Package ‘bnclassify’

November 30, 2019

Title Learning Discrete Bayesian Network Classifiers from Data

Description
State-of-the art algorithms for learning discrete Bayesian network classifiers from data, including a number of those described in Bielza & Larranaga (2014) <doi:10.1145/2576868>, with functions for prediction, model evaluation and inspection.

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BugReports http://github.com/bmihaljevic/bnclassify/issues

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License GPL (>= 2)

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accuracy .......................................................... 2
Compute predictive accuracy.

Description
Compute predictive accuracy.

Usage
accuracy(x, y)

Arguments
x A vector of predicted labels.
y A vector of true labels.

Examples
data(car)
nb <- bnc('nb', 'class', car, smooth = 1)
p <- predict(nb, car)
accuracy(p, car$class)
Learn an AODE ensemble.

**Description**

If there is a single predictor then returns a naive Bayes.

**Usage**

```r
aode(class, dataset, features = NULL)
```

**Arguments**

- `class`: A character. Name of the class variable.
- `dataset`: The data frame from which to learn the classifier.
- `features`: A character vector. The names of the features. This argument is ignored if `dataset` is provided.

**Value**

A `bnc_aode` or a `bnc_dag` (if returning a naive Bayes)

---

Convert to mlr.

**Description**

Convert a `bnc_bn` to a Learner object.

**Usage**

```r
as_mlr(x, dag, id = "1")
```

**Arguments**

- `x`: A `bnc_bn` object.
- `dag`: A logical. Whether to learn structure on each training subsample. Parameters are always learned.
- `id`: A character.

**Examples**

```r
data(car)
nb <- bnc('nb', 'class', car, smooth = 1)
## Not run: library(mlr)
## Not run: nb_mlr <- as_mlr(nb, dag = FALSE, id = "ode_cl_aic")
## Not run: nb_mlr
```
bnc

Learn network structure and parameters.

Description
A convenience function to learn the structure and parameters in a single call. Must provide the name of the structure learning algorithm function; see \texttt{bnclassify} for the list.

Usage

\begin{verbatim}
bnc(dag_learner, class, dataset, smooth, dag_args = NULL, awnb_trees = NULL, awnb_bootstrap = NULL, manb_prior = NULL, wanbia = NULL)
\end{verbatim}

Arguments

\begin{itemize}
\item \texttt{dag_learner} A character. Name of the structure learning function.
\item \texttt{class} A character. Name of the class variable.
\item \texttt{dataset} The data frame from which to learn network structure and parameters.
\item \texttt{smooth} A numeric. The smoothing value ($\alpha$) for Bayesian parameter estimation. Non-negative.
\item \texttt{dag_args} A list. Optional additional arguments to \texttt{dag_learner}.
\item \texttt{awnb_trees} An integer. The number ($M$) of bootstrap samples to generate.
\item \texttt{awnb_bootstrap} A numeric. The size of the bootstrap subsample, relative to the size of \texttt{dataset} (given in [0,1]).
\item \texttt{manb_prior} A numeric. The prior probability for an arc between the class and any feature.
\item \texttt{wanbia} A logical. If TRUE, WANBIA feature weighting is performed.
\end{itemize}

Examples

\begin{verbatim}
data(car)
nb <- bnc('nb', 'class', car, smooth = 1)
nb_manb <- bnc('nb', 'class', car, smooth = 1, manb_prior = 0.3)
ode_cl_aic <- bnc('tan_cl', 'class', car, smooth = 1, dag_args = list(score = 'aic'))
\end{verbatim}

bnclassify

Learn discrete Bayesian network classifiers from data.

Description
State-of-the-art algorithms for learning discrete Bayesian network classifiers from data, with functions prediction, model evaluation and inspection.
Details

The learn more about the package, start with the vignettes: `browseVignettes(package = "bnclassify")`. The following is a list of available functionalities:

Structure learning algorithms:

- **nb**: Naive Bayes (Minsky, 1961)
- **tan_cl**: Chow-Liu’s algorithm for one-dependence estimators (CL-ODE) (Friedman et al., 1997)
- **fssj**: Forward sequential selection and joining (FSSI) (Pazzani, 1996)
- **bsej**: Backward sequential elimination and joining (BSEJ) (Pazzani, 1996)
- **tan_hc**: Hill-climbing tree augmented naive Bayes (TAN-HC) (Keogh and Pazzani, 2002)
- **tan_hcsp**: Hill-climbing super-parent tree augmented naive Bayes (TAN-HCSP) (Keogh and Pazzani, 2002)
- **aode**: Averaged one-dependence estimators (AODE) (Webb et al., 2005)

