# Package 'matie' 

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Description
Uses a ratio of weighted distributions to estimate association between variables in a data set.
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matie-package Measuring Association and Testing Independence Efficiently

## Description

A non-parametric measure of association between variables. The association score, $A$, ranges from 0 (when the variables are independent) to 1 (when they are perfectly associated). $A$ is a kind of $R^{2}$ estimate, and can be thought of as the proportion of variance in one variable explained by another (or explained by a number of other variables - $A$ works for multivariate associations as well).
matie computes $A$ by estimating a generalized $R^{2}$, which is computed from the ratio of the likelihood of an alternative model (allowing dependence between variables) over the likelihood of a null model (that forces the variables to be independent). See http://arxiv.org/abs/1303.1828 for details.
The variables should be continuous. $A$ is calculated from the ranks of the values, and ties are currently broken randomly. Ordinal data can be handled, but the properties of $A$ have not been thoroughly investigated for non-continuous data with many ties. $A$ is not currently implemented for category-valued data.
Version 1.2 provides underflow protection to fix a bug that appeared at high dimensions in earlier versions.

## Details

Package: matie
Type: Package
Version: 1.2
Date: 2013-10-11
License: GPL-3

## Author(s)

Ben Murrell, Dan Murrell, Hugh Murrell. Maintainer: Hugh Murrell [hugh.murrell@gmail.com](mailto:hugh.murrell@gmail.com)

## References

Discovering general multidimensional associations, http://arxiv.org/abs/1303.1828

## Examples

$d<-\operatorname{sbd}(N U L L, n=400, R s q=0.9)$
aScore <- ma(d)
pValue <- ma.test(d,aScore)

Scattergram visualization of associations between all pairs of variables.

## Description

Uses the association array generated by tap to construct an array of association diagrams (pie charts and scatterplots).

## Usage

agram(dataSet, method, ranking, order, ...)

## Arguments

dataSet the $\mathrm{n} \times \mathrm{m}$ data frame representing n samples of the m variables.
method the method to use for linear association (included in the visualization) as performed by cor, one of "pearson", "spearman", "kendall". The default is "pearson".
ranking a logical specifying whether or not to rank the data points before producing the scatter plots. The default is FALSE.
order determines the variable ordering. one of FALSE (the default for no re-grouping) or "PC" (for principal components re-grouping) or "OLO" (for optimal leaf ordering)
... passed on to graphics routines ...

## Details

Displays associations between all pairs of variables as a graphics array using pie-charts above the diagonal depicting the proportion of the total association that can be explained by a linear trend in blue, and the remaining non-linear association in red.

Below the diagonal, scatter plots are shown and colored according to proportional non-linearity (see nl3 returned by ma.nl ).

## Value

Returns nothing.

## Note

The data set can be of any dimension.

## Author(s)

Ben Murrell, Dan Murrell \& Hugh Murrell.

## References

This code was adapted from the corrgram package:
Author: Kevin Wright, Copyright: 2006 Kevin Wright, License: GPL2.

## See Also

ma ma.nl tap

```
Examples
    data(baseballData)
    agram(baseballData,order="OLO",main="All pair associations for baseballData")
```

amap Heatmap and dendrogram from associations between all pairs of vari- ables.

## Description

Clusters variables in a datafrome using dist $=1-\mathrm{A}$ and plots a heatmap with cluster dendrogram attached.

## Usage

amap(dataSet, palette, corAdjusted, method, title, ...)

## Arguments

| dataSet <br> palette | the $n \mathrm{x} m$ data frame representing n samples of the m variables. <br> colour palette to use for the heatmap. |
| :--- | :--- |
| corAdjusted | a flag which if set causes bi-variate A scores to be mutiplied by the sign of the <br> same bi-variate correlation. This gives a direction to the association. defaults to <br> FALSE. |
| method | the method to use for correlation association as performed by cor, one of "pearson", <br> "spearman", "kendall". The default is "spearman". |
| title | a main title for the heatmap plot. |
| $\ldots$ | passed on to graphics routines ... |

## Details

uses heatmap. 2 from the gplots package to display a heatmap and associated dendorgram with bi-variate scores provided by matie's A value. If required these scores can be expanded into the range $[-1,1]$ through multiplication by the sign of the corresponding bi-variate correlation score.

