Package ‘generalCorr’

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<td>Generalized Correlations and Initial Causal Path</td>
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<td>Author</td>
<td>Prof. H. D. Vinod, Fordham University, NY.</td>
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<td>Description</td>
<td>Since causal paths from data are important for all sciences, the package provides sophisticated functions. The idea is simply that if X causes Y (path: X to Y) then non-deterministic variation in X is more `original or independent`` than similar variation in Y. Since causal variables are also exogenous in a model, we provide new exogeneity tests. We compare two flipped kernel regressions: X=f(Y, Z) and Y=g(X,Z), where Z are control variables. Our first two criteria compare absolute cross products of regressor values and residuals (Cr1) and absolute residuals (Cr2), are both quantified by stochastic dominance of four orders (SD1 to SD4). Our third criterion (Cr3) expects X to be better able to predict Y than the other way around using generalized partial correlation. If</td>
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**abs_res**

Absolute residuals of kernel regression of \( x \) on \( y \).

**Description**

This internal function calls the `kern` function to implement kernel regression with the option `residuals=TRUE` and returns absolute residuals.

**Usage**

```r
abs_res(x, y)
```

**Arguments**

- `x` vector of data on the dependent variable
- `y` vector of data on the regressor

**Details**

The first argument is assumed to be the dependent variable. If `abs_res(x,y)` is used, you are regressing \( x \) on \( y \) (not the usual \( y \) on \( x \)).

**Value**

absolute values of kernel regression residuals are returned.

**Note**

This function is intended for internal use.

**Author(s)**

Prof. H. D. Vinod, Economics Dept., Fordham University, NY
abs_stdapd

Examples

```r
## Not run:
set.seed(330)
x = sample(20:50)
y = sample(20:50)
abs_res(x, y)

## End(Not run)
```

---

abs_stdapd  

Absolute values of gradients (apd's) of kernel regressions of x on y when both x and y are standardized.

Description

1) standardize the data to force mean zero and variance unity, 2) kernel regress x on y, with the option ‘gradients = TRUE’ and finally 3) compute the absolute values of gradients

Usage

```r
abs_stdapd(x, y)
```

Arguments

- `x` vector of data on the dependent variable
- `y` data on the regressors which can be a matrix

Details

The first argument is assumed to be the dependent variable. If `abs_stdapd(x, y)` is used, you are regressing x on y (not the usual y on x). The regressors can be a matrix with 2 or more columns. The missing values are suitably ignored by the standardization.

Value

Absolute values of kernel regression gradients are returned after standardizing the data on both sides so that the magnitudes of amorphous partial derivatives (apd’s) are comparable between regression of x on y on the one hand and regression of y on x on the other.

Author(s)

Prof. H. D. Vinod, Economics Dept., Fordham University, NY
Examples

```r
## Not run:
set.seed(330)
x = sample(20:50)
y = sample(20:50)
abs_stdapd(x, y)
```

## End(Not run)

### Description

1) standardize the data to force mean zero and variance unity, 2) kernel regress x on y and a matrix of control variables, with the option ‘gradients = TRUE’ and finally 3) compute the absolute values of gradients

### Usage

```r
abs_stdapdC(x, y, ctrl)
```

### Arguments

- `x`: vector of data on the dependent variable
- `y`: data on the regressors which can be a matrix
- `ctrl`: Data matrix on the control variable(s) beyond causal path issues

### Details

The first argument is assumed to be the dependent variable. If `abs_stdapdC(x, y)` is used, you are regressing x on y (not the usual y on x). The regressors can be a matrix with 2 or more columns. The missing values are suitably ignored by the standardization.

### Value

Absolute values of kernel regression gradients are returned after standardizing the data on both sides so that the magnitudes of amorphous partial derivatives (apd’s) are comparable between regression of x on y on the one hand and regression of y on x on the other.

### Author(s)

Prof. H. D. Vinod, Economics Dept., Fordham University, NY

### See Also

See `abs_stdapd`.
abs_stdres

Examples

```r
## Not run:
set.seed(330)
x = sample(20:50)
y = sample(20:50)
z = sample(20:50)
abs_stdapdc(x, y, ctrl = z)

## End(Not run)
```

Description

1) Standardize the data to force mean zero and variance unity, 2) kernel regress x on y, with the option `residuals = TRUE` and finally 3) compute the absolute values of residuals.

Usage

```r
abs_stdres(x, y)
```

Arguments

- `x` vector of data on the dependent variable
- `y` data on the regressors which can be a matrix

Details

The first argument is assumed to be the dependent variable. If `abs_stdres(x, y)` is used, you are regressing x on y (not the usual y on x). The regressors can be a matrix with 2 or more columns. The missing values are suitably ignored by the standardization.

Value

Absolute values of kernel regression residuals are returned after standardizing the data on both sides so that the magnitudes of residuals are comparable between regression of x on y on the one hand and regression of y on x on the other.

Author(s)

Prof. H. D. Vinod, Economics Dept., Fordham University, NY

References

Examples

```r
## Not run:
set.seed(330)
x = sample(20:50)
y = sample(20:50)
abs_stdresC(x, y)

## End(Not run)
```

---

**abs_stdresC**

*Absolute values of residuals of kernel regressions of x on y when both x and y are standardized and control variables are present.*

---

**Description**

1) standardize the data to force mean zero and variance unity, 2) kernel regress x on y and a matrix of control variables, with the option `residuals = TRUE` and finally 3) compute the absolute values of residuals.

**Usage**

`abs_stdresC(x, y, ctrl)`

**Arguments**

- `x` vector of data on the dependent variable
- `y` data on the regressors which can be a matrix
- `ctrl` Data matrix on the control variable(s) beyond causal path issues

**Details**

The first argument is assumed to be the dependent variable. If `abs_stdresC(x, y)` is used, you are regressing x on y (not the usual y on x). The regressors can be a matrix with 2 or more columns. The missing values are suitably ignored by the standardization.

**Value**

Absolute values of kernel regression residuals are returned after standardizing the data on both sides so that the magnitudes of residuals are comparable between regression of x on y on the one hand and regression of y on x on the other.

**Author(s)**

Prof. H. D. Vinod, Economics Dept., Fordham University, NY
abs_stdrhserC

References


See Also

See abs_stdres.

Examples

```r
## Not run:
set.seed(330)
x=sample(20:50)
y=sample(20:50)
z=sample(21:51)
abs_stdrhserc(x,y,ctrl=z)
## End(Not run)
```

```
abs_stdrhserC  Absolute residuals kernel regressions of standardized x on y and control variables, Ctrl has abs(RHS*y)
```

Description

1) standardize the data to force mean zero and variance unity, 2) kernel regress x on y and a matrix of control variables, with the option ‘residuals = TRUE’ and finally 3) compute the absolute values of residuals.

Usage

```r
abs_stdrhserC(x, y, ctrl, ycolumn = 1)
```

Arguments

- `x`: vector of data on the dependent variable
- `y`: data on the regressors which can be a matrix
- `ctrl`: Data matrix on the control variable(s) beyond causal path issues
- `ycolumn`: if y has more than one column, the column number used when multiplying residuals times this column of y, default=1 or first column of y matrix is used
Details

The first argument is assumed to be the dependent variable. If abs_stdrhserC(x,y) is used, you are regressing x on y (not the usual y on x). The regressors can be a matrix with 2 or more columns. The missing values are suitably ignored by the standardization.

Value

Absolute values of kernel regression residuals are returned after standardizing the data on both sides so that the magnitudes of residuals are comparable between regression of x on y on the one hand and regression of y on x on the other.

Author(s)

Prof. H. D. Vinod, Economics Dept., Fordham University, NY

References


See Also

See abs_stdres.

Examples

```r
## Not run:
set.seed(330)
x/sample(20:50)
y/sample(20:50)
z/sample(21:51)
abs_stdrhserC(x,y,ctrl=z)
## End(Not run)
```

### Description

1) standardize the data to force mean zero and variance unity, 2) kernel regress x on y, with the option ‘gradients = TRUE’ and finally 3) compute the absolute values of Hausman-Wu null hypothesis for testing exogeneity, or E(RHS.regressor*error)=0 where error is approximated by kernel regression residuals.
allPairs

Usage

abs_stdrhserr(x, y)

Arguments

x vector of data on the dependent variable
y data on the regressors which can be a matrix

Details

The first argument is assumed to be the dependent variable. If abs_stdrhserr(x, y) is used, you are regressing x on y (not the usual y on x). The regressors can be a matrix with 2 or more columns. The missing values are suitably ignored by the standardization.

