

# Package ‘Informmeasure’

November 7, 2025

**Type** Package

**Title** R implementation of information measures

**Version** 1.21.0

**Description** This package consolidates a comprehensive set of information measurements, encompassing mutual information, conditional mutual information, interaction information, partial information decomposition, and part mutual information.

**License** Artistic-2.0

**Depends** R (>= 4.0)

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SummarizedExperiment

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|             |                                                                               |
|-------------|-------------------------------------------------------------------------------|
| CMI.measure | <i>A comprehensive function for estimating conditional mutual information</i> |
|-------------|-------------------------------------------------------------------------------|

---

## Description

The CMI.measure function is used to calculate the expected mutual information between two random variables conditioned on the third one from the joint count table.

## Usage

```
CMI.measure(
  XYZ,
  method = c("ML", "Jeffreys", "Laplace", "SG", "minimax", "shrink"),
  lambda.probs,
  unit = c("log", "log2", "log10"),
  verbose = TRUE
)
```

**Arguments**

|              |                                                                                                                                                         |
|--------------|---------------------------------------------------------------------------------------------------------------------------------------------------------|
| XYZ          | a joint count distribution table of three random variables.                                                                                             |
| method       | six probability estimation algorithms are available, "ML" is the default.                                                                               |
| lambda.probs | the shrinkage intensity, only called when the probability estimator is "shrink".                                                                        |
| unit         | the base of the logarithm. The default is natural logarithm, which is "log". For evaluating entropy in bits, it is suggested to set the unit to "log2". |
| verbose      | a logic variable. if verbose is true, report the shrinkage intensity.                                                                                   |

**Details**

Six probability estimation methods are available to evaluate the underlying bin probability from observed counts:

method = "ML": maximum likelihood estimator, also referred to empirical probability,  
 method = "Jeffreys": Dirichlet distribution estimator with prior  $a = 0.5$ ,  
 method = "Laplace": Dirichlet distribution estimator with prior  $a = 1$ ,  
 method = "SG": Dirichlet distribution estimator with prior  $a = 1/\text{length}(XY)$ ,  
 method = "minimax": Dirichlet distribution estimator with prior  $a = \sqrt{\text{sum}(XY)}/\text{length}(XY)$ ,  
 method = "shrink": shrinkage estimator.

**Value**

CMI.measure returns the conditional mutual information.

**References**

# Hausser, J., & Strimmer, K. (2009). Entropy Inference and the James-Stein Estimator, with Application to Nonlinear Gene Association Networks. *Journal of Machine Learning Research*, 1469-1484.

**Examples**

```
# three numeric vectors corresponding to three continuous random variables
x <- c(0.0, 0.2, 0.2, 0.7, 0.9, 0.9, 0.9, 0.9, 1.0)
y <- c(1.0, 2.0, 12, 8.0, 1.0, 9.0, 0.0, 3.0, 9.0)
z <- c(3.0, 7.0, 2.0, 11, 10, 10, 14, 2.0, 11)

# corresponding joint count table estimated by "uniform width" algorithm
XYZ <- discretize3D(x, y, z, "uniform_width")

# corresponding conditional mutual information
CMI.measure(XYZ)
```

---

CMI.plugin

*A plug-in calculator for evaluating conditional mutual information*


---

## Description

CMI.plugin measures the expected mutual information between two random variables conditioned on the third one from the joint probability distribution table.

## Usage

```
CMI.plugin(probs, unit = c("log", "log2", "log10"))
```

## Arguments

|       |                                                                                                                                                         |
|-------|---------------------------------------------------------------------------------------------------------------------------------------------------------|
| probs | the joint probability distribution table of three random variables.                                                                                     |
| unit  | the base of the logarithm. The default is natural logarithm, which is "log". For evaluating entropy in bits, it is suggested to set the unit to "log2". |

## Value

CMI.plugin returns the conditional mutual information.

## References

Wyner, A. D. (1978). A definition of conditional mutual information for arbitrary ensembles. *Information & Computation*, 38(1), 51-59.