## Value

Returns nothing.

## Note

The data set can be of any dimension.

## Author(s)

Ben Murrell, Dan Murrell \& Hugh Murrell.

## References

This code was adapted from Moignard et al.

## See Also

ma tap

## Examples

data(baseballData)
amap(baseballData, corAdjusted=TRUE)
baseballData Baseball player performance and income dataset

## Description

This data set is a collection of performance statistics for a collection of baseball players including a Salary variable.

## Usage

data(baseballData)

## Format

A data frame consisting of 11 variables (columns) for 322 players (rows).

## Source

CRAN: corrgram package

## References

This dataset is a subset of the baseball dataset from the corrgram package.
Author: Kevin Wright, Copyright: 2006 Kevin Wright, License: GPL2.

## Description

Attempts to find the best explanatory set of variables to explain a single variable in a data set. Iterates between adding the next best variable to the set and removing the variable (if any) whose exclusion maximizes the overall score.

## Usage

fbvs(dataSet, one, maxv,linear)

## Arguments

dataSet the $\mathrm{n} x \mathrm{~m}$ data frame representing n observations of m variables.
one a string specifying the name of one variable in the dataset, for which the best explanatory set is required. Defaults to the name of the last variable in the dataset.
$\operatorname{maxv} \quad$ an integer limiting the maximum number of variables in the explanatory set. Defaults to m-1.
linear a boolean flag which causes fbvs to use a linear model to estimate $\mathrm{R}^{\wedge} 2$ instead of matie to estimate A when running the selection algorithm. Defaults to FALSE

## Details

Variable names are only added to the explanatory set if their inclusion results in an increase in the association measure.

## Value

Returns a list containing the following items:

| one | the name of the one variable that requires the explanatory set |
| :--- | :--- |
| best | the best set of explanatory variables |
| Rsq | an estimate for $R^{\wedge} 2$ provided by the best set of explanatory variables |

## Note

The data set can be of any dimension

## Author(s)

Ben Murrell, Dan Murrell \& Hugh Murrell.

## References

Discovering general multidimensional associations, http://arxiv.org/abs/1303.1828

## See Also

ma agram

## Examples

```
    # measure association for all pairs in a subrange of the baseball dataset
    data(baseballData)
    fbvs(baseballData,one="Salary")
    fbvs(baseballData,one="Salary",linear=TRUE)
    fbvs(baseballData,one="Salary",maxv=2)
    fbvs(baseballData,one="Salary",maxv=2,linear=TRUE)
```

fdg Force directed graph visualization of associations between all pairs of variables.

## Description

Constructs and draws a force directed graph using an "all pairs" association matrix to drive attraction in the graph. This adjacency matrix can represent linear or non-linear associations.

## Usage

fdg(dataSet, dataName, method, cutoff, dim)

## Arguments

| dataSet | a data frame |
| :--- | :--- |
| dataName | a string naming the dataSet. (set to NULL if unknown) |
| method | one of "A" for non-linear associations or "Rsq" for linear associations. Defaults <br> to "A". |
| cutoff | a real number between 0 and 1, used to remove edges from the graph with asso- <br> ciation < cutoff. Defaults to 0.1 |
| dim | graph layouts can be generated in 2 or 3 dimensions. note that rgl must be <br> installed for viewing 3 dimensional layouts. |

## Details

The igraph package is used to generate, layout and display the force directed graph. The layout employed is layout. kamada. kawai.

## Value

Returns nothing.

## Note

All non numeric columns and non complete rows are stripped from the data set before the adjacency matrix is computed.

## Author(s)

Ben Murrell, Dan Murrell \& Hugh Murrell.

