

# Package ‘discretedAlgorithm’

March 12, 2020

**Type** Package

**Title** Coordinate-Descent Algorithm for Learning Sparse Discrete  
Bayesian Networks

**Version** 0.0.7

**Description** Structure learning of Bayesian network using coordinate-descent  
algorithm. This algorithm is designed for discrete network assuming a multinomial data set,  
and we use a multi-logit model to do the regression.  
The algorithm is described in Gu, Fu and Zhou (2016) <arXiv:1403.2310>.

**License** GPL (>= 2)

**LazyData** TRUE

**Depends** R (>= 3.2.3)

**Imports** Rcpp (>= 0.11.0), sparsebnUtils (>= 0.0.4), igraph

**Suggests** testthat,

**LinkingTo** Rcpp, RcppEigen

**RoxygenNote** 7.0.2

**SystemRequirements** C++11

**NeedsCompilation** yes

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**Repository** CRAN

**Date/Publication** 2020-03-12 06:40:02 UTC

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cd.run

*cd.run***Description**

Structure learning of discrete Bayesian network

**Usage**

```
cd.run(
  indata,
  weights = NULL,
  lambdas = NULL,
  lambdas.length = 30,
  whitelist = NULL,
  blacklist = NULL,
  error.tol = 1e-04,
  convLb = 0.01,
  weight.scale = 1,
  upperbound = 100,
  alpha = 3,
  permute = FALSE,
  adaptive = FALSE
)
```

**Arguments**

<code>indata</code>	A <code>sparsebnData</code> object.
<code>weights</code>	Weight matrix. Weight can be the $l_2$ norm of a consistent estimate of $\beta_{\{j,i\}}$ . See paper <a href="#">Gu et al. (2016)</a> chapter 3.3 for more details. A weight matrix that is set improperly may cause convergence issues and lead to a suboptimal solution.
<code>lambdas</code>	Numeric vector containing a grid of lambda values (i.e. regularization parameters) to use in the solution path. If missing, a default grid of values will be used based on a decreasing log-scale. To generate a sequence of lambdas see <a href="#">generate.lambdas</a> . For discrete network, the paper provided a way to calculate a maximum lambda that penalizes all parameters to zero, <a href="#">Gu et al. (2016)</a> chapter 3.4. See function <a href="#">max_lambda</a> for details.
<code>lambdas.length</code>	Integer number of values to include in the solution path.
<code>whitelist</code>	A two-column matrix of edges that are guaranteed to be in each estimate (a "white list"). Each row in this matrix corresponds to an edge that is to be whitelisted. These edges can be specified by node name (as a character matrix), or by index (as a numeric matrix).
<code>blacklist</code>	A two-column matrix of edges that are guaranteed to be absent from each estimate (a "black list"). See argument "whitelist" above for more details.
<code>error.tol</code>	Error tolerance for the algorithm, used to test for convergence.

convLb	Small positive number used in Hessian approximation.
weight.scale	A positive number to scale weight matrix.
upperbound	A large positive value used to truncate the adaptive weights. A -1 value indicates that there is no truncation.
alpha	Threshold parameter used to terminate the algorithm whenever the number of edges in the current DAG estimate is $> \alpha * \text{ncol}(\text{data})$ .
permute	A bool parameter, default value is FALSE. If TRUE, will randomize order of going through blocks.
adaptive	A bool parameter, default value is FALSE. If FALSE, a regular lasso algorithm will be run. If TRUE, an adaptive lasso algorithm will be run.

## Details

Estimate structure of a discrete Bayesian network from observational/interventional data using the CD algorithm described in [Gu et al. \(2016\)](#).

Instead of producing a single estimate, this algorithm computes a solution path of estimates based on the values supplied to `lambdas` or `lambdas.length`. This package do not provide a model selection method in this version, users can choose their own model selection criterion. In later version of this package we will provide an empirical model selection method.

This package can handle interventional data by input a list of intervention. See example for more detail.

## Value

A `sparsebnPath` object. The CD Algorithm will be stopped if the number of edges exceeds 3 times of number of variables.