Parameter learning methods (**lp**):

- Bayesian and maximum likelihood estimation
- Weighting attributes to alleviate naive bayes’ independence assumption (WANBIA) (Zaidi et al., 2013)
- Attribute-weighted naive Bayes (AWNB) (Hall, 2007)
- Model averaged naive Bayes (MANB) (Dash and Cooper, 2002)

Model evaluating:

- **cv**: Cross-validated estimate of accuracy
- **logLik**: Log-likelihood
- **AIC**: Akaike’s information criterion (AIC)
- **BIC**: Bayesian information criterion (BIC)

Predicting:

- **predict**: Inference for complete and/or incomplete data (the latter through gRain)

Inspecting models:

- **plot**: Structure plotting (through Rgraphviz)
- **print**: Summary
- **params**: Access conditional probability tables
- **nparams**: Number of free parameters
- and more. See `inspect_bnc_dag` and `inspect_bnc_bn`. 
References


bnc_bn

Bayesian network classifier with structure and parameters.

Description

A Bayesian network classifier with structure and parameters.Returned by lp and bnc functions. You can use it to classify data (with predict). Can estimate its predictive accuracy with cv, plot its structure (with plot), print a summary to console (print), inspect it with functions documented in inspect_bnc_bn and inspect_bnc_dag, and convert it to mlr, grain, and graph objects –see as_mlr and grain_and_graph.

Examples

data(car)
tan <- bnc('tan_cl', 'class', car, smooth = 1)
tan
p <- predict(tan, car)
head(p)
## Not run: plot(tan)
nparams(tan)
### bnc_dag

**Bayesian network classifier structure.**

**Description**

A Bayesian network classifier structure, returned by functions such as `nb` and `tan_cl`. You can plot its structure (with `plot`), print a summary to console (`print`), inspect it with functions documented in `inspect_bnc_dag`, and convert it to a graph object with `grain_and_graph`.

**Examples**

```r
data(car)
nb <- tan_cl('class', car)
nb
## Not run: plot(nb)
narcs(nb)
```

### car

*Car Evaluation Data Set.*

**Description**


**Format**

A `data.frame` with 7 columns and 1728 rows.

**Source**

[http://goo.gl/GTXrCz](http://goo.gl/GTXrCz)

### cmi

**Compute the (conditional) mutual information between two variables.**

**Description**

Computes the (conditional) mutual information between two variables. If z is not `NULL` then returns the conditional mutual information, $I(X; Y | Z)$. Otherwise, returns mutual information, $I(X; Y)$.

**Usage**

```r
cmi(x, y, dataset, z = NULL, unit = "log")
```
Arguments

x A length one character.
y A length one character.
dataset A data frame. Must contain x, y and, optionally, z columns.
z A character vector.
unit A character. Logarithm base. See entropy package.

Details

\[ I(X; Y|Z) = H(X|Z) + H(Y|Z) - H(X, Y, Z) - H(Z), \]

where \( H() \) is Shannon's entropy.

Examples

data(car)

\[ \text{cv('maint', 'class', car)} \]

\[ \text{cv(x, dataset, k, dag = TRUE, mean = TRUE)} \]

Description

Estimate predictive accuracy of a classifier with stratified cross validation. It learns the models from the training subsamples by repeating the learning procedures used to obtain \( x \). It can keep the network structure fixed and re-learn only the parameters, or re-learn both structure and parameters.

Usage

\[ \text{cv(x, dataset, k, dag = TRUE, mean = TRUE)} \]

Arguments

x List of bnc_bn or a single bnc_bn. The classifiers to evaluate.
dataset The data frame on which to evaluate the classifiers.
k An integer. The number of folds.
dag A logical. Whether to learn structure on each training subsample. Parameters are always learned.
mean A logical. Whether to return mean accuracy for each classifier or to return a k-row matrix with accuracies per fold.

Value

A numeric vector of same length as \( x \), giving the predictive accuracy of each classifier. If mean = FALSE then a matrix with \( k \) rows and a column per each classifier in \( x \).
Examples

data(car)
nb <- bnc('nb', 'class', car, smooth = 1)
# CV a single classifier
cv(nb, car, k = 10)
nb_manb <- bnc('nb', 'class', car, smooth = 1, manb_prior = 0.5)
cv(list(nb=nb, manb=nb_manb), car, k = 10)
# Get accuracies on each fold
cv(list(nb=nb, manb=nb_manb), car, k = 10, mean = FALSE)
ode <- bnc('tan_cl', 'class', car, smooth = 1, dag_args = list(score = 'aic'))
# keep structure fixed across training subsamples
cv(ode, car, k = 10, dag = FALSE)

grain_and_graph  
Convert to graph and gRain.