## Examples

```
# three numeric vectors corresponding to three continuous random variables
x <- c(0.0, 0.2, 0.2, 0.7, 0.9, 0.9, 0.9, 0.9, 1.0)
y <- c(1.0, 2.0, 12, 8.0, 1.0, 9.0, 0.0, 3.0, 9.0)
z <- c(3.0, 7.0, 2.0, 11, 10, 10, 14, 2.0, 11)

# corresponding joint count table estimated by "uniform width" algorithm
count_xyz <- discretize3D(x, y, z, "uniform_width")

# the joint probability distribution table of the count data
library("entropy")
probs_xyz <- freqs.empirical(count_xyz)

# corresponding conditional mutual information
CMI.plugin(probs_xyz)
```

---

|              |                                                             |
|--------------|-------------------------------------------------------------|
| discretize1D | <i>Discretize one-dimensional continuous data into bins</i> |
|--------------|-------------------------------------------------------------|

---

## Description

The function of `discretize1D` is used to assign the observations of a set of continuous random variables to bins, and returns a corresponding one-dimensional count table. Two of the most common discretization methods are available: "uniform width" and "uniform frequency".

## Usage

```
discretize1D(x, algorithm = c("uniform_width", "uniform_frequency"))
```

## Arguments

|                        |                                                                              |
|------------------------|------------------------------------------------------------------------------|
| <code>x</code>         | a numeric vector of the random variable <code>x</code> .                     |
| <code>algorithm</code> | two discretization algorithms are available, "uniform_width" is the default. |

## Details

Uniform width-based method ("uniform\_width") divides the continuous data into `N` bins with equal width, while Uniform frequency-based method ("uniform\_frequency") divides the continuous data into `N` bins with (approximate) equal count number. By default in both methods, the number of bins `N` is initialized into a round-off value according to the square root of the data size.

## Value

`discretize1D` returns a one-dimensional count table.

## Examples

```
# a numeric vector corresponding to a continuous random variable
x <- c(0.0, 0.2, 0.2, 0.7, 0.9, 0.9, 0.9, 0.9, 1.0)

# corresponding count table estimated by "uniform width" algorithm
discretize1D(x, "uniform_width")

# corresponding count table estimated by "uniform frequency" algorithm
discretize1D(x, "uniform_frequency")
```

---

discretize1d.uniform\_frequency

*Discretize a set of continuous data into 1-dimensional bins by uniform frequency*

---

### Description

discretize1d.uniform\_frequency assigns the observations of a continuous random variables to bins according to the "uniform frequency" method, and returns a corresponding count table.

### Usage

```
discretize1d.uniform_frequency(x)
```

### Arguments

x                      a numeric vector of a random variable.

### Details

Uniform frequency-based method ("uniform\_frequency") divides the continuous data into N bins with (approximate) equal count number. The number of bins N is initialized into a round-off value according to the square root of the data size.

### Value

discretize1d.uniform\_frequency returns a one-dimensional count table.

### Examples

```
# a numeric vector corresponding to a continuous random variable
x <- c(0.0, 0.2, 0.2, 0.7, 0.9, 0.9, 0.9, 0.9, 1.0)

# corresponding count table estimated by "uniform frequency" algorithm
discretize1d.uniform_frequency(x)
```

---

discretize1d.uniform\_width

*Discretize a set of continuous data into 1-dimensional bins by "uniform width" method*

---

### Description

discretize1d.uniform\_width assigns the observations of continuous random variables to bins according to the "uniform width" method, and returns a corresponding count table.

**Usage**

```
discretize1d.uniform_width(x)
```

**Arguments**

`x` a numeric vector of a random variable.

**Details**

Uniform width-based method ("uniform\_width") divides the continuous data into N bins with equal width. The number of bins N is initialized into a round-off value according to the square root of the data size.

**Value**

`discretize1d.uniform_width` returns a count table.

**Examples**

```
# a numeric vector corresponding to a continuous random variable
x <- c(0.0, 0.2, 0.2, 0.7, 0.9, 0.9, 0.9, 0.9, 1.0)

# corresponding count table estimated by "uniform width" algorithm
discretize1d.uniform_width(x)
```

---

discretize2D

*Discretize 2-dimensional continuous data into bins*


---

**Description**

The function of `discretize2D` is used to assign the observations of two sets of continuous random variables to bins, and returns a corresponding two-dimensional count table. Two of the most common discretization methods are available: "uniform width" and "uniform frequency".

**Usage**

```
discretize2D(x, y, algorithm = c("uniform_width", "uniform_frequency"))
```

**Arguments**

`x` a numeric vector of the random variable `x`.  
`y` a numeric vector of the random variable `y`.  
`algorithm` two discretization algorithms are available, "uniform\_width" is the default.

