Package ‘infotheo’

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Title Information-Theoretic Measures

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Description Implements various measures of information theory based on several entropy estimators.

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Contents

condentropy *conditional entropy computation*

Description

condentropy takes two random vectors, X and Y, as input and returns the conditional entropy, H(X|Y), in nats (base e), according to the entropy estimator method. If Y is not supplied the function returns the entropy of X - see entropy.

Usage

```
condentropy(X, Y=NULL, method="emp")
```

Arguments

X	data.frame denoting a random variable or random vector where columns contain variables/features and rows contain outcomes/samples.
Y	data.frame denoting a conditioning random variable or random vector where columns contain variables/features and rows contain outcomes/samples.
method	The name of the entropy estimator. The package implements four estimators : "emp", "mm", "shrink", "sg" (default:"emp") - see details. These estimators require discrete data values - see discretize.

Details

- "emp" : This estimator computes the entropy of the empirical probability distribution.
- "mm" : This is the Miller-Madow asymptotic bias corrected empirical estimator.
- "shrink" : This is a shrinkage estimate of the entropy of a Dirichlet probability distribution.
- "sg" : This is the Schurmann-Grassberger estimate of the entropy of a Dirichlet probability distribution.

Value

condentropy returns the conditional entropy, H(X|Y), of X given Y in nats.

Author(s)

Patrick E. Meyer

References

Meyer, P. E. (2008). Information-Theoretic Variable Selection and Network Inference from Microarray Data. PhD thesis of the Universite Libre de Bruxelles.

Cover, T. M. and Thomas, J. A. (1990). Elements of Information Theory. John Wiley, New York.

See Also

entropy, mutinformation, natstobits

Examples

```
data(USArrests)
dat<-discretize(USArrests)
H <- condentropy(dat[,1], dat[,2], method = "mm")
```

---

condinformation *conditional mutual information computation*

Description

`condinformation` takes three random variables as input and computes the conditional mutual information in nats according to the entropy estimator `method`. If S is not supplied the function returns the mutual information between X and Y - see mutinformation

Usage

```
condinformation(X, Y, S=NULL, method="emp")
```

Arguments

X	vector/factor denoting a random variable or a data.frame denoting a random vector where columns contain variables/features and rows contain outcomes/samples.
Y	another random variable or random vector (vector/factor or data.frame).
S	the conditioning random variable or random vector (vector/factor or data.frame).
method	The name of the entropy estimator. The package implements four estimators : "emp", "mm", "shrink", "sg" (default:"emp") - see details. These estimators require discrete data values - see discretize.

Details

- "emp" : This estimator computes the entropy of the empirical probability distribution.
- "mm" : This is the Miller-Madow asymptotic bias corrected empirical estimator.
- "shrink" : This is a shrinkage estimate of the entropy of a Dirichlet probability distribution.
- "sg" : This is the Schurmann-Grassberger estimate of the entropy of a Dirichlet probability distribution.

Value

`condinformation` returns the conditional mutual information, I(X;Y|S), in nats.

Author(s)

Patrick E. Meyer

References

Meyer, P. E. (2008). Information-Theoretic Variable Selection and Network Inference from Microarray Data. PhD thesis of the Universite Libre de Bruxelles.

Cover, T. M. and Thomas, J. A. (1990). Elements of Information Theory. John Wiley, New York.

See Also

mutinformation, multiinformation, interinformation, natstobits

Examples

```
data(USArrests)
dat<-discretize(USArrests)
I <- condinformation(dat[,1],dat[,2],dat[,3],method="emp")
```

`discretize` *Unsupervized Data Discretization*

Description

`discretize` discretizes `data` using the equal frequencies or equal width binning algorithm. "equalwidth" and "equalfreq" discretizes each random variable (each column) of the data into `nbins`. "globalequalwidth" discretizes the range of the random vector `data` into `nbins`.

Usage

```
discretize( X, disc="equalfreq", nbins=NROW(X)^(1/3) )
```

Arguments

`X`	A data.frame containing data to be discretized. The columns contains variables and the rows samples.
`disc`	The name of the discretization method to be used :"equalfreq", "equalwidth" or "globalequalwidth" (default : "equalfreq") - see references.
`nbins`	Integer specifying the number of bins to be used for the discretization. By default the number of bins is set to $N^(1/3)$ where N is the number of samples.

Value

`discretize` returns the discretized dataset.