## References

Discovering general multidimensional associations, http://arxiv.org/abs/1303.1828

## See Also

ma cor agram

## Examples

```
    data(baseballData)
    fdg(baseballData,dataName="baseballData",method="A",cutoff=0.35,dim=2)
    # if you have rgl available then try dim=3
    # fdg(baseballData,dataName="baseballData",method="Rsq",cutoff=0.15,dim=3)
```


## Description

A non-parametric measure of association between variables. The association score $A$ ranges from 0 (when the variables are independent) to 1 (when they are perfectly associated). $A$ is a kind of $R^{2}$ estimate, and can be thought of as the proportion of variance in one variable explained by another (or explained by a number of other variables - $A$ works for multivariate associations as well).

## Usage

ma(d, partition, ht, hp, hs, ufp)

## Arguments

$\mathrm{hp} \quad$ power for the hyperbolic correction, default $\mathrm{hp}=0.8120818$.
d
partition
ht
hs
ufp
the $n \times m$ data frame containing $n$ observations of $m$ variables for which the maximal joint/marginal likelihood ratio score is required.
tangent for the hyperbolic correction, default ht $=43.6978644$.
scale for the hyperbolic correction, default hs $=6.0049711$.
for debugging purposes, default FALSE.

## Details

An estimate of association (possibly nonlinear) is computed using a ratio of maximum likelihoods for the marginal distribution and maximum weighted likelihoods for the joint distribution.
Before the computation is carried out the data is ranked using the rwt function from the matie package. This estimate is usually conservative (ie low) and a small-samples hyperbolic correction is applied by adding an offset, os, to the joint likelihood given by:
os $=\left(1-\frac{1}{1+\mathrm{A} \times \mathrm{ht}}\right) \frac{\mathrm{n}^{\mathrm{hp}}}{\mathrm{hs}}$
before the likelihood ratio is re-computed.
As the dimension of the data set increases so does the under-estimation of A even with the hyperbolic correction.

## Value

Returns a list of values ...

| A | a score (including hyperbolic correction) estimating association for the data |
| :--- | :--- |
| rawA | the association score before hyperbolic correction |
| jointKW | the optimal kernel width for the joint distribution |
| altLL | the optimal weighted log likelihood for the alternate distribution <br> nullLL |
| the optimal log likelihood for the marginal distribution |  |
| marginalKW | the optimal kernel width for the marginal distribution |
| wRstat | the optimal weight used for the mixture |
| nRows | the LR statistic, required for computing p values. |
| mCols | n, the number of complete samples in the data set |
| partition | m, the number of variables in the data set |
| ufp | user supplied partition for the variables in the data set |

## Note

The data set can be of any dimension.

## Author(s)

Ben Murrell, Dan Murrell \& Hugh Murrell.

## References

Discovering general multidimensional associations, http://arxiv.org/abs/1303.1828

## See Also

rwt pd sbd shpd std

## Examples

```
    # bivariate association
    d <- shpd(n=1000,m=2,Rsq=0.9)
    ma(d)$A
    #
    # multivariate association (the proportion of variance in "Salary"
    # explained by "Hits" and "Years")
    data(baseballData)
    ma(baseballData,partition=list(11,c(2,7)))$A
```

ma.nl
Calculates degree of nonlinearity for a particular association score.

## Description

This function estimates nonlinear proportion of variance between one variable and a group of variables after linear association between the variable and the group has been removed.

## Usage

ma.nl(Y, X)

## Arguments

$Y \quad$ A vector or a one column data frame.
$\mathrm{X} \quad$ a group of vectors or a data frame with the same number of samples as in Y

## Details

A linear model, $\mathrm{Y} \sim \mathrm{X}$, is constructed and ma is used to compute $\mathrm{R}^{\wedge} 2$ between Y and X .

## Value

Returns a list of real numbers:
Rsq linear association, the value of $R^{\wedge} 2$ due to the linear model $Y \sim X$.
A total association (linear and nonlinear) between Y and the group X.
rA the residual association (the association left in the residuals after the linear part has been regressed out of Y).
nl1 A - Rsq, the nonlinear part of the association.
nl2 (A - Rsq) / A, the nonlinear proportion of the association.
nl3 (A - Rsq) / (1-Rsq), the proportion of total variance that is not explained by a linear model but is explained by A .