**Details**

Uniform width-based method ("uniform\_width") divides the continuous data into N bins with equal width, while Uniform frequency-based method ("uniform\_frequency") divides the continuous data into N bins with (approximate) equal count number. By default in both methods, the number of bins N is initialized into a round-off value according to the square root of the data size.

**Value**

discretize2D returns a 2-dimensional count table.

**Examples**

```
# two numeric vectors that correspond to two continuous random variables
x <- c(0.0, 0.2, 0.2, 0.7, 0.9, 0.9, 0.9, 0.9, 1.0)
y <- c(1.0, 2.0, 12, 8.0, 1.0, 9.0, 0.0, 3.0, 9.0)

# corresponding count table estimated by "uniform width" algorithm
discretize2D(x,y, "uniform_width")

# corresponding count table estimated by "uniform frequency" algorithm
discretize2D(x,y, "uniform_frequency")
```

---

discretize2d.uniform\_frequency

*Discretize two sets of continuous data into 2-dimensional bins by uniform frequency*

---

**Description**

discretize2d.uniform\_frequency assigns the observations of two continuous random variables to bins according to the "uniform frequency" method, and returns a corresponding 2-dimensional count table.

**Usage**

```
discretize2d.uniform_frequency(x, y)
```

**Arguments**

|   |                                                 |
|---|-------------------------------------------------|
| x | a numeric vector of the first random variable.  |
| y | a numeric vector of the second random variable. |

**Details**

Uniform frequency-based method ("uniform\_frequency") divides the continuous data into N bins with (approximate) equal count number. The number of bins N is initialized into a round-off value according to the square root of the data size.

**Value**

discretize2d.uniform\_frequency returns a 2-dimensional count table.

**Examples**

```
# two numeric vectors corresponding to two continuous random variables
x <- c(0.0, 0.2, 0.2, 0.7, 0.9, 0.9, 0.9, 1.0)
y <- c(1.0, 2.0, 12, 8.0, 1.0, 9.0, 0.0, 3.0, 9.0)

# corresponding joint count table estimated by "uniform frequency" algorithm
discretize2d.uniform_frequency(x,y)
```

---

discretize2d.uniform\_width

*Discretize two sets of continuous data into 2-dimensional bins by "uniform width" method*

---

**Description**

discretize2d.uniform\_width assigns the observations of two continuous random variables to bins according to the "uniform width" method, and returns a corresponding 2-dimensional count table.

**Usage**

```
discretize2d.uniform_width(x, y)
```

**Arguments**

|   |                                                 |
|---|-------------------------------------------------|
| x | a numeric vector of the first random variable.  |
| y | a numeric vector of the second random variable. |

**Details**

Uniform width-based method ("uniform\_width") divides the continuous data into N bins with equal width. The number of bins N is initialized into a round-off value according to the square root of the data size.

**Value**

discretize2d.uniform\_width returns a 2-dimensional count table.

**Examples**

```
# two numeric vectors corresponding to two continuous random variables
x <- c(0.0, 0.2, 0.2, 0.7, 0.9, 0.9, 0.9, 1.0)
y <- c(1.0, 2.0, 12, 8.0, 1.0, 9.0, 0.0, 3.0, 9.0)

# corresponding joint count table estimated by "uniform width" algorithm
discretize2d.uniform_width(x,y)
```

---

discretize3D

*Discretize 3-dimensional continuous data into bins*


---

### Description

The function of discretize3D is used to assign the observations of three sets of continuous random variables to bins, and returns a corresponding three-dimensional count table. Two of the most common discretization methods are available: "uniform width" and "uniform frequency".

### Usage

```
discretize3D(x, y, z, algorithm = c("uniform_width", "uniform_frequency"))
```

### Arguments

|           |                                                                              |
|-----------|------------------------------------------------------------------------------|
| x         | a numeric vector of the random variable x.                                   |
| y         | a numeric vector of the random variable y.                                   |
| z         | a numeric vector of the random variable z.                                   |
| algorithm | two discretization algorithms are available, "uniform_width" is the default. |

### Details

Uniform width-based method ("uniform\_width") divides the continuous data into N bins with equal width, while Uniform frequency-based method ("uniform\_frequency") divides the continuous data into N bins with (approximate) equal count number. By default in both methods, the number of bins N is initialized into a round-off value according to the square root of the data size.

