

# Package ‘sparseSEM’

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**Type** Package

**Title** Sparse-aware Maximum Likelihood for Structural Equation Models

**Version** 2.5

**Date** 2013-09-03

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**Description** Sparse-aware maximum likelihood for structural equation models in inferring gene regulatory networks

**License** GPL

**NeedsCompilation** yes

**Repository** CRAN

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sparseSEM-package	<i>sparseSEM: Sparse-aware Maximum Likelihood for Structural Equation Models in Inferring Gene Regulatory Networks</i>
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## Description

state-of-the-art sparse aware maximum likelihood function for structural equation models. Two penalty functions including the Lasso and Elastic net available. Version 2.5: Fix a bug in internal function cv\_gene\_nets\_support\_adaENcv; no memory issue with Valgrind check.

## Details

Package:	sparseSEM
Type:	Package
Version:	2.5
Date:	2014-09-03
License:	GPL

## Author(s)

Anhui Huang  
 Maintainer: Anhui Huang <a.huang1@umiami.edu>

## References

1. Cai, X., Bazerque, J.A., and Giannakis, G.B. (2013). Inference of Gene Regulatory Networks with Sparse Structural Equation Models Exploiting Genetic Perturbations. PLoS Comput Biol 9, e1003068.
2. Huang A., Bazerque J. A., Giannakis G. B., DUroso G., Myers C. L., Cai X., Elastic Net algorithm for inferring gene regulatory networks based on structural equation models, to be submitted.

## Examples

```
library(sparseSEM)
```

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## Description

B is the M by M matrix defining network topology

**Usage**

```
data(B)
```

**Format**

The format is: M by M, where M is the number of vertices (genes) num [1:30, 1:30] 0 0 0 0 0 ...

**Details**

If B is not available (real data): the stat output that describes the true accuracy and FDR should be ignored.

**References**

1. Cai, X., Bazerque, J.A., and Giannakis, G.B. (2013). Inference of Gene Regulatory Networks with Sparse Structural Equation Models Exploiting Genetic Perturbations. PLoS Comput Biol 9, e1003068.
2. Huang A., Bazerque J. A., Giannakis G. B., DUroso G., Myers C. L., Cai X., Elastic Net algorithm for inferring gene regulatory networks based on structural equation models, to be submitted.

**Examples**

```
data(B)
```

elasticNetSML

*The Elastic Net penalty for SEM***Description**

For each alpha from 0.95 to 0.05 at a step of 0.05, the function perform 5 fold CV for lambda\_max to lambda\_min in 20 step to determine the optimal alpha and lambda for the data.

**Usage**

```
elasticNetSML(Y, X, Missing, B, Verbose = 0)
```

**Arguments**

Y	gene expression M by N matrix
X	cis_eQTL M by N matrix
Missing	missing data in Y
B	true network topology if available
Verbose	describe the information output from 0 - 10, larger number means more output

## Details

the function perform CV and parameter inference, calculate power and FDR

## Value

Bout	the matrix B from sparseSEM
fout	f: the weight for matrix X
stat	compute the power and FDR statistics if the ture topology is provided
simTime	computational time

## Note

Difference in three functions:

- 1) elasticNetsML: Default alpha = 0.95: -0.05: 0.05; default 20 lambdas
- 2) elasticNetsMLcv: user supplied alphas (one or more), lambdas; compute the optimal parameters and network parameters
- 3) elasticNetsMLpoint: user supplied one alpha and one lambda, compute the network parameters

## Author(s)

Anhui Huang; Dept of Electrical and Computer Engineering, Univ of Miami, Coral Gables, FL

## References

1. Cai, X., Bazerque, J.A., and Giannakis, G.B. (2013). Inference of Gene Regulatory Networks with Sparse Structural Equation Models Exploiting Genetic Perturbations. PLoS Comput Biol 9, e1003068.
2. Huang A., Bazerque J. A., Giannakis G. B., DUroso G., Myers C. L., Cai X., Elastic Net algorithm for inferring gene regulatory networks based on structural equation models, to be submitted.