## Author(s)

Ben Murrell, Dan Murrell \& Hugh Murrell.

## References

Discovering general multidimensional associations, http://arxiv.org/abs/1303.1828

## See Also

ma agram

## Examples

$\mathrm{X} 1=\operatorname{runif}(1000)$
$X 2=\operatorname{runif}(1000)$
$Y=\sin (0.5 * \mathrm{pi} * \mathrm{X} 1)+\sin (0.5 * \mathrm{pi} * X 2)+r n o r m(1000) * 0.000001$
ma.nl(Y, cbind(X1,X2))
\#
\# in the case of bivariate associations all these measures
\# are symmetric apart from rA, the residual association
$X=r u n i f(1000)$
$Y=\sin (0.5 * p i * X)+r n o r m(1000) * 0.01$
ma.nl( $\mathrm{Y}, \mathrm{X}) \$ \mathrm{~F} A$
ma.nl(X,Y)\$rA
ma.test $\quad p$-value for an association score.

## Description

This function computes the p-value for an association score using interpolation from a precomputed table (fast - only available for the bivariate case) or using a permutation test.

## Usage

ma.test(d, maStruct, permPartition, lookup, reps)

## Arguments

d
the data set
maStruct the structure returned by a call to ma. Must be provided. No default.
permPartition a permutation partition for the data set depending on the statistical question being asked. Defaults to the partition returned by the call to ma.
lookup logical, if TRUE then a p-value is interpolated from a table of precomputed pvalues. If FALSE then a monte carlo simulation is carried out. Table lookup is only accurate for associations on bivariate data with number of samples $<=400$. By default, lookup is TRUE.
reps no of repeats for the monte carlo simulation. defaults to 1000 .

## Details

Computes a p value for an association from the likelihood ratio statistic computed by ma. Uses interpolation by default for bivariate associations, and permutation testing for multivariate associations.

## Value

Returns a real number in the range $[0,1]$.

## Author(s)

Ben Murrell, Dan Murrell \& Hugh Murrell.

## References

Discovering general multidimensional associations, http://arxiv.org/abs/1303.1828

## See Also

ma

## Examples

```
    d <- shpd(n=100,m=2,Rsq=0.2)
    aScore <- ma(d)
    ma.test(d, aScore)
    # or set lookup to FALSE if you have computing time available
    # ma.test(d, aScore, lookup=FALSE, reps=10000)
```

pd Plot density (after an ma calculation).

## Description

Optimal kernel widths output by ma are employed to recompute the weighted joint distribution for two variables in a data set, and a contour plot for this distribution is drawn.

## Usage

$\mathrm{pd}(\mathrm{d}, \mathrm{iv}=1, \mathrm{jv}=2)$

## Arguments

d
an nx m data frame with $\mathrm{m}>1$.
iv the column index of the independent variable
jv the column index of the dependent variable

## Details

A data set of two variables is extracted from the user's data set and a full distribution is calculated using weighted marginal and joint likelihoods. The optimal kernel sizes and weighting are first computed via a call to ma.

## Value

An nxn distribution of weighted likelihoods is returned.

## Note

The data set must contain at least 2 columns.

## Author(s)

Ben Murrell, Dan Murrell \& Hugh Murrell.

## References

Discovering general multidimensional associations, http://arxiv.org/abs/1303.1828

## See Also

## Examples

```
    f <- function(x,name="Sinusoidal",def="y = 1 + sin(x)"){
        return(1 + sin(x))
    }
    d <- sbd(f,min=-2*pi,max=2*pi,n=1000,Rsq=0.9)
    ma(d)$A
    dist <- pd(d)
```

rwt
Rank with ties

## Description

This function replaces variable values in a data set with their ranks, using a random tie breaking strategy. It is called by ma and pd.

```
    sbd Generates sample bivariate data.
```


## Description

This function generates a sample bivariate data set.