### Value

discretize3D returns a 3-dimensional count table.

### Examples

```
# three vectors that correspond to three continuous random variables
x <- c(0.0, 0.2, 0.2, 0.7, 0.9, 0.9, 0.9, 0.9, 1.0)
y <- c(1.0, 2.0, 12, 8.0, 1.0, 9.0, 0.0, 3.0, 9.0)
z <- c(3.0, 7.0, 2.0, 11, 10, 10, 14, 2.0, 11)

# corresponding count table estimated by "uniform width" algorithm
discretize3D(x,y,z, "uniform_width")

# corresponding count table estimated by "uniform frequency" algorithm
discretize3D(x,y,z, "uniform_frequency")
```

---

`discretize3d.uniform_frequency`*Discretize three sets of continuous data into 3-dimensional bins by uniform frequency*

---

## Description

`discretize3d.uniform_frequency` assigns the observations of three continuous random variables to bins according to the "uniform frequency" method, and returns a corresponding 3-dimensional count table.

## Usage

```
discretize3d.uniform_frequency(x, y, z)
```

## Arguments

|                |                                                 |
|----------------|-------------------------------------------------|
| <code>x</code> | a numeric vector of the first random variable.  |
| <code>y</code> | a numeric vector of the second random variable. |
| <code>z</code> | a numeric vector of the third random variable.  |

## Details

Uniform frequency-based method ("uniform\_frequency") divides the continuous data into N bins with (approximate) equal count number. The number of bins N is initialized into a round-off value according to the square root of the data size.

## Value

`discretize3d.uniform_frequency` returns a 3-dimensional count table.

## Examples

```
# three numeric vectors corresponding to three continuous random variables
x <- c(0.0, 0.2, 0.2, 0.7, 0.9, 0.9, 0.9, 0.9, 1.0)
y <- c(1.0, 2.0, 12, 8.0, 1.0, 9.0, 0.0, 3.0, 9.0)
z <- c(3.0, 7.0, 2.0, 11, 10, 10, 14, 2.0, 11)

# corresponding joint count table estimated by "uniform frequency" algorithm
discretize3d.uniform_frequency(x,y,z)
```

---

`discretize3d.uniform_width`

*Discretize three sets of continuous data into 3-dimensional bins by "uniform width" method*

---

## Description

`discretize3d.uniform_width` assigns the observations of three continuous random variables to bins according to the "uniform width" method, and returns a corresponding 3-dimensional count table.

## Usage

```
discretize3d.uniform_width(x, y, z)
```

## Arguments

|                |                                                 |
|----------------|-------------------------------------------------|
| <code>x</code> | a numeric vector of the first random variable.  |
| <code>y</code> | a numeric vector of the second random variable. |
| <code>z</code> | a numeric vector of the third random variable.  |

## Details

The uniform width-based method ("uniform\_width") that divides the continuous data into N bins with equal width. The number of bins is initialized into a round-off value according to the square root of the data size.

## Value

`discretize3d.uniform_width` returns a 3-dimensional count table.

## Examples

```
# three numeric vectors corresponding to three continuous random variables
x <- c(0.0, 0.2, 0.2, 0.7, 0.9, 0.9, 0.9, 0.9, 1.0)
y <- c(1.0, 2.0, 12, 8.0, 1.0, 9.0, 0.0, 3.0, 9.0)
z <- c(3.0, 7.0, 2.0, 11, 10, 10, 14, 2.0, 11)

# corresponding joint count table estimated by "uniform width" algorithm
discretize3d.uniform_width(x,y,z)
```

II.measure

*A comprehensive function for evaluating interaction information***Description**

The II.measure function is used to calculate the amount information contained in a set of variables from the joint count table. The number of variables here is limited to three.

