

# Package: SELF (via r-universe)

August 22, 2024

**Type** Package

**Title** A Structural Equation Embedded Likelihood Framework for Causal Discovery

**Version** 0.1.1

**Author** Ruichu Cai [ths, aut], Jie Qiao [aut, cre], Zhenjie Zhang [ths, aut], Zhifeng Hao [ths, aut]

**Maintainer** Jie Qiao <qiaojie2004@vip.qq.com>

**Description** Provides the SELF criteria to learn causal structure.  
Please cite ``Ruichu Cai, Jie Qiao, Zhenjie Zhang, Zhifeng Hao.  
SELF: Structural Equation Embedded Likelihood Framework for  
Causal Discovery. AAI. 2018."`

**License** GPL-2

**LazyData** true

**Imports** data.table (>= 1.10.4), xgboost (>= 0.6-4), Rcpp (>= 0.12.10),  
CompareCausalNetworks (>= 0.1.0), bnlearn (>= 4.1.1)

**LinkingTo** Rcpp

**RoxygenNote** 6.0.1

**Encoding** UTF-8

**NeedsCompilation** yes

**Repository** CRAN

**Date/Publication** 2017-11-22 13:24:22 UTC

## Contents

SELF-package . . . . .	2
fhc . . . . .	2
indicators . . . . .	4
mmpcAnm . . . . .	4
randomGraph . . . . .	5
synthetic_data_linear . . . . .	5
synthetic_data_nonlinear . . . . .	6

<b>Index</b>	<b>7</b>
--------------	----------

---

SELF-package	<i>SELF: A Structural Equation Embedded Likelihood Framework for Causal Discovery</i>
--------------	---

---

### Description

Provides the SELF criteria to learn causal structure. Please cite "Ruichu Cai, Jie Qiao, Zhenjie Zhang, Zhifeng Hao. SELF: Structural Equation Embedded Likelihood Framework for Causal Discovery. AAAI. 2018."

### Author(s)

**Maintainer:** Jie Qiao <qiaojie2004@vip.qq.com>

**Authors:**

- Ruichu Cai <cairuichu@gmail.com> [thesis advisor]
- Zhenjie Zhang <zhenjie@adsc.com.sg> [thesis advisor]
- Zhifeng Hao <zfhao@gdut.edu.cn> [thesis advisor]

---

fhc	<i>Fast Hill-Climbing</i>
-----	---------------------------

---

### Description

The function for the causal structure learning.

### Usage

```
fhc(D, G = NULL, min_increase = 0.01, score_type = "bic", file = "",
    verbose = TRUE, save_model = FALSE, bw = "nrd0", booster = "gbtree",
    gamma = 10, nrounds = 30, ...)
```

### Arguments

D	Input Data.
G	An initial graph for hill climbing. Default: empty graph.
min_increase	Minimum score increase for faster convergence.
score_type	You can choose "bic", "log", "aic" score to learn the causal structure. Default: bic
file	Specifies the output folder and its path to save the model at each iteration.
verbose	Show the progress bar for each iteration.
save_model	Save the meta data during the iteration so that you can easily restore progress and evaluate the model during iteration.

bw	the smoothing bandwidth which is the parameter of the function stats::density(Kernel stats::density Estimation)
booster	Choose the regression method, it could be "lm", "gbtree" and "gblinear". The "lm" and "gblinear" is the linear regression methods and "gbtree" is the nonlinear regression method. Default: gbtree
gamma	The parameter in xgboost: minimum loss reduction required to make a further partition on a leaf node of the tree. the larger, the more conservative the algorithm will be.
nrounds	the maximum number of trees for xgboost.Default:30.
...	other parameters for xgboost.see also: help(xgboost)

### Value

The adjacency matrix of the casual structure.