Value

Absolute values of kernel regression RHS*residuals are returned after standardizing the data on both sides so that the magnitudes of Hausman-Wu null values are comparable between regression of x on y on the one hand and flipped regression of y on x on the other.

Author(s)

Prof. H. D. Vinod, Economics Dept., Fordham University, NY

Examples

## Not run:
set.seed(330)
x = sample(20:50)
y = sample(20:50)
abs_stdrhserr(x, y)

## End(Not run)

allPairs

Report causal identification for all pairs of variables in a matrix.

Description

This is a convenient way to study all possible (perhaps too many) causal directions in a matrix. It calls abs_stdapd, abs_stdres, comp_portfo2, etc. and returns a matrix with 7 columns with detailed output.

Usage

allPairs(mtx, dig = 6, verbo = FALSE, typ = 1, rnam = FALSE)
**Arguments**

- **mtx**: Input matrix with variable names
- **dig**: Digits of accuracy in reporting (=6, default)
- **verbo**: Logical variable, set to 'TRUE' if printing is desired
- **typ**: Causal direction criterion number (typ=1 is default) Criterion 1 (Cr1) compares kernel regression absolute values of gradients. Criterion 2 (Cr2) compares kernel regression absolute values of residuals. Criterion 3 (Cr3) compares kernel regression based r*(x|y) with r*(y|x).
- **rnam**: Logical variable, default rnam=FALSE means the user does not want the row names to be (somewhat too cleverly) assigned by the function.

**Value**

A 7-column matrix called 'outcause' with names of variables X and Y in the first two columns and the name of the 'causal' variable in 3rd col. Remaining four columns report numerical computations of SD1 to SD4, r*(x|y), r*(y|x). Pearson r and p-values for its traditional significance testing.

**Note**

The cause reported in the third column is identified from the sign of the first SD1 only, ignoring SD2, SD3 and SD4 under both Cr1 and Cr2. It is a good idea to loop a call to this function with typ=1:3. One can print the resulting 'outcause' matrix with the xtable(outcause) for the Latex output. A similar (perhaps better) function included in this package, called somePpairs, incorporates all SD1 to SD4 and all three criteria Cr1 to Cr3 to report a 'sum' of indexes representing the signed number whose sign can more comprehensively help determine the causal direction(s).

**Author(s)**

Prof. H. D. Vinod, Economics Dept., Fordham University, NY

**References**

Vinod, H. D.'Generalized Correlation and Kernel Causality with Applications in Development Economics' in Communications in Statistics -Simulation and Computation, 2015, [http://dx.doi.org/10.1080/03610918.2015.1122048](http://dx.doi.org/10.1080/03610918.2015.1122048)

**See Also**

somePairs, somePpairs

**Examples**

```r
data(mtcars)
for(j in 1:3){
a1=allPairs(mtcars[,1:3], typ=j)
print(a1)}
```
**badCol**

*internal badCol*

---

**Description**

intended for internal use

**Usage**

data(badCol)

**Format**

The format is: int 4

---

**bigfp**

*Compute the numerical integration by the trapezoidal rule.*

---

**Description**

See page 220 of Vinod’s “Hands-on Intermediate Econometrics Using R,” cited below for the trapezoidal integration formula needed for stochastic dominance. The book explains pre-multiplication by two large sparse matrices denoted by \( I_F, I_f \). Here we accomplish the same computation without actually creating the large sparse matrices. For example, the \( I_f \) is replaced by \texttt{cumsum} in this code (unlike the R code in my textbook).

**Usage**

\texttt{bigfp(d, p)}

**Arguments**

- \( d \): A vector of consecutive interval lengths, upon combining both data vectors
- \( p \): Vector of probabilities of the type \( 1/2T, 2/2T, 3/2T \), etc. to 1.

**Value**

Returns a result after pre-multiplication by \( I_F, I_f \) matrices, without actually creating the large sparse matrices. This is an internal function.

**Note**

This is an internal function, called by the function \texttt{stochdom2}, for comparison of two portfolios in terms of stochastic dominance (SD) of orders 1 to 4. Typical usage is: \texttt{sd1b=bigfp(d=dj, p=rhs)} \texttt{sd2b=bigfp(d=dj, p=sd1b)} \texttt{sd3b=bigfp(d=dj, p=sd2b)} \texttt{sd4b=bigfp(d=dj, p=sd3b)}. This produces numerical evaluation vectors for the four orders, SD1 to SD4.
bootPairs

Compute matrix of n999 rows and p-1 columns of bootstrap ‘sum’ (strength from Cr1 to Cr3).

Description

Maximum entropy bootstrap (meboot) package is used for statistical inference using the sum of three signs sg1 to sg3 from the three criteria Cr1 to Cr3 to assess preponderance of evidence in favor of a sign. (+1, 0, -1). The bootstrap output can be analyzed to assess approximate preponderance of a particular sign which determines the causal direction.

Usage

bootPairs(mtx, ctrl = 0, n999 = 9)

Arguments

mtx data matrix with two or more columns
ctrl data matrix having control variable(s) if any
n999 Number of bootstrap replications (default=9)

Value

out When mtx has p columns, out of bootPairs(mtx) is a matrix of n999 rows and p-1 columns each containing resampled ‘sum’ values summarizing the weighted sums associated with all three criteria from the function silentPairs(mtx) applied to each bootstrap sample separately.

Note

This computation is computer intensive and generally very slow. It may be better to use it at a later stage in the investigation when a preliminary causal determination is already made. A positive sign for j-th weighted sum reported in the column ‘sum’ means that the first variable listed in the argument matrix mtx is the ‘kernel cause’ of the variable in the (j+1)-th column of mtx.

Author(s)

Prof. H. D. Vinod, Economics Dept., Fordham University, NY
References


See Also

See Also silentPairs.

Examples

```r
## Not run:
options(np.messages = FALSE)
set.seed(34); x=sample(1:10); y=sample(2:11)
bb=bootPairs(cbind(x, y), n999=29)
apply(bb,2,summary) #gives summary stats for n999 bootstrap sum computations

bb=bootPairs(airquality, n999=999); options(np.messages=FALSE)
apply(bb,2,summary) #gives summary stats for n999 bootstrap sum computations

data('EuroCrime')
attach(EuroCrime)
bootPairs(cbind(crim, off), n999=29)#First col. crim causes officer deployment,
#hence positives signs are most sensible for such call to bootPairs
#note that n999=29 is too small for real problems, chosen for quickness here.

## End(Not run)
```

**bootPairs**

*Compute matrix of n999 rows and p-1 columns of bootstrap ‘sum’ index (strength from older criterion Cr1, with newer Cr2 and Cr3).*

**Description**

Maximum entropy bootstrap (meboot) package is used for statistical inference using the sum of three signs sg1 to sg3 from the three criteria Cr1 to Cr3 to assess preponderance of evidence in favor of a sign. (+1, 0, -1). The bootstrap output can be analyzed to assess approximate preponderance of a particular sign which determines the causal direction.

**Usage**

```r
bootPairs(mtx, ctrl = 0, n999 = 9)
```
Arguments

mtx  data matrix with two or more columns
ctrl data matrix having control variable(s) if any
n999 Number of bootstrap replications (default=9)

Value

out When mtx has p columns, out of bootPairs(mtx) is a matrix of n999 rows and p-1 columns each containing resampled ‘sum’ values summarizing the weighted sums associated with all three criteria from the function silentPairs(mtx) applied to each bootstrap sample separately.

Note

This computation is computer intensive and generally very slow. It may be better to use it at a later stage in the investigation when a preliminary causal determination is already made. A positive sign for j-th weighted sum reported in the column ‘sum’ means that the first variable listed in the argument matrix mtx is the ‘kernel cause’ of the variable in the (j+1)-th column of mtx.

Author(s)

Prof. H. D. Vinod, Economics Dept., Fordham University, NY

References


See Also

See Also silentPairs0, bootPairs has the version with later version of Cr1.

Examples

```R
# Not run:
options(np.messages = FALSE)
set.seed(34); x=sample(1:10); y=sample(2:11)
bb=bootPairs0(cbind(x,y),n999=29)
apply(bb,2,summary) #gives summary stats for n999 bootstrap sum computations

bb=bootPairs0(airquality,n999=999);options(np.messages=FALSE)
apply(bb,2,summary) #gives summary stats for n999 bootstrap sum computations
```
data('EuroCrime')
attach(EuroCrime)
bootPairs8(cbind(crim,off),n999=29)#First col. crim causes officer deployment,
#hence positives signs are most sensible for such call to bootPairs
#note that n999=29 is too small for real problems, chosen for quickness here.