**Usage**

```
II.measure(
  XYZ,
  method = c("ML", "Jeffreys", "Laplace", "SG", "minimax", "shrink"),
  lambda.probs,
  unit = c("log", "log2", "log10"),
  verbose = TRUE
)
```

**Arguments**

|              |                                                                                                                                                         |
|--------------|---------------------------------------------------------------------------------------------------------------------------------------------------------|
| XYZ          | a joint count distribution table of three random variables.                                                                                             |
| method       | six probability estimation algorithms are available, "ML" is the default.                                                                               |
| lambda.probs | the shrinkage intensity, only called when the probability estimator is "shrink".                                                                        |
| unit         | the base of the logarithm. The default is natural logarithm, which is "log". For evaluating entropy in bits, it is suggested to set the unit to "log2". |
| verbose      | a logic variable. if verbose is true, report the shrinkage intensity.                                                                                   |

**Details**

Six probability estimation methods are available to evaluate the underlying bin probability from observed counts:

method = "ML": maximum likelihood estimator, also referred to empirical probability,  
 method = "Jeffreys": Dirichlet distribution estimator with prior  $a = 0.5$ ,  
 method = "Laplace": Dirichlet distribution estimator with prior  $a = 1$ ,  
 method = "SG": Dirichlet distribution estimator with prior  $a = 1/\text{length}(XY)$ ,  
 method = "minimax": Dirichlet distribution estimator with prior  $a = \sqrt{\text{sum}(XY)}/\text{length}(XY)$ ,  
 method = "shrink": shrinkage estimator.

**Value**

II.measure returns the interaction information.

**References**

Hausser, J., & Strimmer, K. (2009). Entropy Inference and the James-Stein Estimator, with Application to Nonlinear Gene Association Networks. *Journal of Machine Learning Research*, 1469-1484.  
 McGill, W. J. (1954). Multivariate information transmission. *Psychometrika*, 19(2), 97-116.

**Examples**

```
# three numeric vectors corresponding to three continuous random variables
x <- c(0.0, 0.2, 0.2, 0.7, 0.9, 0.9, 0.9, 0.9, 1.0)
y <- c(1.0, 2.0, 12, 8.0, 1.0, 9.0, 0.0, 3.0, 9.0)
z <- c(3.0, 7.0, 2.0, 11, 10, 10, 14, 2.0, 11)

# corresponding joint count table estimated by "uniform width" algorithm
XYZ <- discretize3D(x, y, z, "uniform_width")

# corresponding interaction information
II.measure(XYZ)
```

II.plugin

*A plug-in calculator for evaluating the interaction information***Description**

II.plugin measures the amount information contained in a set of variables from the joint probability distribution table. The number of variables here is limited to three.

**Usage**

```
II.plugin(probs, unit = c("log", "log2", "log10"))
```

**Arguments**

|       |                                                                                                                                                         |
|-------|---------------------------------------------------------------------------------------------------------------------------------------------------------|
| probs | the joint probability distribution table of three random variables.                                                                                     |
| unit  | the base of the logarithm. The default is natural logarithm, which is "log". For evaluating entropy in bits, it is suggested to set the unit to "log2". |

**Value**

II.plugin returns the interaction information.

**References**

Mcgill, W. J. (1954). Multivariate information transmission. *Psychometrika*, 19(2), 97-116.

**Examples**

```
# three numeric vectors corresponding to three continuous random variables
x <- c(0.0, 0.2, 0.2, 0.7, 0.9, 0.9, 0.9, 0.9, 1.0)
y <- c(1.0, 2.0, 12, 8.0, 1.0, 9.0, 0.0, 3.0, 9.0)
z <- c(3.0, 7.0, 2.0, 11, 10, 10, 14, 2.0, 11)

# corresponding joint count table estimated by "uniform width" algorithm
count_xyz <- discretize3D(x, y, z, "uniform_width")
```

```
# the joint probability distribution table of the count data
library("entropy")
probs_xyz <- freqs.empirical(count_xyz)

# corresponding interaction information
II.plugin(probs_xyz)
```

---

MI.measure

*A comprehensive function for evaluating mutual information*


---

## Description

The MI.measure function is used to calculate the mutual information between two random variables from the joint count table.