Author(s)

Patrick E. Meyer, Frederic Lafitte, Gianluca Bontempi, Korbinian Strimmer

References

Meyer, P. E. (2008). Information-Theoretic Variable Selection and Network Inference from Microarray Data. PhD thesis of the Universite Libre de Bruxelles.

Dougherty, J., Kohavi, R., and Sahami, M. (1995). Supervised and unsupervised discretization of continuous features. In International Conference on Machine Learning.

Yang, Y. and Webb, G. I. (2003). Discretization for naive-bayes learning: managing discretization bias and variance. Technical Report 2003/131 School of Computer Science and Software Engineering, Monash University.

Examples

```
data(USArrests)
nbins<- sqrt(NROW(USArrests))
ew.data <- discretize(USArrests,"equalwidth", nbins)
ef.data <- discretize(USArrests,"equalfreq", nbins)
gew.data <- discretize(USArrests,"globalequalwidth", nbins)
```

`entropy` *entropy computation*

Description

`entropy` takes the dataset as input and computes the entropy according to the entropy estimator `method`.

Usage

```
entropy(X, method="emp")
```

Arguments

`X`	data.frame denoting a random vector where columns contain variables/features and rows contain outcomes/samples.
`method`	The name of the entropy estimator. The package implements four estimators : "emp", "mm", "shrink", "sg" (default:"emp") - see details. These estimators require discrete data values - see `discretize`.

Details

- "emp" : This estimator computes the entropy of the empirical probability distribution.
- "mm" : This is the Miller-Madow asymptotic bias corrected empirical estimator.
- "shrink" : This is a shrinkage estimate of the entropy of a Dirichlet probability distribution.
- "sg" : This is the Schurmann-Grassberger estimate of the entropy of a Dirichlet probability distribution.

Value

`entropy` returns the entropy of the data in nats.

Author(s)

Patrick E. Meyer

References

Meyer, P. E. (2008). Information-Theoretic Variable Selection and Network Inference from Microarray Data. PhD thesis of the Universite Libre de Bruxelles.

J. Beirlant, E. J. Dudewica, L. Gyofi, and E. van der Meulen (1997). Nonparametric entropy estimation : An overview. Journal of Statistics.

Hausser J. (2006). Improving entropy estimation and the inference of genetic regulatory networks. Master thesis of the National Institute of Applied Sciences of Lyon.

See Also

`condentropy`, `mutinformation`, `natstobits`

Examples

```
data(USArrests)
H <- entropy(discretize(USArrests),method="shrink")
```

`infotheo` *Information Theory package*

Description

The package infotheo provide various estimators for computing information-theoretic measures from data

Author(s)

Patrick E. Meyer

References

Meyer, P. E. (2008). Information-Theoretic Variable Selection and Network Inference from Microarray Data. PhD thesis of the Universite Libre de Bruxelles.

See Also

`entropy`, `condentropy`, `mutinformation`, `condinformation`, `multiinformation`, `interinformation`, `natstobits`

`interinformation` *interaction information computation*

Description

`interinformation` takes a dataset as input and computes the the interaction information among the random variables in the dataset using the entropy estimator `method`. This measure is also called synergy or complementarity.

Usage

```
interinformation(X, method="emp")
```

Arguments

`X`	data.frame denoting a random vector where columns contain variables/features and rows contain outcomes/samples.
`method`	The name of the entropy estimator. The package implements four estimators : "emp", "mm", "shrink", "sg" (default:"emp") - see details. These estimators require discrete data values - see `discretize`.

Details

- "emp" : This estimator computes the entropy of the empirical probability distribution.
- "mm" : This is the Miller-Madow asymptotic bias corrected empirical estimator.
- "shrink" : This is a shrinkage estimate of the entropy of a Dirichlet probability distribution.
- "sg" : This is the Schurmann-Grassberger estimate of the entropy of a Dirichlet probability distribution.

Value

`interinformation` returns the interaction information (also called synergy or complementarity), in nats, among the random variables (columns of the data.frame).

Author(s)

Patrick E. Meyer

References

Meyer, P. E. (2008). Information-Theoretic Variable Selection and Network Inference from Microarray Data. PhD thesis of the Universite Libre de Bruxelles.

Jakulin, A. and Bratko, I. (2004). Testing the significance of attribute interactions. In Proc. of 21st International Conference on Machine Learning (ICML).