## End(Not run)

---

**bootQuantile**  
*Compute confidence intervals [quantile(s)] of indexes from bootPairs output*

**Description**

Begin with the output of bootPairs function, a (n999 by p-1) matrix when there are p columns of data, bootQuantile produces a (k by p-1) mtx of quantile(s) of bootstrap output assuming that there are k quantiles needed.

**Usage**

```r
bootQuantile(out, probs = c(0.025, 0.975), per100 = TRUE)
```

**Arguments**

- **out**: output from bootPairs with p-1 columns and n999 rows
- **probs**: quantile evaluation probabilities. The default is k=2, probs=c(.025, .975) for a 95 percent confidence interval. Note that there are k=2 quantiles desired for each column with this specification
- **per100**: logical (default per100=TRUE) to change the range of 'sum' to [-100, 100] values which are easier to interpret

**Value**

CI k quantiles evaluated at probs as a matrix with k rows and quantile of pairwise p-1 indexes representing p-1 column pairs (fixing the first column in each pair). This function summarizes the output of of bootPairs(mtx) (a n999 by p-1 matrix) each containing resampled 'sum' values summarizing the weighted sums associated with all three criteria from the function silentPairs(mtx) applied to each bootstrap sample separately. #'

**Author(s)**

Prof. H. D. Vinod, Economics Dept., Fordham University, NY
References


See Also

See Also silentPairs.

Examples

```r
## Not run:
options(npNmessages = FALSE)
set.seed(34); x = sample(1:10); y = sample(2:11)
b = bootPairs(cbind(x, y), n999 = 29)
bootQuantile(b) # gives summary stats for n999 bootstrap sum computations

b = bootPairs(airquality, n999 = 999); options(npNmessages = FALSE)
bootQuantile(b, tau = 0.476) # signs for n999 bootstrap sum computations

data('EuroCrime')
attach(EuroCrime)
b = bootPairs(cbind(crim, off), n999 = 29) # col.1 = crim causes off
# hence positive signs are more intuitively meaningful.
# note that n999 = 29 is too small for real problems, chosen for quickness here.
bootQuantile(b) # quantile matrix for n999 bootstrap sum computations

## End(Not run)
```

bootSign

Probability of unambiguously correct (+ or -) sign from bootPairs output

Description

If there are p columns of data, bootSign produces a p-1 by 1 vector of probabilities of correct signs assuming that the mean of n999 values has the correct sign and assuming that m of the ‘sum’ index values inside the range [-tau, tau] are neither positive nor negative but indeterminate or ambiguous (being too close to zero). That is, the denominator of P(+1) or P(-1) is (n999-m) if m signs are too close to zero. Thus it measures the bootstrap success rate in identifying the correct sign, when the sign of the average of n999 bootstraps is assumed to be correct.
Usage

\texttt{bootSign(out, tau = 0.476)}

Arguments

\begin{itemize}
  \item \texttt{out} output from \texttt{bootPairs} with \(p-1\) columns and \(n999\) rows
  \item \texttt{tau} threshold to determine what value is too close to zero, default \(\tau=0.476\) is equivalent to 15 percent threshold for the unanimity index \(ui\)
\end{itemize}

Value

\texttt{sgn} When \(mtx\) has \(p\) columns, \texttt{sgn} reports pairwise \(p-1\) signs representing (fixing the first column in each pair) the average sign after averaging the output of \texttt{bootPairs(mtx)} (a \(n999\) by \(p-1\) matrix) each containing resampled \textquote{sum} values summarizing the weighted sums associated with all three criteria from the function \texttt{silentPairs(mtx)} applied to each bootstrap sample separately. #'

Author(s)

Prof. H. D. Vinod, Economics Dept., Fordham University, NY

References

Vinod, H. D. \textquote{Generalized Correlation and Kernel Causality with Applications in Development Economics} in Communications in Statistics -Simulation and Computation, 2015, \url{http://dx.doi.org/10.1080/03610918.2015.1122048}


Vinod, H. D. \textquote{Causal Paths and Exogeneity Tests in Generalcorr Package for Air Pollution and Monetary Policy} (June 6, 2017). Available at SSRN: \url{https://ssrn.com/abstract=2982128}

See Also

See Also \texttt{silentPairs, bootQuantile, bootSignPcent}.

Examples

\begin{verbatim}
## Not run:
options(np.messages = FALSE)
set.seed(34); x = sample(1:10); y = sample(2:11)
bb = bootPairs(cbind(x, y), n999 = 29)
bootSign(bb, tau = 0.476) # gives success rate in n999 bootstrap sum computations

bb = bootPairs(airquality, n999 = 999); options(np.messages = FALSE)
bootSign(bb, tau = 0.476); # signs for n999 bootstrap sum computations

data('EuroCrime'); options(np.messages = FALSE)
attach(EuroCrime)
bb = bootPairs(cbind(crim, off), n999 = 29) # col.1 = crim causes off
# hence positive signs are more intuitively meaningful.
\end{verbatim}
#note that n999=29 is too small for real problems, chosen for quickness here.
bootSign(bb, tau=0.476) # gives success rate in n999 bootstrap sum computations

## End(Not run)

| bootsignpcent | Probability of unambiguously correct (+ or -) sign from bootPairs output transformed to percentages. |

### Description
If there are p columns of data, bootSignPcent produces a p-1 by 1 vector of probabilities of correct signs assuming that the mean of n999 values has the correct sign and assuming that m of the 'ui' index values inside the range [-tau, tau] are neither positive nor negative but indeterminate or ambiguous (being too close to zero). That is, the denominator of P(+1) or P(-1) is (n999-m) if m signs are too close to zero. Thus it measures the bootstrap success rate in identifying the correct sign, when the sign of the average of n999 bootstraps is assumed to be correct.

### Usage
```r
bootSignPcent(out, tau = 5)
```

### Arguments
- **out**: output from bootPairs with p-1 columns and n999 rows
- **tau**: threshold to determine what value is too close to zero, default tau=5 is 5 percent threshold for the unanimity index ui

### Value
- **sgn**: When mtx has p columns, sgn reports pairwise p-1 signs representing (fixing the first column in each pair) the average sign after averaging the output of of bootPairs(mtx) (a n999 by p-1 matrix) each containing resampled 'sum' values summarizing the weighted sums associated with all three criteria from the function silentPairs(mtx) applied to each bootstrap sample separately. #'

### Author(s)
Prof. H. D. Vinod, Economics Dept., Fordham University, NY

### References


See Also

See Also silentPairs, bootQuantile, bootSign.

Examples

```r
## Not run:
options(np.messages = FALSE)
set.seed(34); x = sample(1:10); y = sample(2:11)
bb = bootPairs(cbind(x, y), n999 = 29)
bootSignPcent(bb, tau = 5) # gives success rate in n999 bootstrap sum computations

bb = bootPairs(airquality, n999 = 999); options(np.messages = FALSE)
bootSignPcent(bb, tau = 5) # success rate for signs from n999 bootstraps

data('EuroCrime'); options(np.messages = FALSE)
attach(EuroCrime)
bb = bootPairs(cbind(crime, off), n999 = 29) # col.1 = crim causes off
# hence positive signs are more intuitively meaningful.
# note that n999 = 29 is too small for real problems, chosen for quickness here.
bootSignPcent(bb, tau = 5) # successful signs from n999 bootstraps

## End(Not run)
```

bootSummary

Compute usual summary stats of 'sum' indexes from bootPairs output

Description

Begin with the output of bootPairs function, a (n999 by p-1) matrix when there are p columns of data, bootSummary produces a (6 by p-1) mtx of summary of bootstrap output (Min, 1st Qu, Median, Mean, 3rd Qi, Max)

Usage

```r
bootSummary(out, per100 = TRUE)
```

Arguments

- `out`: output from bootPairs with p-1 columns and n999 rows in input here
- `per100`: logical (default per100 = TRUE) to change the range of 'sum' to [-100, 100] values which are easier to interpret

Value

summ summary output from the (n999 by p-1) matrix output of bootPairs mtx each containing resampled 'sum' values summarizing the weighted sums associated with all three criteria from the function silentPairs mtx applied to each bootstrap sample separately.
Author(s)
Prof. H. D. Vinod, Economics Dept., Fordham University, NY

References

See Also
See Also silentPairs.