## Usage

```
MI.measure(
  XY,
  method = c("ML", "Jeffreys", "Laplace", "SG", "minimax", "shrink"),
  lambda.probs,
  unit = c("log", "log2", "log10"),
  verbose = TRUE
)
```

## Arguments

|              |                                                                                                                                                         |
|--------------|---------------------------------------------------------------------------------------------------------------------------------------------------------|
| XY           | a joint count distribution table of two random variables.                                                                                               |
| method       | six probability estimation algorithms are available, "ML" is the default.                                                                               |
| lambda.probs | the shrinkage intensity, only called when the probability estimator is "shrink".                                                                        |
| unit         | the base of the logarithm. The default is natural logarithm, which is "log". For evaluating entropy in bits, it is suggested to set the unit to "log2". |
| verbose      | a logic variable. if verbose is true, report the shrinkage intensity.                                                                                   |

## Details

Six probability estimation methods are available to evaluate the underlying bin probability from observed counts:

```
method = "ML": maximum likelihood estimator, also referred to empirical probability,
method = "Jeffreys": Dirichlet distribution estimator with prior a = 0.5,
method = "Laplace": Dirichlet distribution estimator with prior a = 1,
method = "SG": Dirichlet distribution estimator with prior a = 1/length(XY),
method = "minimax": Dirichlet distribution estimator with prior a = sqrt(sum(XY))/length(XY),
method = "shrink": shrinkage estimator.
```

## Value

MI.measure returns the mutual information.

## References

- Hausser, J., & Strimmer, K. (2009). Entropy Inference and the James-Stein Estimator, with Application to Nonlinear Gene Association Networks. *Journal of Machine Learning Research*, 1469-1484.
- Wyner, A. D. (1978). A definition of conditional mutual information for arbitrary ensembles. *Information & Computation*, 38(1), 51-59.

## Examples

```
# two numeric vectors corresponding to two continuous random variables
x <- c(0.0, 0.2, 0.2, 0.7, 0.9, 0.9, 0.9, 0.9, 1.0)
y <- c(1.0, 2.0, 12, 8.0, 1.0, 9.0, 0.0, 3.0, 9.0)

# corresponding joint count table estimated by "uniform width" algorithm
XY <- discretize2D(x, y, "uniform_width")

# corresponding mutual information
MI.measure(XY)
```

---

MI.plugin

*A plug-in calculator for evaluating mutual information*


---

## Description

MI.plugin measures the mutual information between two random variables from the joint probability distribution table.

## Usage

```
MI.plugin(probs, unit = c("log", "log2", "log10"))
```

## Arguments

|       |                                                                                                                                                         |
|-------|---------------------------------------------------------------------------------------------------------------------------------------------------------|
| probs | the joint probability distribution table of two random variables.                                                                                       |
| unit  | the base of the logarithm. The default is natural logarithm, which is "log". For evaluating entropy in bits, it is suggested to set the unit to "log2". |

## Value

MI.plugin returns the mutual information.

## Examples

```
# two numeric vectors corresponding to two continuous random variables
x <- c(0.0, 0.2, 0.2, 0.7, 0.9, 0.9, 0.9, 0.9, 1.0)
y <- c(1.0, 2.0, 12, 8.0, 1.0, 9.0, 0.0, 3.0, 9.0)

# corresponding joint count table estimated by "uniform width" algorithm
count_xy <- discretize2D(x, y, "uniform_width")
```

```
# the joint probability distribution table of the count data
library("entropy")
probs_xy <- freqs.empirical(count_xy)

# corresponding mutual information
MI.plugin(probs_xy)
```

---

|             |                                                                                      |
|-------------|--------------------------------------------------------------------------------------|
| PID.measure | <i>A comprehensive function for evaluating the partial information decomposition</i> |
|-------------|--------------------------------------------------------------------------------------|

---

## Description

The PID.measure function is used to decompose two source information acting on the common target into four parts: joint information (synergy), unique information from source x, unique information from source y and shared information (redundancy). The input of the PID.measure is the joint count table.

## Usage

```
PID.measure(
  XYZ,
  method = c("ML", "Jeffreys", "Laplace", "SG", "minimax", "shrink"),
  lambda.probs,
  unit = c("log", "log2", "log10"),
  verbose = TRUE
)
```

## Arguments

|              |                                                                                                                                                         |
|--------------|---------------------------------------------------------------------------------------------------------------------------------------------------------|
| XYZ          | a joint count distribution table of three random variables                                                                                              |
| method       | six probability estimation algorithms are available, "ML" is the default.                                                                               |
| lambda.probs | the shrinkage intensity, only called when the probability estimator is "shrink".                                                                        |
| unit         | the base of the logarithm. The default is natural logarithm, which is "log". For evaluating entropy in bits, it is suggested to set the unit to "log2". |
| verbose      | a logic variable. if verbose is true, report the shrinkage intensity.                                                                                   |