### Examples

```
## Not run:
#x->y->z
set.seed(0)
x=rnorm(4000)
y=x^2+runif(4000,-1,1)*0.1
z=y^2+runif(4000,-1,1)*0.1
data=data.frame(x,y,z)
fhc(data,gamma=10,booster = "gbtree")

#x->y->z linear data
set.seed(0)
x=rnorm(4000)
y=3*x+runif(4000,-1,1)*0.1
z=3*y+runif(4000,-1,1)*0.1
data=data.frame(x,y,z)
fhc(data,booster = "lm")

#randomGraph with linear data

set.seed(0)
G=randomGraph(dim=10,indegree=1.5)
data=synthetic_data_linear(G=G,sample_num=4000)
fitG=fhc(data,booster = "lm")
indicators(fitG,G)

## End(Not run)
```

---

 indicators

*Calculate the f1,precision,recall score of the graph*


---

**Description**

Calculate the f1,precision,recall score of the graph

**Usage**

```
indicators(pred, real)
```

**Arguments**

pred            Predicted graph

real            Real graph

**Value**

f1,precision,recall score.

**Examples**

```
pred<-matrix(c(0,0,0,0,1,0,1,1,0),nrow=3,ncol=3)
real<-matrix(c(0,0,0,0,1,0,1,0,0),nrow=3,ncol=3)
indicators(pred,real)
```

---

 mmpcAnm

*mmpc algorithm with additive noise model*


---

**Description**

The nonlinear data comparison algorithm. We use the mmpc algorithm to learn a causal skeleton and use ANM to recognize the direction

**Usage**

```
mmpcAnm(data)
```

**Arguments**

data            The data

---

randomGraph	<i>Generate a random graph</i>
-------------	--------------------------------

---

**Description**

Generate a random graph based on the given dimension size and average indegree

**Usage**

```
randomGraph(dim, indegree, maxite = 10000)
```

**Arguments**

dim	The dimension of the random graph
indegree	The average indegree of random graph for each nodes
maxite	The maximum iterations to find the random graph

**Value**

Return a random graph

**Examples**

```
randomGraph(dim=10, indegree=1)
```

---

synthetic_data_linear	<i>synthetic linear data base on the graph</i>
-----------------------	--

---

**Description**

Synthetic linear data base on the graph. The noises are sampled from the super-gaussian distribution. The coefficients are sample from  $U(-1,-0.5), U(0.5,1)$

**Usage**

```
synthetic_data_linear(G, sample_num, ratio = 1, return_noise = FALSE)
```

**Arguments**

G	An adjacency matrix.
sample_num	The number of samples
ratio	The noise ratio It will grow or shrink the value of the noise
return_noise	Whether return the noise of each nodes for further analysis.

**Value**

Return a synthetic data

**Examples**

```
G<-matrix(c(0,1,1,1,0,0,0,0,0,0,0,0,0,0,0),nrow = 4,ncol = 4)
data=synthetic_data_linear(G,100)
```

---

synthetic\_data\_nonlinear

*synthetic nonlinear data base on the graph*

---

**Description**

synthetic nonlinear data base on the graph. The data generation mechanism is  $y=\text{scale}(a1b1x^2+a2b2x^3+a3b3x^4+a4b4\sin(x))$

**Usage**

```
synthetic_data_nonlinear(G, sample_num, ratio = 1, return_noise = FALSE)
```

**Arguments**

G	An adjacency matrix.
sample_num	The number of samples
ratio	The noise ratio. It will grow or shrink the value of the noise.
return_noise	Whether return the noise of each nodes for further analysis.

**Value**

Return a synthetic data

**Examples**

```
G<-matrix(c(0,1,1,1,0,0,0,0,0,0,0,0,0,0,0),nrow = 4,ncol = 4)
data=synthetic_data_nonlinear(G,100)
```

# Index

`fhc`, [2](#)

`indicators`, [4](#)

`mmpcAnm`, [4](#)

`randomGraph`, [5](#)

`SELF (SELF-package)`, [2](#)

`SELF-package`, [2](#)

`synthetic_data_linear`, [5](#)

`synthetic_data_nonlinear`, [6](#)