Description

Convert a bnc_dag to graphNEL and grain objects.

Usage

as_graphNEL(x)
as_grain(x)

Arguments

x  
The bnc_bn object. The Bayesian network classifier.

Functions

• as_graphNEL: Convert to a graphNEL.
• as_grain: Convert to a grain.

Examples

data(car)
nb <- bnc('nb', 'class', car, smooth = 1)
# Requires the grain and graph packages installed
## Not run: g <- as_grain(nb)
## Not run: gRain::querygrain.grain(g)$buying
Greedy wrapper algorithms for learning Bayesian network classifiers. All algorithms use cross-validated estimate of predictive accuracy to evaluate candidate structures.

Usage

fssj(class, dataset, k, epsilon = 0.01, smooth = 0, cache_reset = NULL)
bsej(class, dataset, k, epsilon = 0.01, smooth = 0, cache_reset = NULL)
tan_hc(class, dataset, k, epsilon = 0.01, smooth = 0, cache_reset = NULL)
kdb(class, dataset, k, kdbk = 2, epsilon = 0.01, smooth = 0, cache_reset = NULL)
tan_hcsp(class, dataset, k, epsilon = 0.01, smooth = 0, cache_reset = NULL)

Arguments

class A character. Name of the class variable.
dataset The data frame from which to learn the classifier.
k An integer. The number of folds.
epsilon A numeric. Minimum absolute improvement in accuracy required to keep searching.
smooth A numeric. The smoothing value (\(\alpha\)) for Bayesian parameter estimation. Non-negative.
cache_reset A numeric. Number of iterations after which to reset the cache of conditional probability tables. A small number reduces the amount of memory used. NULL means the cache is never reset (the default).
kdbk An integer. The maximum number of feature parents per feature.

Value

A bnc_dag object.

References

Examples

data(car)
tanhc <- tan_hc('class', car, k = 5, epsilon = 0)
## Not run: plot(tanhc)

inspect_bnc_bn

Inspect a Bayesian network classifier (with structure and parameters).

Description

Functions for inspecting a bnc_bn object. In addition, you can query this object with the functions documented in inspect_bnc_dag.

Usage

nparams(x)
manb_arc_posterior(x)
awnb_weights(x)
params(x)
values(x)
classes(x)

Arguments

x

The bnc_bn object. The Bayesian network classifier.

Functions

- nparams: Returns the number of free parameters in the model.
- manb_arc_posterior: Returns the posterior of each arc from the class according to the MANB method.
- awnb_weights: Returns the AWNB feature weights.
- params: Returns the list of CPTs, in the same order as vars.
- values: Returns the possible values of each variable, in the same order as vars.
- classes: Returns the possible values of the class variable.
Examples

data(car)
nb <- bnc('nb', 'class', car, smooth = 1)
nparams(nb)
 nb <- bnc('nb', 'class', car, smooth = 1, manb_prior = 0.5)
manb_arc_posterior(nb)
 nb <- bnc('nb', 'class', car, smooth = 1, awnb_bootstrap = 0.5)
awnb_weights(nb)

inspect_bnc_dag

Inspect a Bayesian network classifier structure.

Description

Functions for inspecting a bnc_dag object.

Usage

class_var(x)
features(x)
vars(x)
families(x)
modelstring(x)
feature_families(x)
narcs(x)
is_semi_naive(x)
is_anb(x)
is_nb(x)
is_ode(x)

Arguments

x The bnc_dag object. The Bayesian network classifier structure.
learn_params

Functions

- **class_var**: Returns the class variable.
- **features**: Returns the features.
- **vars**: Returns all variables (i.e., features + class).
- **families**: Returns the family of each variable.
- **modelstring**: Returns the model string of the network in bnlearn format (adding a space in between two families).
- **feature_families**: Returns the family of each feature.
- **narcs**: Returns the number of arcs.
- **is_semi_naive**: Returns TRUE if x is a semi-naive Bayes.
- **is_anb**: Returns TRUE if x is an augmented naive Bayes.
- **is_nb**: Returns TRUE if x is a naive Bayes.
- **is_ode**: Returns TRUE if x is a one-dependence estimator.