## Details

Six probability estimation methods are available to evaluate the underlying bin probability from observed counts:

```
method = "ML": maximum likelihood estimator, also referred to empirical probability,
method = "Jeffreys": Dirichlet distribution estimator with prior  $a = 0.5$ ,
method = "Laplace": Dirichlet distribution estimator with prior  $a = 1$ ,
method = "SG": Dirichlet distribution estimator with prior  $a = 1/\text{length}(XY)$ ,
method = "minimax": Dirichlet distribution estimator with prior  $a = \sqrt{\text{sum}(XY)}/\text{length}(XY)$ ,
method = "shrink": shrinkage estimator.
```

**Value**

PID.measure returns a list that includes synergistic information, unique information from x, unique information from y, redundant information and the sum of the four parts of information.

**References**

Hausser, J., & Strimmer, K. (2009). Entropy Inference and the James-Stein Estimator, with Application to Nonlinear Gene Association Networks. *Journal of Machine Learning Research*, 1469-1484.

Williams, P. L., & Beer, R. D. (2010). Nonnegative Decomposition of Multivariate Information. *arXiv: Information Theory*.

Chan, T. E., Stumpf, M. P., & Babbie, A. C. (2017). Gene Regulatory Network Inference from Single-Cell Data Using Multivariate Information Measures. *Cell Systems*, 5(3).

**Examples**

```
# three numeric vectors corresponding to three continuous random variables
x <- c(0.0, 0.2, 0.2, 0.7, 0.9, 0.9, 0.9, 0.9, 1.0)
y <- c(1.0, 2.0, 12, 8.0, 1.0, 9.0, 0.0, 3.0, 9.0)
z <- c(3.0, 7.0, 2.0, 11, 10, 10, 14, 2.0, 11)

# corresponding joint count table estimated by "uniform width" algorithm
XYZ <- discretize3D(x, y, z, "uniform_width")

# corresponding partial information decomposition
PID.measure(XYZ)

# corresponding count table estimated by "uniform frequency" algorithm
XYZ <- discretize3D(x, y, z, "uniform_frequency")

# corresponding partial information decomposition
PID.measure(XYZ)
```

---

PID.plugin

---

*A plug-in calculator for evaluating partial information decomposition*


---

**Description**

PID.plugin decomposes two source information acting on the common target into four parts: joint information (synergy), unique information from source x, unique information from source y and shared information (redundancy). The input of PMI.plugin is the joint probability distribution table.

**Usage**

```
PID.plugin(probs, unit = c("log", "log2", "log10"))
```

**Arguments**

|                    |                                                                                                                                                         |
|--------------------|---------------------------------------------------------------------------------------------------------------------------------------------------------|
| <code>probs</code> | the joint probability distribution of three random variables.                                                                                           |
| <code>unit</code>  | the base of the logarithm. The default is natural logarithm, which is "log". For evaluating entropy in bits, it is suggested to set the unit to "log2". |

**Value**

PID.plugin returns a list that includes synergistic information, unique information from source x, unique information from source y, redundant information and the sum of the four parts of information.

**References**

- Williams, P. L., & Beer, R. D. (2010). Nonnegative Decomposition of Multivariate Information. arXiv: Information Theory.
- Chan, T. E., Stumpf, M. P., & Babbie, A. C. (2017). Gene Regulatory Network Inference from Single-Cell Data Using Multivariate Information Measures. *Cell systems*, 5(3).

**Examples**

```
# three numeric vectors corresponding to three continuous random variables
x <- c(0.0, 0.2, 0.2, 0.7, 0.9, 0.9, 0.9, 1.0)
y <- c(1.0, 2.0, 12, 8.0, 1.0, 9.0, 0.0, 3.0, 9.0)
z <- c(3.0, 7.0, 2.0, 11, 10, 10, 14, 2.0, 11)

# corresponding joint count table estimated by "uniform width" algorithm
count_xyz <- discretize3D(x, y, z, "uniform_width")

# the joint probability distribution table of the count data
library("entropy")
probs_xyz <- freqs.empirical(count_xyz)

# corresponding partial information decomposition
PID.plugin(probs_xyz)
```

---

PMI.measure

*A comprehensive function for evaluating part mutual information*


---

**Description**

The PMI.measure function is used to calculate the non-linearly direct dependencies between two variables conditioned on the third one from the joint count table.