Examples

```r
## Not run:
options(np.messages = FALSE)
set.seed(34); x=sample(1:10); y=sample(2:11)
b=bootPairs(cbind(x,y), n999=29)
bootSummary(bb) #gives summary stats for n999 bootstrap sum computations

b=bootPairs(airquality, n999=999); options(np.messages=FALSE)
bootSummary(bb)#signs for n999 bootstrap sum computations

data('EuroCrime')
attach(EuroCrime)
b=bootPairs(cbind(crim, off), n999=29) #col.1= crim causes off
#hence positive signs are more intuitively meaningful.
#note that n999=29 is too small for real problems, chosen for quickness here.
bootSummary(bb)#signs for n999 bootstrap sum computations

## End(Not run)
```

causeSummary | Kernel causality summary of evidence for causal paths from three criteria

Description
Allowing input matrix of control variables, this function produces a 5 column matrix summarizing the results where the estimated signs of stochastic dominance order values, (+1, 0, -1), are weighted by wt=c(1.2, 1.1, 1.05, 1) to compute an overall result for all orders of stochastic dominance by a weighted sum for the criteria Cr1 and Cr2 and added to the Cr3 estimate as: (+1, 0, -1). The final range for the unanimity of sign index is [-100, 100].
Usage

causeSummary(mtx, nam = colnames(mtx), ctrl = 0, dig = 6, wt = c(1.2, 1.1, 1.05, 1), sumwt = 4)

Arguments

mtx The data matrix with many columns, y the first column is fixed and then paired with all columns, one by one, and still called x for the purpose of flipping.

nam vector of column names for mtx. Default: colnames(mtx)

ctrl data matrix for designated control variable(s) outside causal paths

dig Number of digits for reporting (default dig=6).

wt Allows user to choose a vector of four alternative weights for SD1 to SD4.

sumwt Sum of weights can be changed here =4(default).

Details

The reason for slightly declining weights on the signs from SD1 to SD4 is simply that the local mean comparisons implicit in SD1 are known to be more reliable than local variance implicit in SD2, local skewness implicit in SD3 and local kurtosis implicit in SD4. The reason for slightly declining sampling unreliability of higher moments is simply that SD4 involves fourth power of the deviations from the mean and SD3 involves 3rd power, etc. The summary results for all three criteria are reported in one matrix called out:

Value

If there are p columns in the input matrix, x1, x2, ..., xp, say, and if we keep x1 as a common member of all causal direction pairs (x1, x(1+j)) for (j=1, 2, ..., p-1) which can be flipped. That is, either x1 is the cause or x(1+j) is the cause in a chosen pair. The control variables are not flipped. The printed output of this function reports the results for p-1 pairs indicating which variable (by name) causes which other variable (also by name). It also prints strength or signed summary strength index in range [-100,100]. A positive sign of the strength index means x1 kernel causes x(1+j), whereas negative strength index means x(1+j) kernel causes x1. The function also prints Pearson correlation and its p-value. This function also returns a matrix of p-1 rows and 5 columns entitled: "cause", "response", "strength", "corr." and "p-value", respectively with self-explanatory titles. The first two columns have names of variables x1 or x(1+j), depending on which is the cause. The ‘strength’ column has absolute value of summary index in range [0,100] providing summary of causal results based on preponderance of evidence from Cr1 to Cr3 from four orders of stochastic dominance, etc. The order of input columns matters. The fourth column ‘corr.’ reports the Pearson correlation coefficient while the fifth column has the p-value for testing the null of zero Pearson coeff. This function calls silentPairs allowing for control variables. The output of this function can be sent to `xtable` for a nice Latex table.

Note

The European Crime data has all three criteria correctly suggesting that high crime rate kernel causes the deployment of a large number of police officers. Since Cr1 to Cr3 near unanimously suggest ‘crim’ as the cause of ‘off’, strength index 100 suggests unanimity. attach(EuroCrime); causeSummary(cbind(crim,
Author(s)

Prof. H. D. Vinod, Economics Dept., Fordham University, NY.

References


See Also

See bootPairs, causeSummary0 has an older version of this function.

See someCPairs

silentPairs

Examples

```
## Not run:
mtx=as.matrix(mtcars[,1:3])
ctrl=as.matrix(mtcars[,4:5])
  causeSummary(mtx,ctrl,nam=colnames(mtx))

## End(Not run)

options(np.messages=FALSE)
set.seed(234)
z=runif(10,2,11)# z is independently created
x=sample(1:10)+z/10 #x is somewhat indep and affected by z
y=1+2*x+3*z+rnorm(10)
w=runif(10)
x2=x;x2[4]=NA;y2=y;y2[8]=NA;y2=W2;w2[4]=NA
  causeSummary(mtx=cbind(x2,y2), ctrl=cbind(z, w2))
```

| causeSummary0 | Older Kernel causality summary of evidence for causal paths from three criteria |
**Description**

Allowing input matrix of control variables, this function produces a 5 column matrix summarizing the results where the estimated signs of stochastic dominance order values, (+1, 0, -1), are weighted by \( wt = c(1.2, 1.1, 1.05, 1) \) to compute an overall result for all orders of stochastic dominance by a weighted sum for the criteria Cr1 and Cr2 and added to the Cr3 estimate as: (+1, 0, -1). The final range for the unanimity of sign index is \([-100, 100]\).

**Usage**

```r
causeSummary0(mtx, nam = colnames(mtx), ctrl = 0, dig = 6, wt = c(1.2, 1.1, 1.05, 1), sumwt = 4)
```

**Arguments**

- `mtx`: The data matrix with many columns, y the first column is fixed and then paired with all columns, one by one, and still called x for the purpose of flipping.
- `nam`: vector of column names for `mtx`. Default: `colnames(mtx)`
- `ctrl`: data matrix for designated control variable(s) outside causal paths
- `dig`: Number of digits for reporting (default `dig`=6).
- `wt`: Allows user to choose a vector of four alternative weights for SD1 to SD4.
- `sumwt`: Sum of weights can be changed here =4(default).

**Details**

The reason for slightly declining weights on the signs from SD1 to SD4 is simply that the local mean comparisons implicit in SD1 are known to be more reliable than local variance implicit in SD2, local skewness implicit in SD3 and local kurtosis implicit in SD4. The reason for slightly declining sampling unreliability of higher moments is simply that SD4 involves fourth power of the deviations from the mean and SD3 involves 3rd power, etc. The summary results for all three criteria are reported in one matrix called `out`:

**Value**

If there are p columns in the input matrix, x1, x2, ..., xp, say, and if we keep x1 as a common member of all causal direction pairs (x1, x(1+j)) for (j=1, 2, ..., p-1) which can be flipped. That is, either x1 is the cause or x(1+j) is the cause in a chosen pair. The control variables are not flipped. The printed output of this function reports the results for p-1 pairs indicating which variable (by name) causes which other variable (also by name). It also prints strength or signed summary strength index in range \([-100,100]\). A positive sign of the strength index means x1 kernel causes x(1+j), whereas negative strength index means x(1+j) kernel causes x1. The function also prints Pearson correlation and its p-value. This function also returns a matrix of p-1 rows and 5 columns entitled: “cause”, “response”, “strength”, “corr.” and “p-value”, respectively with self-explanatory titles. The first two columns have names of variables x1 or x(1+j), depending on which is the cause. The ‘strength’ column has absolute value of summary index in range \([0,100]\) providing summary of causal results based on preponderance of evidence from Cr1 to Cr3 from four orders of stochastic dominance, etc. The order of input columns matters. The fourth column ‘corr.’ reports the Pearson correlation coefficient while the fifth column has the p-value for testing the null of zero Pearson coeff. This
function calls `silentPairs0` (the older version) allowing for control variables. The output of this function can be sent to ‘xtable’ for a nice Latex table.

**Note**

The European Crime data has all three criteria correctly suggesting that high crime rate kernel causes the deployment of a large number of police officers. Since Cr1 to Cr3 near unanimously suggest ‘crim’ as the cause of ‘off’, strength index 100 suggests unanimity. `attach(EuroCrime); causeSummary0(cbind(crim,off))`. Both versions give identical result for this example. Old version of Cr1 using gradients was also motivated by the same Hausman-Wu test statistic.

**Author(s)**

Prof. H. D. Vinod, Economics Dept., Fordham University, NY.