## Usage

sbd(func, min, max, $n, R s q)$

## Arguments

func a user supplied function of one variable, $y=\operatorname{func}(x)$, near which data is generated.
min min value for the domain of func
$\max \quad \max$ value for the domain of func
$\mathrm{n} \quad$ number of sample points to generate
Rsq coefficient of determination for the data set

## Details

If func is NULL then a normal bivariate data set of n samples is generated with correlation coefficient sqrt(Rsq). If func is passed by the user then $n$ sample points are scattered about $y=f u n c(x)$ with variance governed by the Rsq parameter

## Value

Returns an n x 2 bivariate data set

## Note

See examples below on how to set up user defined functions

## Author(s)

Ben Murrell, Dan Murrell \& Hugh Murrell.

## References

Discovering general multidimensional associations, http://arxiv.org/abs/1303.1828

## See Also

ma

## Examples

```
    f <- function(x,name="Sinusoidal",def="y = 1 + sin(x)"){
        return(1 + sin(x))
    }
    d <- sbd(f,min=-2*pi,max=2*pi,n=500,Rsq=0.9)
    ma(d)$A
    plot(d)
```

    shpd Generates sample hyperplane data.
    
## Description

This function generates a sample hyperplane data set.

## Usage

$\operatorname{shpd}(n, m=2, R s q=0.7, R i=0)$

## Arguments

| n | number of sample points to generate <br> m |
| :--- | :--- |
| Rsq | a hyperplane of dimension $\mathrm{m}-1$ will be generated in m space <br> the desired coefficient of determination for the hyperplane, indicates how far <br> data points will vary from the plane. |
| Ri | correlation coefficient for "independent"" variables within the hyperplane |

## Details

Scatters data around the hyperplane: $\mathrm{Vm}=\operatorname{sum}(\mathrm{V} 1 \ldots \mathrm{Vm}-1)+$ noise where noise is adjusted so that the final dataset has coefficient of determination equal to Rsq. Variables V1..Vm-1 are assumed to be independent but the user can make them dependent on each other by setting the Vi parameter away from zero.

## Value

Returns a n x m data set

## Author(s)

Ben Murrell, Dan Murrell \& Hugh Murrell.

## References

Discovering general multidimensional associations, http://arxiv.org/abs/1303.1828

## See Also

ma

## Examples

d <- shpd(500,3,Rsq=0.8,Ri=0.01)
ma(d)\$A
ma(d, partition=list(1,2))\$A
ma(d, partition=list(3,1))\$A
ma(d, partition=list(3,2))\$A
ma(d, partition=list(3, c(1,2)))\$A
$\operatorname{cor}(\mathrm{d})^{\wedge} 2$
\# if m=3 and if you have rgl
\# you can view the data set in 3D
\# library("rgl")
\# plot3d(d)

Semi-partial association (computes association while controlling for variables)

## Description

Computes the semi-partial association between a response variable and an explanatory variable, after controlling for a control variable.

## Usage

$\operatorname{spa}(\mathrm{Y}, \mathrm{X}, \mathrm{C})$

## Arguments

Y

C

X the explanatory variable, a vector or column from a dataset
the response variable, a vector or column from a dataset the control variable, a vector or column from a dataset

## Details

A semi-partial association (possibly nonlinear) is computed via:

$$
\operatorname{ma}(c b i n d(C, X, Y)) \$ A-m a(c b i n d(C, Y)) \$ A
$$

Inspired by the linear semi-partial correlation given by:

```
spcor.test(Y,X,C)
```

from the ppcor package.

## Value

Returns a real number in the range $[0,1]$.

## Note

The parameters $\mathrm{Y}, \mathrm{X}$ and C must be vectors of the same length.

## Author(s)

Ben Murrell, Dan Murrell \& Hugh Murrell.