McGill, W. J. (1954). Multivariate information transmission. Psychometrika, 19.

See Also

condinformation, multiinformation, mutinformation, natstobits

Examples

```
data(USArrests)
dat<-discretize(USArrests)
ii <- interinformation(dat, method = "sg")
```

---

multiinformation *multiinformation computation*

Description

multiinformation takes a dataset as input and computes the multiinformation (also called total correlation) among the random variables in the dataset. The value is returned in nats using the entropy estimator estimator.

Usage

```
multiinformation(X, method ="emp")
```

Arguments

X	data.frame containing a set of random variables where columns contain variables/features and rows contain outcomes/samples.
method	The name of the entropy estimator. The package implements four estimators : "emp", "mm", "shrink", "sg" (default:"emp") - see details. These estimators require discrete data values - see discretize.

Details

- "emp" : This estimator computes the entropy of the empirical probability distribution.
- "mm" : This is the Miller-Madow asymptotic bias corrected empirical estimator.
- "shrink" : This is a shrinkage estimate of the entropy of a Dirichlet probability distribution.
- "sg" : This is the Schurmann-Grassberger estimate of the entropy of a Dirichlet probability distribution.

Value

multiinformation returns the multiinformation (also called total correlation) among the variables in the dataset (in nats).

Author(s)

Patrick E. Meyer

References

Meyer, P. E. (2008). Information-Theoretic Variable Selection and Network Inference from Microarray Data. PhD thesis of the Universite Libre de Bruxelles.

Studeny, M. and Vejnarova, J. (1998). The multiinformation function as a tool for measuring stochastic dependence. In Proceedings of the NATO Advanced Study Institute on Learning in graphical models,

See Also

`condinformation`, `mutinformation`, `interinformation`, `natstobits`

Examples

```
data(USArrests)
dat<-discretize(USArrests)
M <- multiinformation(dat)
```

`mutinformation` *mutual information computation*

Description

`mutinformation` takes two random variables as input and computes the mutual information in nats according to the entropy estimator `method`. If Y is not supplied and X is a matrix-like argument, the function returns a matrix of mutual information between all pairs of variables in the dataset X.

Usage

```
mutinformation(X, Y, method="emp")
```

Arguments

`X`	vector/factor denoting a random variable or a data.frame denoting a random vector where columns contain variables/features and rows contain outcomes/samples.
`Y`	another random variable or random vector (vector/factor or data.frame).
`method`	The name of the entropy estimator. The package implements four estimators : "emp", "mm", "shrink", "sg" (default:"emp") - see details. These estimators require discrete data values - see `discretize`.

Details

- "emp" : This estimator computes the entropy of the empirical probability distribution.
- "mm" : This is the Miller-Madow asymptotic bias corrected empirical estimator.
- "shrink" : This is a shrinkage estimate of the entropy of a Dirichlet probability distribution.
- "sg" : This is the Schurmann-Grassberger estimate of the entropy of a Dirichlet probability distribution.

Value

`mutinformation` returns the mutual information I(X;Y) in nats.

Author(s)

Patrick E. Meyer

References

Meyer, P. E. (2008). Information-Theoretic Variable Selection and Network Inference from Microarray Data. PhD thesis of the Universite Libre de Bruxelles.

Cover, T. M. and Thomas, J. A. (1990). Elements of Information Theory. John Wiley, New York.

See Also

condinformation, multiinformation, interinformation, natstobits

Examples

```
data(USArrests)
dat<-discretize(USArrests)
#computes the MIM (mutual information matrix)
I <- mutinformation(dat,method= "emp")
I2<- mutinformation(dat[,1],dat[,2])
```

---

natstobits *convert nats into bits*

Description

`natstobits` takes a value in nats (a double) as input and returns the value in bits (a double).

Usage

```
natstobits(H)
```

Arguments

H	double denoting a value (in nats), as returned by one of the function of the infotheo package

Details

Information-theoretic quantities can have different units depending on the base of the logarithm used in their computation. All the function of tha package use a base e, hence the unit is the nat. The value in bit is given by using the base 2, hence the conversion is done by multiplying by log2(e) = 1.442695.

Value

`natstobits` returns a double that is the conversion of the nats value into bits.

Author(s)

Patrick E. Meyer

Examples

```
data(USArrests)
H <- entropy(discretize(USArrests))
natstobits(H)
```

Index