**References**


**See Also**

See `bootPairs`

See `someCPairs`

`silentPairs`

**Examples**

```r
## Not run:
mtx<-as.matrix(mtcars[,1:3])
ctrl<-as.matrix(mtcars[,4:5])
  causeSummary0(mtx,ctrl,nam=colnames(mtx))

## End(Not run)

options(np.messages=FALSE)
set.seed(234)
z=runif(10,2,11)# z is independently created
x=sample(1:10)+z/10 #x is somewhat indep and affected by z
y=1+2*x+3*z+rnorm(10)
w=runif(10)
x2=x;x2[4]=NA;y2=y;y2[8]=NA;w2=w;w2[4]=NA
causeSummary0(mtx=cbind(x2,y2), ctrl=cbind(z,w2))
```
cofactor

Compute cofactor of a matrix based on row r and column c.

Description

Compute cofactor of a matrix based on row r and column c.

Usage

cofactor(x, r, c)

Arguments

x  matrix whose cofactor is desired to be computed
r  row number
c  column number

Value

cofactor of x, w.r.t. row r and column c.

Note

needs the function ‘minor” in memory. attaches sign (-1)^(r+c) to the minor.

Author(s)

Prof. H. D. Vinod, Economics Dept., Fordham University, NY

See Also

minor(x,r,c)

Examples

## The function is currently defined as
function (x, r, c)
{
    out = minor(x, r, c) * ((-1)^(r + c))
    return(out)
}
**comp_portfo2**

*Compresses two vectors (portfolios) using stochastic dominance of orders 1 to 4.*

**Description**

Given two vectors of portfolio returns this function calls the internal function wtdpapb to report the simple means of four sophisticated measures of stochastic dominance.

**Usage**

```r
comp_portfo2(xa, xb)
```

**Arguments**

- `xa` Data on returns for portfolio A in the form of a T by 1 vector
- `xb` Data on returns for portfolio B in the form of a T by 1 vector

**Value**

Returns four numbers which are averages of four sophisticated measures of stochastic dominance measurements called SD1 to SD4.

**Note**

It is possible to modify this function to report the median or standard deviation or any other descriptive statistic by changing the line in the code `@mean = apply(outb, 2, mean)` toward the end of this function. A trimmed mean may be of interest when outliers are suspected.

```r
require(np)
```

Make sure that functions wtdpapb, bigfp, stochdom2 are in the memory. and options(np.messages=FALSE)

**Author(s)**

Prof. H. D. Vinod, Economics Dept., Fordham University, NY

**References**


**See Also**

- stochdom2
Examples

set.seed(30)
xa=sample(20:30)# generally lower returns
xb=sample(32:40)# higher returns in xb
gp = comp_portfo2(xa, xb)# all Av(sdi) positive means xb dominates
# positive SD1 to SD4 means xb dominates xa as it should

da

description

intended for internal use only

Usage
da

data(da)

Format

The format is: int 4

diff.e0

Description

Internal diff.e0

Usage
data(diff.e0)
dig

Internal dig

Description
Intended for internal use

Usage
data(dig)

Format
The format digs: int 78

e0

Internal e0

Description
intended for internal use only

Usage
e0

EuroCrime

European Crime Data

Description
This data set refers to crime in European countries during 2008. The sources are World Bank and Eurostat. The crime statistics refers to homicides. It avoids possible reporting bias from the presence of police officers, because homicide reporting in most countries is standardized. Typical usage is: data(EuroCrime); attach(EuroCrime). The secondary source 'quandl.com' was used for collecting these data.

Details
The variables included in the dataset are:

• Country Name of the European country
• crim Per capita crime rate
• off Per capita deployment of police officers
This package provides convenient software tools for causal path determinations using Vinod (2014, 2015) and extends them. A matrix of asymmetric generalized correlations $r^*(x|y)$ is reported by the functions rstar and gmcmtx0. The $r^*(x|y)$ measures the strength of the dependence of $x$ on $y$. If $|r^*(x|y)| > |r^*(y|x)|$ it suggests that $y$ is more likely the "kernel cause" of $x$. This package refers to the $r^*$ based criterion as criterion 3 (Cr3) and further adds two additional ways of comparing two kernel regressions helping identify the 'cause' called criterion 1 and 2 (Cr1 and Cr2) using absolute values of gradients and residuals, respectively. See references below. The package has one-line commands summarizing all three criteria leading to high (over 70%) success rates in causal path identifications.

The usual partial correlations are generalized for the asymmetric matrix of $r^*$'s. Partial correlations help assess the effect of $x$ on $y$ after removing the effect of a set of (control) variables. See parcor_ijk and parcor_ridg. Another way of generalizing partial correlations by using incremental R-square values in kernel regressions are provided in functions mag_ctrl and someMagPairs.

The package provides additional tools for causal assessment, for printing the causal detections in a clear, comprehensive compact summary form, such as somePairs, someOPairs, someCPairs for matrix algebra, such as cofactor, for outlier detection get0outlier, for numerical integration by the trapezoidal rule, stochastic dominance stochdom2 and comp_portfo2, etc. The function causeSummary gives an overall summary of causal path results. The compact function silentPairs gives one-line summary of causal path strengths, where negative strength means that variable 'causes' the variable in the first column.

The package has a function pcause for bootstrap-based statistical inference and another one for a heuristic t-test called heurist. Pairwise deletion of missing data is done in napair, while triplet-wise deletion is in natriplet intended for use when control variable(s) are also present. If one has panel data, functions Panel1Lag and Panel2Lag are relevant.

In simultaneous equation models where endogeneity of regressors is feared, we suggest using Prof. Koopmans' method which suggests ignoring endogeneity issues for all variables "causing" the dependent variable assessed by our three criteria. Weighted summary of all three criteria is in someCPairs.

A vignette provided with this package generalCorr at CRAN describes the usage of the package with examples. Type the following command: vignette("generalCorr-vignette", package="generalCorr") to read the vignette. See also additional citations in the vignette, the references here and their citations for further details.
getOutliers

getOutliers Function to compute outliers and their count using Tukey method using 1.5 times interquartile range (IQR) to define boundaries.

Description
Function to compute outliers and their count using Tukey method using 1.5 times interquartile range (IQR) to define boundaries.

Usage
getOutliers(x, verbo = TRUE, mult = 1.5)

Arguments
x vector of data.
verbo set to TRUE(default) assuming printed details are desired.
mult =1.5(default), the number of times IQR is used in defining outlier boundaries.

Value
below which items are lower than the lower limit
above which items are larger than the upper limit
lowLim the lower boundary for outlier detection
upLim the upper boundary for outlier detection
nUP count of number of data points above upper boundary
nLO count of number of data points below lower boundary

Note
The function removes the missing data before checking for outliers.

References


**gmc0**

**Author(s)**

Prof. H. D. Vinod, Economics Dept., Fordham University, NY

**Examples**

```r
set.seed(101); x = sample(1:100)[1:15]; x[16] = 150; x[17] = NA
g0outliers(x)#correctly identifies outlier=150
```

**Description**

intended for internal use only

**Usage**

```r
gmc0
```

---

**gmc1**

**internal gmc1**

---

**Description**

intended for internal use only

**Usage**

```r
gmc1
```
**gmcmtx0**

Compute the matrix $R^*$ of generalized correlation coefficients.

**Description**

This function checks for missing data for each pair individually. It then uses the `kern` function to kernel regress $x$ on $y$, and conversely $y$ on $x$. It needs the library `np` which reports $R$-squares of each regression. This function reports their square roots after assigning them the observed sign of the Pearson correlation coefficient. Its advantages are (i) it is asymmetric yielding causal direction information, by relaxing the assumption of linearity implicit in usual correlation coefficients. (ii) The $r^*$ correlation coefficients are generally larger upon admitting arbitrary nonlinearities.

**Usage**

```r
gmcmtx0(mym, nam = colnames(mym))
```

**Arguments**

- `mym`: A matrix of data on variables in columns
- `nam`: Column names of the variables in the data matrix

**Value**

A non-symmetric $R^*$ matrix of generalized correlation coefficients

**Author(s)**

Prof. H. D. Vinod, Economics Dept., Fordham University, NY

**References**


**Examples**

```r
gmcmtx0(mtcars[,1:3])
```

```r
# Not run:
set.seed(34); x=matrix(sample(1:600)[1:99],ncol=3)
```


colnames(x) = c('V1', 'V2', 'V3')
gmcmtx0(x)
## End(Not run)

---

**gmcmtxZ**

*compute the matrix \( R^* \) of generalized correlation coefficients.*

**Description**

This function checks for missing data separately for each pair using \texttt{kernel} function to kernel regress \( x \) on \( y \), and conversely \( y \) on \( x \). It needs the library ‘np’ which reports R-squares of each regression. This function reports their square roots with the sign of the Pearson correlation coefficients. Its appeal is that it is asymmetric yielding causal direction information, by relaxing the assumption of linearity implicit in usual correlation coefficients.