## References

Discovering general multidimensional associations, http://arxiv.org/abs/1303.1828

## See Also

ma

## Examples

\# When the association between $Y$ and $X$ is entirely explained by $C$
C <- rnorm(1000)
$X<-C+r n o r m(1000) * 0.5$
$Y<-C+r n o r m(1000) * 0.5$
\# See the relationship without controlling for $C$
ma(cbind ( $X, Y$ )) \$A
\# See the relationship with $C$ as a covariate (should be close to 0)
$\operatorname{spa}(\mathrm{Y}, \mathrm{X}, \mathrm{C})$
\# if you have ppcor then you can verify that
\# the linear semi-partial correlation is similar,
\# as these associations are all linear
\# spcor.test(Y, X,C)\$estimate^2
\#
\# When the association between $Y$ and $X$ is only partially explained by $C$
C <- rnorm(1000)
$X<-C+r n o r m(1000) * 0.5$
$Y<-X+r n o r m(1000) * 0.5$
\# See the relationship without controlling for $C$
ma(cbind ( $\mathrm{X}, \mathrm{Y}$ )) \$A
\# See the relationship with $C$ as a covariate
\# (should be lower than the uncontrolled one, but not as low as 0)

```
spa(Y,X,C)
# if you have ppcor then you can verify that
# the linear semi-partial correlation is similar,
# as these associations are all linear
spcor.test(Y,X,C)$estimate^2
#
#
# if you have rgl you can plot the data
# library(rgl)
# plot3d(X,C,Y)
```


## Description

This function generates a sample trivariate data set.

## Usage

std(func, $x$ Min, $x$ Max, $y$ Min, $y$ Max, $n, R s q$ )

## Arguments

| func | a user supplied function of two variables, $\mathrm{z}=$ func $(\mathrm{x}, \mathrm{y})$, near which data is gen- <br> erated |
| :--- | :--- |
| xMin | min value for the x domain of func |
| xMax | max value for the x domain of func |
| yMin | min value for the $y$ domain of func |
| yMax | max value for the $y$ domain of func |
| n | number of sample points to generate |
| Rsq | coefficient of determination for the data set |

## Details

If func is NULL then a normal trivariate data set of n samples is generated with correlation coefficients all set to sqrt(Rsq). If func is passed by the user then n sample points are scattered about $\mathrm{z}=\mathrm{func}(\mathrm{x}, \mathrm{y})$ with variance governed by the Rsq parameter.

## Value

Returns an $\mathrm{n} \times 3$ trivariate data set.

## Note

See examples below on how to set up user defined functions.

## Author(s)

Ben Murrell, Dan Murrell \& Hugh Murrell.

## References

Discovering general multidimensional associations, http://arxiv.org/abs/1303.1828

## See Also

ma sbd

## Examples

```
    f <- function(x,y,name="MexicanHat", def="z=(1-t^2)exp(-t^2div2), t^2=x^2+y^2"){
        t <- sqrt(x^2 + y^2)
        z<- (1.0 - t^2) * exp(- t * t / 2)
        return(z)
    }
    d <- std(f, xMin=-2, xMax=2, yMin=-2, yMax=2, n=500, Rsq=0.85)
    ma(d)$A
    # if you have rgl you can view the data set in 3D
    # library("rgl")
    # plot3d(d)
```

    tap Test all pairs (computes association score for all pairs of variables).
    
## Description

Tries all pairs in an $\mathrm{n} x \mathrm{~m}$ user supplied data set ( n observations of m variables). Returns a square matrix of association measures.

## Usage

tap(dataSet,one)

## Arguments

dataSet the $\mathrm{n} x \mathrm{~m}$ data frame representing n observations of m variables.
one a string specifying the name of one variable in the dataset, for testing all pairs against one.

## Details

All pairs of variables in a user supplied data set are measured for A association. Returns an $m \times m$ data frame ( or m-1 $\times \mathrm{m}-1$ when one is set) storing A values for each pair of variables in the all pairs test.

## Value

Returns a square data frame.

## Note

The data set can be of any dimension.

## Author(s)

Ben Murrell, Dan Murrell \& Hugh Murrell.

## References

Discovering general multidimensional associations, http://arxiv.org/abs/1303.1828

## See Also

ma

## Examples

```
# measure association for all pairs in a subrange of the baseball dataset
data(baseballData)
    ap <- tap(baseballData)
```


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