Examples

```r
data(car)
b <- bnc('nb', 'class', car, smooth = 1)
narcs(b)
is_ode(b)
```

Description

Learn parameters with maximum likelihood or Bayesian estimation, the weighting attributes to alleviate naive bayes’ independence assumption (WANBIA), attribute weighted naive Bayes (AWNB), or the model averaged naive Bayes (MANB) methods. Returns a `bnc_bn`.

Usage

```r
lp(x, dataset, smooth, awnb_trees = NULL, awnb_bootstrap = NULL,
   manb_prior = NULL, wanbia = NULL)
```

Arguments

- **x**: The `bnc_dag` object. The Bayesian network classifier structure.
- **dataset**: The data frame from which to learn network parameters.
- **smooth**: A numeric. The smoothing value (\(\alpha\)) for Bayesian parameter estimation. Non-negative.
- **awnb_trees**: An integer. The number (\(M\)) of bootstrap samples to generate.
- **awnb_bootstrap**: A numeric. The size of the bootstrap subsample, relative to the size of dataset (given in \([0,1]\)).
- **manb_prior**: A numeric. The prior probability for an arc between the class and any feature.
- **wanbia**: A logical. If TRUE, WANBIA feature weighting is performed.
Details

`learn_params` learns the parameters of each local distribution \( \theta_{ijk} = P(X_i = k \mid \text{Pa}(X_i) = j) \) as

\[
\theta_{ijk} = \frac{N_{ijk} + \alpha}{N_{ij} + r_i \alpha},
\]

where \( N_{ijk} \) is the number of instances in dataset in which \( X_i = k \) and \( \text{Pa}(X_i) = j \), \( N_{ij} = \sum_k N_{ijk} \), \( r_i \) is the cardinality of \( X_i \), and all hyperparameters of the Dirichlet prior equal to \( \alpha \). \( \alpha = 0 \) corresponds to maximum likelihood estimation. Returns a uniform distribution when \( N_{ij} + r_i \alpha = 0 \). With partially observed data, the above amounts to available case analysis.

WANBIA learns a unique exponent 'weight' per feature. They are computed by optimizing conditional log-likelihood, and are bounded with all \( w_i \in [0, 1] \). For WANBIA estimates, set `wanbia` to `TRUE`.

In order to get the AWNB parameter estimate, provide either the `awnb_bootstrap` and/or the `awnb_trees` argument. The estimate is:

\[
\theta_{ijk}^{\text{AWNB}} = \frac{\theta_{ijk}^{w_i}}{\sum_{k=1}^r \theta_{ijk}^{w_i}},
\]

while the weights \( w_i \) are computed as

\[
w_i = \frac{1}{M} \sum_{t=1}^M \sqrt{\frac{1}{d_{i,t}}},
\]

where \( M \) is the number of bootstrap samples from dataset and \( d_{i,t} \) the minimum testing depth of \( X_i \) in an unpruned classification tree learned from the \( t \)-th subsample (\( d_{i,t} = 0 \) if \( X_i \) is omitted from \( t \)-th tree).

The MANB parameters correspond to Bayesian model averaging over the naive Bayes models obtained from all \( 2^n \) subsets over the \( n \) features. To get MANB parameters, provide the `manb_prior` argument.

Value

A `bnc_bn` object.

References


Examples

```r
data(car)
nb <- nb('class', car)  # Maximum likelihood estimation
mle <- lp(nb, car, smooth = 0)

# Bayesian estimation
bayes <- lp(nb, car, smooth = 0.5)

# MANB
manb <- lp(nb, car, smooth = 0.5, manb_prior = 0.5)

# AWNB
awnb <- lp(nb, car, smooth = 0.5, awnb_trees = 10)
```

Description

Compute (penalized) log-likelihood and conditional log-likelihood score of a `bnc_bn` object on a data set. Requires a data frame argument in addition to `object`.

Usage

```r
## S3 method for class 'bnc_bn'
AIC(object, ...)

## S3 method for class 'bnc_bn'
BIC(object, ...)

## S3 method for class 'bnc_bn'
logLik(object, ...)

cLogLik(object, ...)
```

Arguments

- `object` A `bnc_bn` object.
- `...` A data frame (`D`).