## Examples

```
## Not run:

### Generate some random data
dat <- matrix(rbinom(200, size = 3, prob = 0.4), nrow = 20)
# for observational data
dat_obs <- sparsebnUtils::sparsebnData(dat, type = "discrete")
# for interventional data
data_size <- nrow(dat)
ivn <- lapply(1:data_size, function(x){return(as.integer(x/10))})
# if there is no intervention for an observation, use 0.
# cd algorithm can handle multiple interventions for a single observation.
dat_int <- sparsebnUtils::sparsebnData(dat, ivn = ivn, type = "discrete")

# Run with default settings for observational data
cd.run(indata = dat_obs)
# Run with default settings for interventional data
cd.run(indata = dat_int)
# Run adaptive algorithm for observational data
cd.run(indata = dat_obs, adaptive = TRUE)
```

```
### Optional: Adjust settings
n_node <- ncol(dat)

# Run algorithm with a given weight
# Careful with this option.
weights <- matrix(1, nrow = n_node, ncol = n_node)

# Run with adjusted settings
cd.run(indata = dat_obs, weights = weights, lambdas.length = 10)

# Note: Normally, users do not need to change default settings.

## End(Not run)
```

---

coef\_gen

*coef\_gen*

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## Description

coefficient generating function

## Usage

```
coef_gen(edge_list, n_levels = NULL, FUN = NULL, flip = TRUE)
```

## Arguments

edge_list	a <a href="#">edgeList</a> object.
n_levels,	a list of number of levels for each node.
FUN,	a probability distribution to generate coefficients
flip,	a bool parameter. If true, will randomly flip the sign of coefficients.

## Value

A list of coefficient matrix

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data_gen	<i>data_gen</i>
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**Description**

A function that generate discrete data set.

**Usage**

```
data_gen(
  graph,
  n,
  ivn = NULL,
  n_levels = NULL,
  params = NULL,
  FUN = NULL,
  flip = TRUE
)
```

**Arguments**

graph	a <a href="#">edgeList</a> object.
n	size of the data set, a scalar
ivn,	a list of intervention for each data point.
n_levels,	a list of number of levels for each node, default is binary data set.
params,	coefficient list (optional).
FUN,	a function to generate magnitude of influence (optional).
flip,	a bool parameter. If true, when generating coefficients, will randomly flip the sign of coefficients.

**Value**

data matrix

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generate_discrete_data	<i>generate_discrete_data</i>
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**Description**

data generating function

**Usage**

```
generate_discrete_data(
  graph,
  params,
  n,
  ivn = NULL,
  ivn.rand = TRUE,
  n_levels = NULL
)
```

**Arguments**

graph	A <code>edgeList</code> object.
params	Coefficient list.
n	Size of the data set, a scalar
ivn	List of interventions.
ivn.rand	If TRUE, random values will be drawn uniformly for each intervention. Otherwise, these values need to be supplied manually in ivn.
n_levels	A vector of number of levels for each node. Default is binary data.

**Value**

data matrix

**Examples**

```
### generate observational data
gr <- sparsebnUtils::random.graph(5, 5) # use sparsebnUtils package to generate a random graph
names(gr) = c("V1", "V2", "V3", "V4", "V5")
nlevels <- c(3, 5, 2, 2, 3)
gr.params <- coef_gen(edge_list = gr, n_levels = nlevels)
data.obs <- discretecdAlgorithm::generate_discrete_data(graph = gr,
                                                       n = 100,
                                                       n_levels = nlevels,
                                                       params = gr.params)

### generate experimental data
ivn <- as.list(c(rep("V1", 50), rep("V2", 50))) # 50 interventions on V1, 50 interventions on V2
data.ivn <- discretecdAlgorithm::generate_discrete_data(graph = gr,
                                                       n = 100,
                                                       n_levels = nlevels,
                                                       params = gr.params,
                                                       ivn = ivn)

### Use pre-specified values for interventions
### In this toy example, we assume that all intervened nodes were fixed to
### to the value 1, although this can be any number of course.
ivn.vals <- lapply(ivn, function(x) sapply(x, function(x) 1)) # replace all entries with a 1
```

```
data.ivn <- discretedAlgorithm::generate_discrete_data(graph = gr,
                                                    n = 100,
                                                    n_levels = nlevels,
                                                    params = gr.params,
                                                    ivn = ivn.vals,
                                                    ivn.rand = FALSE)
```

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max\_lambda

*max\_lambda*


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### Description

A method to calculate the value of maximum lambda along a solution path. See paper [Gu et al. \(2016\)](#) chapter 3.4 for more detail.

### Usage

```
max_lambda(indata, weights = NULL, weight.scale = 1, upperbound = 100)
```

### Arguments

indata	A sparsebnData object
weights	Weight matrix
weight.scale	A positive number to scale weight matrix.
upperbound	A large positive value used to truncate the adaptive weights. A -1 value indicates that there is no truncation.

### Value

The maximum lambda along the solution path.

### Examples

```
## Not run:

### Generate some random data
dat <- matrix(rbinom(200, size = 3, prob = 0.4), nrow = 20)
# for observational data
dat <- sparsebnUtils::sparsebnData(dat, type = "discrete")

# generate the maximum lambda
max_lambda(indata = dat)

## End(Not run)
```

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