**Usage**

\[
\text{gmcmtxZ(mym, nam = colnames(mym))}
\]

**Arguments**

- \texttt{mym} \hspace{1cm} A matrix of data on variables in columns
- \texttt{nam} \hspace{1cm} Column names of the variables in the data matrix

**Value**

A non-symmetric \( R^* \) matrix of generalized correlation coefficients

**Note**

This allows the user to change \texttt{gmcmtx0} and further experiment with my code.

**Author(s)**

Prof. H. D. Vinod, Economics Dept., Fordham University, NY

**References**

Vinod, H. D. ‘Generalized Correlation and Kernel Causality with Applications in Development Economics’ in Communications in Statistics -Simulation and Computation, 2015, \url{http://dx.doi.org/10.1080/03610918.2015.1122048}
Examples

## Not run:
set.seed(34); x = matrix(sample(1:600)[1:99], ncol=3)
colnames(x) = c('V1', 'V2', 'V3')
gmcmtxZ(x)

## End(Not run)

---

**gmcxy_np**

*Function to compute generalized correlation coefficients $r^*(x|y)$ and $r^*(y|x)$.*

**Description**

This function uses the ‘np’ package and assumes that there are no missing data.

**Usage**

```r
gmcxy_np(x, y)
```

**Arguments**

- `x` vector of x data
- `y` vector of y data

**Value**

- `corxy` $r^*(x|y)$ from regressing x on y, where y is the kernel cause.
- `coryx` $r^*(y|x)$ from regressing y on x, where x is the cause.

**Note**

This is provided if the user want to avoid calling kern.

**Author(s)**

Prof. H. D. Vinod, Economics Dept., Fordham University, NY

**References**


Examples

```r
## Not run:
set.seed(34); x = sample(1:10); y = sample(2:11)
gmcxy_np(x, y)
## End(Not run)
```

goodCol

**Description**

intended for internal use only

**Usage**

```r
goodCol
```

heurist

*Heuristic t test of the difference between two generalized correlations.*

**Description**

Function to run a heuristic t test of the difference between two generalized correlations.

**Usage**

```r
heurist(rxy, ryx, n)
```

**Arguments**

- `rxy`  
generalized correlation r*(x|y) where y is the kernel cause.
- `ryx`  
generalized correlation r*(y|x) where x is the kernel cause.
- `n`  
Sample size needed to determine the degrees of freedom for the t test.

**Value**

Prints the t statistics and p-values.

**Note**

This function requires Revele’s R package called ‘psych’ in memory. This test is known to be conservative (i.e., often fails to reject the null hypothesis of zero difference between the two generalized correlation coefficients.)
Author(s)

Prof. H. D. Vinod, Economics Dept., Fordham University, NY

Examples

```r
set.seed(34); x = sample(1:10); y = sample(2:11)
g1 = gmcxy_np(x, y)
n = length(x)
h1 = heurist(g1$corxy, g1$coryx, n)
print(h1)
print(h1$t)  # t statistic
print(h1$p)  # p-value
```

i      internal i

Description

intended for internal use

Usage

data(i)

Format

The format is: int 78

ibad     internal object

Description

intended for internal use

ii      internal ii

Description

intended for internal use
internal j

Description
intended for internal use

Usage
data(j)

Format
The format is: int 4

kern
Kernel regression with options for residuals and gradients.

Description
Function to run kernel regression with options for residuals and gradients assuming no missing data.

Usage
kern(dep.y, reg.x, tol = 0.1, ftol = 0.1, gradients = FALSE, 
residuals = FALSE)

Arguments
dep.y Data on the dependent (response) variable
reg.x Data on the regressor (stimulus) variables
tol Tolerance on the position of located minima of the cross-validation function (default =0.1)
ftol Fractional tolerance on the value of cross validation function evaluated at local minima (default =0.1)
gradients Make this TRUE if gradients computations are desired
residuals Make this TRUE if residuals are desired

Value
Creates a model object ‘mod’ containing the entire kernel regression output. Type names(mod) to reveal the variety of outputs produced by ‘npreg’ of the ‘np’ package. The user can access all of them at will by using the dollar notation of R.
Note

This is a work horse for causal identification.

Author(s)

Prof. H. D. Vinod, Economics Dept., Fordham University, NY

References


See Also

See `kern_ctrl`.

Examples

```r
## Not run:
sample.seed(34);x=matrix(sample(1:600)[1:50],ncol=2)
require(np); options(np.messages=FALSE)
k1=kern(x[,1],x[,2])
print(k1$r2) #prints the R square of the kernel regression

## End(Not run)
```

---

`kern_ctrl`  
*Kernel regression with control variables and optional residuals and gradients.*

Description

Allowing matrix input of control variables, this function runs kernel regression with options for residuals and gradients.

Usage

```r
kern_ctrl(dep.y, reg.x, ctrl, tol = 0.1, ftol = 0.1, gradients = FALSE, residuals = FALSE)
```
**kern_ctrl**

**Arguments**

- `dep.y`: Data on the dependent (response) variable
- `reg.x`: Data on the regressor (stimulus) variable
- `ctrl`: Data matrix on the control variable(s) kept outside the causal paths. A constant vector is not allowed as a control variable.
- `tol`: Tolerance on the position of located minima of the cross-validation function (default=0.1)
- `ftol`: Fractional tolerance on the value of cross validation function evaluated at local minima (default=0.1)
- `gradients`: Set to TRUE if gradients computations are desired
- `residuals`: Set to TRUE if residuals are desired

**Value**

Creates a model object `mod` containing the entire kernel regression output. If this function is called as `mod=kern_ctrl(x,y,ctrl=z)`, the researcher can simply type `names(mod)` to reveal the large variety of outputs produced by `npreg` of the `np` package. The user can access all of them at will using the dollar notation of R.

**Note**

This is a work horse for causal identification.

**Author(s)**

Prof. H. D. Vinod, Economics Dept., Fordham University, NY

**References**


**See Also**

See `kern`.

**Examples**

```r
## Not run:
set.seed(34);x=matrix(sample(1:600)[1:50],ncol=5)
require(np)
k1=kern_ctrl(x[,1],x[,2],ctrl=x[,4:5])
print(k1$R2) #prints the R square of the kernel regression

## End(Not run)
```
Description
Uses Vinod (2015) and runs kernel regression of x on y, and also of y on x by using the ‘np’ package. The function goes on to compute a summary magnitude of the overall approximate partial derivative dx/dy (and dy/dx), after adjusting for units by using an appropriate ratio of standard deviations. Of course, the real partial derivatives of nonlinear functions are generally distinct for each observation.

Usage

mag(x, y)

Arguments

x Vector of data on the dependent variable
y Vector of data on the regressor

Value
vector of two magnitudes of kernel regression partials dx/dy and dy/dx.

Note
This function is intended for use only after the direction of causal path is already determined by various functions in this package (e.g. somePairs). For example, if the researcher knows that x causes y, then only dy/dx denoted by dydx is relevant. The other output of the function dxdy is to be ignored. Similarly, only ‘dxdy’ is relevant if y is known to be the cause of x.

Author(s)
Prof. H. D. Vinod, Economics Dept., Fordham University, NY

References


See Also
See mag_ctrl.
Examples

```r
set.seed(123); x = sample(1:10); y = 1 + 2 * x + rnorm(10)
mag(x, y) # dxdy approx = .5 and dydx approx = 2 will be nice.
```

**Description**

Uses Vinod (2015) and runs kernel regressions: \( x \sim y + ctrl \) and \( x \sim ctrl \) to evaluate the ‘incremental change’ in R-squares. Let \((rxy; ctrl)\) denote the square root of that ‘incremental change’ after its sign is made the same as that of the Pearson correlation coefficient from \( \text{cor}(x, y) \). One can interpret \((rxy; ctrl)\) as a generalized partial correlation coefficient when \( x \) is regressed on \( y \) after removing the effect of control variable(s) in \( ctrl \). It is more general than the usual partial correlation coefficient, since this one allows for nonlinear relations among variables. Next, the function computes ‘dxdy’ obtained by multiplying \((rxy; ctrl)\) by the ratio of standard deviations, \( sd(x)/sd(y) \). Now our ‘dxdy’ approximates the magnitude of the partial derivative \( (dx/dy) \) in a causal model where \( y \) is the cause and \( x \) is the effect. The function also reports entirely analogous ‘dydx’ obtained by interchanging \( x \) and \( y \).

