 3 plotted graphs are aligned
`...`	System reserved (No specific usage)

Author(s)

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Lasso. *The Annals of Statistics*, 2006.

See Also

huge

---

plot.roc *Plot function for S3 class "roc"*

Description

Plot the ROC curve for an object with S3 class "roc"

Usage

```
## S3 method for class 'roc'
plot(x, ...)
```

Arguments

x	An object with S3 class "roc"
...	System reserved (No specific usage)

Author(s)

Tuo Zhao, Han Liu, Kathryn Roeder, John Lafferty, and Larry Wasserman
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References

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See Also

huge.roc

---

plot.select — *Plot function for S3 class "select"*

Description

Plot the optimal graph by model selection

Usage

```
## S3 method for class 'select'
plot(x, ...)
```

Arguments

x	An object with S3 class "select"
...	System reserved (No specific usage)

Author(s)

Tuo Zhao, Han Liu, Kathryn Roeder, John Lafferty, and Larry Wasserman
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References

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See Also

`huge.select`

`plot.sim` *Plot function for S3 class "sim"*

Description

Visualize the covariance matrix, the empirical covariance matrix, the adjacency matrix and the graph pattern of the true graph structure

Usage

```
## S3 method for class 'sim'
plot(x, ...)
```

Arguments

`x`	An object with S3 class `"sim"`
`...`	System reserved (No specific usage)

Author(s)

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See Also

`huge.generator` and `huge`

`print.huge` *Print function for S3 class "huge"*

Description

Print the information about the model usage, the graph path length, graph dimension, sparsity level

Usage

```
## S3 method for class 'huge'
print(x, ...)
```

Arguments

`x`	An object with S3 class "huge"
`...`	System reserved (No specific usage)

Author(s)

Tuo Zhao, Han Liu, Kathryn Roeder, John Lafferty, and Larry Wasserman
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See Also

`huge` and `huge`

`print.roc` *Print function for S3 class "roc"*

Description

Print the information about true positive rates, false positive rates, the area under curve and maximum F1 score

Usage

```
## S3 method for class 'roc'
print(x, ...)
```

Arguments

`x`	An object with S3 class `"roc"`
`...`	System reserved (No specific usage)

Author(s)

Tuo Zhao, Han Liu, Kathryn Roeder, John Lafferty, and Larry Wasserman
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11. N. Meinshausen and P. Buhlmann. High-dimensional Graphs and Variable Selection with the Lasso. *The Annals of Statistics*, 2006.

See Also

`huge.roc` and `huge`

`print.select` *Print function for S3 class "select"*

Description

Print the information about the model usage, graph dimension, model selection criterion, sparsity level of the optimal graph

Usage

```
## S3 method for class 'select'
print(x, ...)
```

Arguments

`x`	An object with S3 class "select"
`...`	System reserved (No specific usage)

Author(s)

Tuo Zhao, Han Liu, Kathryn Roeder, John Lafferty, and Larry Wasserman
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11. N. Meinshausen and P. Buhlmann. High-dimensional Graphs and Variable Selection with the Lasso. *The Annals of Statistics*, 2006.

See Also

`huge.select` and `huge`

print.sim *Print function for S3 class "sim"*

Description

Print the information about the sample size, the dimension, the pattern and sparsity of the true graph strcture.

Usage

```
## S3 method for class 'sim'
print(x, ...)
```

Arguments

x	An object with S3 class "sim"
...	System reserved (No specific usage)

Author(s)

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11. N. Meinshausen and P. Buhlmann. High-dimensional Graphs and Variable Selection with the

Lasso. *The Annals of Statistics*, 2006.

See Also

huge.generator and huge.generator

`stockdata` *Stock price of S&P 500 companies from 2003 to 2008*

Description

This data set consists of stock price and company information.

Usage

```
data(stockdata)
```

Format

The format is a list containing conatins two matrices. 1. data - 1258x452, represents the 452 stocks' close prices for 1258 trading days. 2. info - 452x3: The 1st column: the query symbol for each company. The 2nd column: the categoriy for each company. The 3rd column: the full name of each company.

Details

This data set can be used to perform high-dimensional graph estimation to analyze the relationships between S&P 500 companies.

Author(s)

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Source

It is publicly available at http://ichart.finance.yahoo.com

References

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Examples

```
data(stockdata)
image(stockdata$data)
stockdata$info
```

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