## Examples

```
library(sparseSEM)
data(B);
data(Y);
data(X);
data(Missing);
#Example is commented to satisfy CRAN's CPU time limit requirement.
#OUT <- elasticNetSML(Y, X, Missing, B, Verbose = 1);
```

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elasticNetSMLcv	<i>The Elastic Net penalty for SEM with user supplied alphas and lambdas</i>
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## Description

While elasticNetSML function has a set of default (alpha, lambda) and the optimal one is chosen by 5 fold cv, elasticNetSMLcv tests the combination of a set of alpha and lambda, and choose one as the optimal parameters. elasticNetSMLcv should be combined with elasticNetSMLpoint to obtain the network inference. For each alpha from the set of alphas provided, the function perform 5 fold CV for each user supplied lambda to determine the optimal alpha and lambda for the data.

## Usage

```
elasticNetSMLcv(Y, X, Missing, B, alpha_factors, lambda_factors, Verbose)
```

## Arguments

Y	gene expression M by N matrix
X	cis_eQTL M by N matrix
Missing	missing data in Y
B	true network topology if available
alpha_factors	alpha_factors: the set of alphas to be tested, and is in range of (0, 1);
lambda_factors	penalty lambda_factor: the set of lambda to be tested, and is in range of (0, 1);
Verbose	describe the information output from 0 - 10, larger number means more output

## Details

the function perform CV and parameter inference, calculate power and FDR

## Value

Bout	the matrix B from sparseSEM
fout	f: the weight for matrix X
stat	compute the power and FDR statistics if the true topology is provided
simTime	computational time
residual	only meaningful for 1 alpha: col1: lambdas; col2: mean of residual error in k-fold CV col3: standard error of residual error in k-fold CV

## Note

Difference in three functions:

- 1) elasticNetsML: Default alpha = 0.95: -0.05: 0.05; default 20 lambdas
- 2) elasticNetSMLcv: user supplied alphas (one or more), lambdas; compute the optimal parameters and network parameters
- 3) elasticNetSMLpoint: user supplied one alpha and one lambda, compute the network parameters

## Author(s)

Anhui Huang; Dept of Electrical and Computer Engineering, Univ of Miami, Coral Gables, FL

## References

1. Cai, X., Bazerque, J.A., and Giannakis, G.B. (2013). Inference of Gene Regulatory Networks with Sparse Structural Equation Models Exploiting Genetic Perturbations. PLoS Comput Biol 9, e1003068.
2. Huang A., Bazerque J. A., Giannakis G. B., DUroso G., Myers C. L., Cai X., Elastic Net algorithm for inferring gene regulatory networks based on structural equation models, to be submitted.

## Examples

```
library(sparseSEM)
data(B);
data(Y);
data(X);
data(Missing);
OUT <- elasticNetSMLcv(Y, X, Missing, B, alpha_factors = c(0.75, 0.5, 0.25),
lambda_factors=c(0.1, 0.01, 0.001), Verbose = 1);
```

elasticNetSMLpoint     *The Elastic Net penalty for SEM*

## Description

This function can be used after elasticNetSMLcv determines the optimal parameters. For user supplied one alpha in range of (0,1) and one lambda, the function perform selection path from lambda\_max to lambda to determine the optimal network topology.

## Usage

```
elasticNetsMLpoint(Y, X, Missing, B, alpha_factor, lambda_factor, Verbose)
```

## Arguments

Y	gene expression M by N matrix
X	cis_eQTL M by N matrix
Missing	missing data in Y
B	true network topology if available
alpha_factor	alpha_factor: in range of (0, 1); must be scalar
lambda_factor	penalty lambda_factor: in range of (0, 1); must be scalar
Verbose	describe the information output from 0 - 10, larger number means more output

## Details

the function perform selection path from lambda\_max to lambda, calculate power and FDR

## Value

Bout	the matrix B from sparseSEM
fout	f: the weight for matrix X
stat	compute the power and FDR statistics if the ture topology is provided
simTime	computational time

## Note

Difference in three functions:

- 1) elasticNetSML: Default alpha = 0.95: -0.05: 0.05; default 20 lambdas
- 2) elasticNetSMLcv: user supplied alphas (one or more), lambdas; compute the optimal parameters and network parameters
- 3) elasticNetSMLpoint: user supplied one alpha and one lambda, compute the network parameters

## Author(s)

Anhui Huang; Dept of Electrical and Computer Engineering, Univ of Miami, Coral Gables, FL

## References

1. Cai, X., Bazerque, J.A., and Giannakis, G.B. (2013). Inference of Gene Regulatory Networks with Sparse Structural Equation Models Exploiting Genetic Perturbations. PLoS Comput Biol 9, e1003068.
2. Huang A., Bazerque J. A., Giannakis G. B., DUroso G., Myers C. L., Cai X., Elastic Net algorithm for inferring gene regulatory networks based on structural equation models, to be submitted.