**Usage**

```
PMI.measure(
  XYZ,
  method = c("ML", "Jeffreys", "Laplace", "SG", "minimax", "shrink"),
  lambda.probs,
  unit = c("log", "log2", "log10"),
  verbose = TRUE
)
```

**Arguments**

|              |                                                                                                                                                         |
|--------------|---------------------------------------------------------------------------------------------------------------------------------------------------------|
| XYZ          | a joint count distribution table of three random variables.                                                                                             |
| method       | six probability estimation algorithms are available, "ML" is the default.                                                                               |
| lambda.probs | the shrinkage intensity, only called when the probability estimator is "shrink".                                                                        |
| unit         | the base of the logarithm. The default is natural logarithm, which is "log". For evaluating entropy in bits, it is suggested to set the unit to "log2". |
| verbose      | a logic variable. if verbose is true, report the shrinkage intensity.                                                                                   |

**Details**

Six probability estimation methods are available to evaluate the underlying bin probability from observed counts:

method = "ML": maximum likelihood estimator, also referred to empirical probability,  
 method = "Jeffreys": Dirichlet distribution estimator with prior  $a = 0.5$ ,  
 method = "Laplace": Dirichlet distribution estimator with prior  $a = 1$ ,  
 method = "SG": Dirichlet distribution estimator with prior  $a = 1/\text{length}(XY)$ ,  
 method = "minimax": Dirichlet distribution estimator with prior  $a = \sqrt{\text{sum}(XY)}/\text{length}(XY)$ ,  
 method = "shrink": shrinkage estimator.

**Value**

PMI.measure returns the part mutual information.

**References**

Hausser, J., & Strimmer, K. (2009). Entropy Inference and the James-Stein Estimator, with Application to Nonlinear Gene Association Networks. *Journal of Machine Learning Research*, 1469-1484.

Zhao, J., Zhou, Y., Zhang, X., & Chen, L. (2016). Part mutual information for quantifying direct associations in networks. *Proceedings of the National Academy of Sciences of the United States of America*, 113(18), 5130-5135.

**Examples**

```
# three numeric vectors corresponding to three continuous random variables
x <- c(0.0, 0.2, 0.2, 0.7, 0.9, 0.9, 0.9, 0.9, 1.0)
y <- c(1.0, 2.0, 12, 8.0, 1.0, 9.0, 0.0, 3.0, 9.0)
z <- c(3.0, 7.0, 2.0, 11, 10, 10, 14, 2.0, 11)
```

```
# corresponding joint count table estimated by "uniform width" algorithm
XYZ <- discretize3D(x, y, z, "uniform_width")

# corresponding part mutual information
PMI.measure(XYZ)
```

PMI.plugin

*A plug-in calculator for evaluating the part mutual information***Description**

PMI.plugin measures the non-linearly direct dependencies between two variables conditioned on the third one from the joint probability distribution table.

**Usage**

```
PMI.plugin(probs, unit = c("log", "log2", "log10"))
```

**Arguments**

|       |                                                                                                                                                         |
|-------|---------------------------------------------------------------------------------------------------------------------------------------------------------|
| probs | the joint probability distribution table of three random variables.                                                                                     |
| unit  | the base of the logarithm. The default is natural logarithm, which is "log". For evaluating entropy in bits, it is suggested to set the unit to "log2". |

**Value**

PMI.plugin returns the part mutual information.

**References**

Zhao, J., Zhou, Y., Zhang, X., & Chen, L. (2016). Part mutual information for quantifying direct associations in networks. *Proceedings of the National Academy of Sciences of the United States of America*, 113(18), 5130-5135.

**Examples**

```
# three numeric vectors corresponding to three continuous random variables
x <- c(0.0, 0.2, 0.2, 0.7, 0.9, 0.9, 0.9, 0.9, 1.0)
y <- c(1.0, 2.0, 12, 8.0, 1.0, 9.0, 0.0, 3.0, 9.0)
z <- c(3.0, 7.0, 2.0, 11, 10, 10, 14, 2.0, 11)

# corresponding joint count table estimated by "uniform width" algorithm
count_xyz <- discretize3D(x, y, z, "uniform_width")

# the joint probability distribution table of the count data
library("entropy")
probs_xyz <- freqs.empirical(count_xyz)

# corresponding part mutual information
PMI.plugin(probs_xyz)
```

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