**Usage**

```r
mag_ctrl(x, y, ctrl)
```

**Arguments**

- **x** Vector of data on the dependent variable.
- **y** Vector of data on the regressor.
- **ctrl** data matrix for designated control variable(s) outside causal paths. A constant vector is not allowed as a control variable.

**Value**

vector of two magnitudes ‘dxdy’ (effect when \( x \) is regressed on \( y \)) and ‘dydx’ for reverse regression. Both regressions remove the effect of control variable(s).

**Note**

This function is intended for use only after the causal path direction is already determined by various functions in this package (e.g. `someCPairs`). That is, after the researcher knows whether \( x \) causes \( y \) or vice versa. The output of this function is a vector of two numbers: \( (dxdy, dydx) \), in that order, representing the magnitude of effect of one variable on the other. We expect the researcher to use only ‘dxdy’ if \( y \) is the known cause, or ‘dydx’ if \( x \) is the cause. These approximate overall measures may not be well-defined in some applications, because the real partial derivatives of nonlinear functions are generally distinct for each evaluation point.
Author(s)
Prof. H. D. Vinod, Economics Dept., Fordham University, NY

References

See Also
See mag

Examples

set.seed(123); x=sample(1:10); z=runif(10); y=1+2*x+3*x+z+runorm(10)
options(np.messages=FALSE)
mag.ctrl(x,y,z)#dx/dy=0.47 is approximately 0.5, but dy/dx=1.41 is not approx=2,

<table>
<thead>
<tr>
<th>min.e0</th>
<th>internal min.e0</th>
</tr>
</thead>
</table>

Description
intended for internal use only

Usage
min.e0

<table>
<thead>
<tr>
<th>minor</th>
<th>Function to do compute the minor of a matrix defined by row r and column c.</th>
</tr>
</thead>
</table>

Description
Function to do compute the minor of a matrix defined by row r and column c.

Usage
minor(x, r, c)
**Arguments**

- **x**: The input matrix
- **r**: The row number
- **c**: The column number

**Value**

The appropriate ‘minor’ matrix defined from the input matrix.

**Note**

This function is needed by the cofactor function.

**Author(s)**

Prof. H. D. Vinod, Economics Dept., Fordham University, NY

**Examples**

```r
## Not run:
x = matrix(1:20, ncol = 4)
minor(x, 1, 2)
## End(Not run)
```

---

**mtx**

---

**internal mtx**

**Description**

intended for internal use only

**Usage**

```r
mtx
```

---

**mtx0**

**internal mtx0**

**Description**

intended for internal use only

**Usage**

```r
mtx0
```
**mtx2**

*internal mtx2*

**Description**

intended for internal use only

**Usage**

mtx2

---

**n**

*internal n*

**Description**

intended for internal use

**Usage**

n

**Format**

The format is: int 78

---

**nall**

*internal nall*

**Description**

intended for internal use only

**Usage**

nall
<table>
<thead>
<tr>
<th>nam.badCol</th>
<th>internal nam.badCol</th>
</tr>
</thead>
</table>

**Description**
intended for internal use only

**Usage**
nam.badCol

<table>
<thead>
<tr>
<th>nam.goodCol</th>
<th>internal nam.goodCol</th>
</tr>
</thead>
</table>

**Description**
intended for internal use only

**Usage**
nam.goodCol

<table>
<thead>
<tr>
<th>nam.mtx0</th>
<th>internal nam.mtx0</th>
</tr>
</thead>
</table>

**Description**
intended for internal use only

**Usage**
nam.mtx0


napair  

*Function to do pairwise deletion of missing rows.*

**Description**

The aim in pair-wise deletions is to retain the largest number of available data pairs with all non-missing data.

**Usage**

```
napair(x, y)
```

**Arguments**

- `x`: Vector of x data
- `y`: Vector of y data

**Value**

- `newx`: A new vector x after removing pairwise missing data
- `newy`: A new vector y after removing pairwise missing data

**Author(s)**

Prof. H. D. Vinod, Economics Dept., Fordham University, NY

**Examples**

```r
## Not run:
x = sample(1:10); y = sample(1:10); x[2] = NA; y[3] = NA
napair(x, y)
## End(Not run)
```

---

naTriplet  

*Function to do matched deletion of missing rows from x, y and control variable(s).*

**Description**

The aim in three-way deletions is to retain only the largest number of available data triplets with all non-missing data.
Usage

naTriplet(x, y, ctrl)

Arguments

x Vector of x data
y Vector of y data
ctrl Data matrix on the control variable(s) kept beyond causal path determinations

Value

newx A new vector x after removing triplet-wise missing data
newy A new vector or matrix y after removing triplet-wise missing data
newctrl A new vector or matrix ctrl after removing triplet-wise missing data

Author(s)

Prof. H. D. Vinod, Economics Dept., Fordham University, NY

See Also

See napair.

Examples

## Not run:
x=sample(1:10); y=sample(1:10); x[2]=NA; y[3]=NA
w=sample(2:11)
natriplet(x,y,w)
## End(Not run)
Panel2Lag

---

p1 internal p1

Description

intended for internal use only

Usage

p1

Panel2Lag Function to compute a vector of 2 lagged values of a variable from panel data.

Description

The panel data have a set of time series for each entity (e.g. country) arranged such that all time series data for one entity is together. The data for the second entity should be below the entire data for first entity. When a variable is lagged twice, special care is needed to insert NA's for the first two time points (e.g. weeks) for each entity (country).

Usage

Panel2Lag(ID, xj)

Arguments

ID Location of the column having time identities (e.g. the week number)
xj Data on variable to be lagged linked to ID

Value

Vector containing 2 lagged values of xj.

Note

This function is provided for convenient user modifications.

Author(s)

Prof. H. D. Vinod, Economics Dept., Fordham University, NY

See Also

A more general function Panel1Lag has examples.
PanelLag

Function for computing a vector of one-lagged values of \( x_j \), a variable from panel data.

Description

Panel data have a set of time series for each entity (e.g. country) arranged such that all time series data for one entity is together, and the data for the second entity should be below the entire data for first entity and so on for entities. In such a data setup, when a variable is lagged once, special care is needed to insert an NA for the first time point in the data (e.g. week) for each entity.

Usage

\[ \text{PanelLag}(ID, x_j, \text{lag} = 1) \]

Arguments

- **ID**: Location of the column having time identities (e.g. week number).
- **x_j**: Data vector of variable to be lagged and is linked with the ID.
- **lag**: Number of lags desired (lag=1 is the default).

Value

Vector containing one-lagged values of variable \( x_j \).

Author(s)

Prof. H. D. Vinod, Economics Dept., Fordham University, NY

Examples

```r
# Not run:
indiv = gl(6,12,labels=LETTERS[1:6])
# creates A,A,A 12 times B B B also 12 times etc.
set.seed(99); cost = sample(30:90, 72, replace=TRUE)
revenu = sample(50:110, 72, replace=TRUE); month = rep(1:12,6)
df = data.frame(indiv,month,cost,revenu); head(df); tail(df)
L2cost = PanelLag(ID=month,xj=df[, 'cost'], lag=2)
head(L2cost)
tail(L2cost)

gmcmtx0(cbind(revenu,cost,L2cost))

gmcxy_np(revenu,cost)

# End(Not run)
```
parcorMany

Report many generalized partial correlation coefficients allowing control variables.

Description

This function calls parcor_ijk function which uses original data to compute generalized partial correlations between $X_{idep}$ and $X_j$ where $j$ can be any one of the remaining variables in the input matrix mtx. Partial correlations remove the effect of variables $x_k$ other than $X_i$ and $X_j$. Calculation further allows for the presence of control variable(s) (if any) to remain always outside the input matrix and whose effect is also removed in computing partial correlations.

Usage

parcorMany(mtx, ctrl = 0, dig = 4, idep = 1, verbo = FALSE)

Arguments

- mtx: Input data matrix with at least 3 columns.
- ctrl: Input vector or matrix of data for control variable(s), default is ctrl=0 when control variables are absent
- dig: The number of digits for reporting (=4, default)
- idep: The column number of the first variable (=1, default)
- verbo: Make this TRUE for detailed printing of computational steps

Value

A five column ‘out’ matrix containing partials. The first column has the name of the idep variable. The second column has the name of the j variable, while the third column has partial correlation coefficients $r^*(i,j \mid k)$.