## Examples

```
library(sparseSEM)
data(B);
data(Y);
data(X);
data(Missing);
OUT <- elasticNetSMLpoint(Y, X, Missing, B,
alpha_factor = 0.5, lambda_factor = 0.1, Verbose = 1);
```

**lassoSML**

*The Lasso penalty for SML*

## Description

Upon lambda\_max to lambda\_min in 20 step, the function compute 5 fold CV to determine the optimal lambda for the data.

## Usage

```
lassoSML(Y, X, Missing, B, Verbose = 5)
```

## Arguments

Y	gene expression M by N matrix
X	cis_eQTL M by N matrix
Missing	missing data in Y
B	true network topology if available
Verbose	describe the information output from 0 - 10, larger number means more output

## Details

the function perform CV and parameter inference, calculate power and FDR

## Value

Bout	the matrix B from SEM
fout	f: the weight for matrix X
stat	compute the power and FDR statistics if the true topology is provided
simTime	computational time

## Author(s)

Anhui Huang; Dept of Electrical and Computer Engineering, Univ of Miami, Coral Gables, FL

## References

1. Cai, X., Bazerque, J.A., and Giannakis, G.B. (2013). Inference of Gene Regulatory Networks with Sparse Structural Equation Models Exploiting Genetic Perturbations. PLoS Comput Biol 9, e1003068.
2. Huang A., Bazerque J. A., Giannakis G. B., DUroso G., Myers C. L., Cai X., Elastic Net algorithm for inferring gene regulatory networks based on structural equation models, to be submitted.

## Examples

```
library(sparseSEM)
data(B);
data(Y);
data(X);
data(Missing);
OUT <- lassoSML(Y, X, Missing, B, Verbose = 1);
```

Missing

*Missing gene expression data*

## Description

M by N matrix corresponding to elements of Y. 0 denotes no missing, while 1 denotes missing

## Usage

```
data(Missing)
```

## Format

The format is: num [1:30, 1:200] 0 0 0 0 0 0 0 0 0 ...

## References

1. Cai, X., Bazerque, J.A., and Giannakis, G.B. (2013). Inference of Gene Regulatory Networks with Sparse Structural Equation Models Exploiting Genetic Perturbations. PLoS Comput Biol 9, e1003068.
2. Huang A., Bazerque J. A., Giannakis G. B., DUroso G., Myers C. L., Cai X., Elastic Net algorithm for inferring gene regulatory networks based on structural equation models, to be submitted.

## Examples

```
data(Missing)
```

X

*Genotype matrix***Description**

X is the M by N matrix corresponding to M cis-eQTL for M genes

**Usage**

```
data(X)
```

**Format**

The format is: int [1:30, 1:200] 2 1 3 1 2 3 2 1 2 2 ...

**Details**

current implementation only consider 1 eQTL per gene

**References**

1. Cai, X., Bazerque, J.A., and Giannakis, G.B. (2013). Inference of Gene Regulatory Networks with Sparse Structural Equation Models Exploiting Genetic Perturbations. PLoS Comput Biol 9, e1003068.
2. Huang A., Bazerque J. A., Giannakis G. B., DUroso G., Myers C. L., Cai X., Elastic Net algorithm for inferring gene regulatory networks based on structural equation models, to be submitted.

**Examples**

```
data(X)
```

Y

*Gene expression matrix***Description**

Y is the M by N matrix describes the expression profile of M genes in N samples

**Usage**

```
data(Y)
```

**Format**

The format is: num [1:30, 1:200] 3.02 1.12 -2.24 3.58 2.18 ...

**Details**

Gene expression data

**References**

1. Cai, X., Bazerque, J.A., and Giannakis, G.B. (2013). Inference of Gene Regulatory Networks with Sparse Structural Equation Models Exploiting Genetic Perturbations. PLoS Comput Biol 9, e1003068.
2. Huang A., Bazerque J. A., Giannakis G. B., DUroso G., Myers C. L., Cai X., Elastic Net algorithm for inferring gene regulatory networks based on structural equation models, to be submitted.

**Examples**

```
data(Y)
```

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