Details

log-likelihood = \( \log P(D \mid \theta) \),

Akaïke’s information criterion (AIC) = \( \log P(D \mid \theta) - \frac{1}{2} |\theta| \),

The Bayesian information criterion (BIC) score: = \( \log P(D \mid \theta) - \frac{\log N}{2} |\theta| \),

where \( |\theta| \) is the number of free parameters in `object`, \( D \) is the data set and \( N \) is the number of instances in \( D \).

cLogLik computes the conditional log-likelihood of the model.
Examples

data(car)
nb <- bnc('nb', 'class', car, smooth = 1)
logLik(nb, car)
AIC(nb, car)
BIC(nb, car)
cLogLik(nb, car)

---

nb

Learn a naive Bayes network structure.

Description

Learn a naive Bayes network structure.

Usage

nb(class, dataset = NULL, features = NULL)

Arguments

class  A character. Name of the class variable.
dataset The data frame from which to learn the classifier.
features A character vector. The names of the features. This argument is ignored if
dataset is provided.

Value

A bnc_dag object.

Examples

data(car)
nb <- nb('class', car)
nb2 <- nb('class', features = letters[1:10])
## Not run: plot(nb2)
plot.bnc_dag

Plot the structure.

Description

If node labels are too small to be viewed properly, you may fix label fontsize with argument fontsize. Also, you may try multiple different layouts.

Usage

## S3 method for class 'bnc_dag'
plot(x, y, layoutType = "dot", fontsize = NULL, ...)

Arguments

x
  The bnc_dag object. The Bayesian network classifier structure.
y
layoutType
  a character. Optional.
fontsize
  integer Font size for node labels. Optional.
...
  Not used.

Examples

# Requires the graph and Rgraphviz packages to be installed.
data(car)
b <- nb('class', car)
b <- nb('class', car)
## Not run: plot(b)
## Not run: plot(b, fontsize = 20)
## Not run: plot(b, layoutType = 'circo')
## Not run: plot(b, layoutType = 'fdp')
## Not run: plot(b, layoutType = 'osage')
## Not run: plot(b, layoutType = 'twopi')
## Not run: plot(b, layoutType = 'neato')

predict.bnc_fit

Predicts class labels or class posterior probability distributions.

Description

Predicts class labels or class posterior probability distributions.
Usage

```r
## S3 method for class 'bnc_fit'
predict(object, newdata, prob = FALSE, ...)
```

Arguments

- `object`: A `bnc_bn` object.
- `newdata`: A data frame containing observations whose class has to be predicted.
- `prob`: A logical. Whether class posterior probability should be returned.
- `...`: Ignored.

Details

Ties are resolved randomly. Inference is much slower if `newdata` contains `NA`s.

Value

If `prob=FALSE`, then returns a length-`N` factor with the same levels as the class variable in `x`, where `N` is the number of rows in `newdata`. Each element is the most likely class for the corresponding row in `newdata`. If `prob=TRUE`, returns a `N` by `C` numeric matrix, where `C` is the number of classes; each row corresponds to the class posterior of the instance.

Examples

```r
data(car)
nb <- bnc('nb', 'class', car, smooth = 1)
p <- predict(nb, car)
head(p)
p <- predict(nb, car, prob = TRUE)
head(p)
```

---

**tan_chowliu**

Learns a one-dependence estimator using Chow-Liu’s algorithm.

Description

Learns a one-dependence Bayesian classifier using Chow-Liu’s algorithm, by maximizing either log-likelihood, the AIC or BIC scores; maximizing log-likelihood corresponds to the well-known tree augmented naive Bayes (Friedman et al., 1997). When maximizing AIC or BIC the output might be a forest-augmented rather than a tree-augmented naive Bayes.

Usage

```r
tan_cl(class, dataset, score = "loglik", root = NULL)
```
voting

Arguments

class A character. Name of the class variable.
dataset The data frame from which to learn the classifier.
score A character. The score to be maximized. 'loglik', 'bic', and 'aic' return
the maximum likelihood, maximum BIC and maximum AIC tree/forest, respectively.
root A character. The feature to be used as root of the augmenting tree. Only one
feature can be supplied, even in case of an augmenting forest. This argument is
optional.

Value

A bnc_dag object.

References


Examples

data(car)
ll <- tan_cl('class', car, score = 'loglik')
## Not run: plot(ll)
ll <- tan_cl('class', car, score = 'loglik', root = 'maint')
## Not run: plot(ll)
aic <- tan_cl('class', car, score = 'aic')
bic <- tan_cl('class', car, score = 'bic')

voting  Congress Voting Data Set.

Description

Data set from the UCI repository https://archive.ics.uci.edu/ml/datasets/Congressional+
Voting+Records.

Format

A data.frame with 17 columns and 435 rows.

Source

http://goo.gl/GTXrCz
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