Note

We want to get all partial correlation coefficients.

Author(s)

Prof. H. D. Vinod, Economics Dept., Fordham University, NY.

References

parcorMtx

See Also

See Also parcor_ijk.

Examples

set.seed(234)
z=runif(10,2,11)# z is independently created
x=sample(1:10)+z/10  # x is partly indep and partly affected by z
y=1+2*x+3*z+rnorm(10)# y depends on x and z not vice versa
mtx=cbind(x,y,z)
parcorMany(mtx)

## Not run:
set.seed(34);x=matrix(sample(1:600)[1:99],nrow=3)
colnames(x)=c('V1', 'v2', 'V3')
parcorMany(x, idep=3)

## End(Not run)

parcorMtx Matrix of generalized partial correlation coefficients, always leaving out control variables, if any.

Description

This function calls parcor_ijk function which uses original data to compute generalized partial correlations between $X_i$ and $X_j$ where $j$ can be any one of the remaining variables in the input matrix $mtx$. Partial correlations remove the effect of variables $x_k$ other than $X_i$ and $X_j$. Calculation further allows for the presence of control variable(s) (if any) to remain always outside the input matrix and whose effect is also removed in computing partial correlations.

Usage

parcorMtx(mtx, ctrl = 0, dig = 4, verbo = FALSE)

Arguments

mtx Input data matrix with p columns. p is at least 3 columns.
ctrl Input vector or matrix of data for control variable(s), default is ctrl=0 when control variables are absent
dig The number of digits for reporting (=4, default)
verbo Make this TRUE for detailed printing of computational steps

Value

A p by p ‘out’ matrix containing partials $r^*(i,j | k)$ and $r^*(j,i | k)$.
Note

We want to get all partial correlation coefficient pairs removing other column effects. Vinod (2018) shows why one needs more than one criterion to decide the causal paths or exogeneity.

Author(s)

Prof. H. D. Vinod, Economics Dept., Fordham University, NY.

References


See Also

See Also `parcor_ijk`.

Examples

```r
set.seed(234)
z = runif(10, 2, 11)# z is independently created
x = sample(1:10) + z/10  # x is partly indep and partly affected by z
y = 1 + 2*x + 3*z + rnorm(10)# y depends on x and z not vice versa
mtx = cbind(x, y, z)
parcorMtx(mtx)
```

```r
# Not run:
set.seed(34); x = matrix(sample(1:600)[1:99], ncol=3)
colnames(x) = c("V1", "V2", "V3")
parcorMtx(x)
```

```r
# End(Not run)
```

`parcorSilent` *Silently compute generalized (ridge-adjusted) partial correlation coefficients from matrix R*.
Description

This function calls \texttt{parcor\_ijk0LD} function which uses a generalized correlation matrix \(R^*\) as input to compute generalized partial correlations between \(X_i\) and \(X_j\) where \(j\) can be any one of the remaining variables. Computation removes the effect of all other variables in the matrix. It further adjusts the resulting partial correlation coefficients to be in the appropriate \([-1,1]\) range by using an additive constant in the fashion of ridge regression.

Usage

\[
\text{parcorSilent}(\text{gmc0}, \text{dig} = 4, \text{idep} = 1, \text{verbo} = \text{FALSE}, \text{incr} = 3)
\]

Arguments

- \texttt{gmc0}\:
  This must be a \(p\) by \(p\) matrix \(R^*\) of generalized correlation coefficients.
- \texttt{dig}\:
  The number of digits for reporting (=4, default)
- \texttt{idep}\:
  The column number of the first variable (=1, default)
- \texttt{verbo}\:
  Make this TRUE for detailed printing of computational steps
- \texttt{incr}\:
  Incremental constant for iteratively adjusting ‘ridgek’ where ridgek is the constant times the identity matrix used to make sure that the gmc0 matrix is positive definite. If not, this function iteratively increases the incr till relevant partial correlations are within the \([-1,1]\) interval.

Value

A five column ‘out’ matrix containing partials. The first column has the name of the idep variable. The second column has the name of the \(j\) variable, while the third column has \(r^*(i,j \mid k)\). The 4-th column has \(r^*(j,i \mid k)\) (denoted partji), and the 5-th column has \(rijMrji\), that is the difference in absolute values (abs(partij) - abs(partji)).

Note

The ridgek constant created by the function during the first round may not be large enough to make sure that other pairs of \(r^*(i,j \mid k)\) are within the \([-1,1]\) interval. The user may have to choose a suitably larger input incr to get all relevant partial correlation coefficients in the correct \([-1,1]\) interval.

Author(s)

Prof. H. D. Vinod, Economics Dept., Fordham University, NY.

References


See Also

See Also `parcor_i j k` for a better version using original data as input.

Examples

```r
set.seed(234)
z = runif(10, 2, 11)# z is independently created
x = sample(1:10) + z/10 # x is partly indep and partly affected by z
y = 1 + 2 * x + 3 * z + rnorm(10)# y depends on x and z not vice versa
mtx = cbind(x, y, z)
g1 = gmcmtx0(mtx)
parcor_i j k_OLD(g1, 1, 2) # ouji > ouij implies i=x is the cause of j=y
parcor_ridg(g1, idep=1)
parcorSilent(g1, idep=1)
```

## Not run:

```r
set.seed(34); x = matrix(sample(1:600)[1:99], ncol=3)
colnames(x) = c('V1', 'V2', 'V3')
g1 = gmcmtx0(x)
parcorSilent(g1, idep=1)
```

### End(Not run)

---

**parcor_i j k**  
*Generalized partial correlation coefficients between Xi and Xj after removing the effect of Xk via nonparametric regression residuals.*

Description

This function uses data on two column vectors, xi, xj and xk which can be a vector or a matrix usually of the remaining variables in the model including optional control variables. It works with kernel regression (xi on xk) and (xj on xk) residuals, removes missing data from input variables before proceeding.

Usage

```r
parcor_i j k(xi, xj, xk)
```

Arguments

- `xi` Input vector of data for variable xi
- `xj` Input vector of data for variable xj
- `xk` Input data for variables in xk, usually control variables
Value

\texttt{ouij} \quad \text{Generalized partial correlation} \ X_i \text{ with } X_j \text{ (cause) after removing } \ x_k

\texttt{ouji} \quad \text{Generalized partial correlation} \ X_j \text{ with } X_i \text{ (cause) after removing } \ x_k

allowing for control variables.

Note

This function calls \texttt{kern},

Author(s)

Prof. H. D. Vinod, Economics Dept., Fordham University, NY.

See Also

See \texttt{parcor_linear}.

Examples

```r
## Not run:
set.seed(34); x = matrix(sample(1:600)[1:99], ncol=3)
colnames(x) = c('V1', 'V2', 'V3')
parcor_ijk(gm, 2, 3)
## End(Not run)```

\texttt{parcor_ijkOLD} \quad \text{Generalized partial correlation coefficient between } X_i \text{ and } X_j \text{ after removing the effect of all others. (older version, deprecated)}

Description

This function uses a generalized correlation matrix \( R^* \) as input to compute generalized partial correlations between \( X_i \) and \( X_j \), where \( j \) can be any one of the remaining variables. Computation removes the effect of all other variables in the matrix. The user is encouraged to remove all known irrelevant rows and columns from the \( R^* \) matrix before submitting it to this function.

Usage

\texttt{parcor_ijkOLD(x, i, j)}

Arguments

\begin{itemize}
    \item \texttt{x} \quad \text{Input a } p \text{ by } p \text{ matrix } R^* \text{ of generalized correlation coefficients.}
    \item \texttt{i} \quad \text{A column number identifying the first variable.}
    \item \texttt{j} \quad \text{A column number identifying the second variable.}
\end{itemize}
**parcor_linear**

**Value**

- **ouij**: Partial correlation $X_i$ with $X_j$ (=cause) after removing all other $X$’s
- **ouji**: Partial correlation $X_j$ with $X_i$ (=cause) after removing all other $X$’s
- **myk**: A list of column numbers whose effect has been removed

**Note**

This function calls **minor**, and **cofactor** and is called by **parcor_ridge**.

**Examples**

```r
## Not run:
set.seed(34); x = matrix(sample(1:600)[1:99], ncol=3)
colnames(x) = c('V1', 'V2', 'V3')
gm1 = gmcmtx0(x)
parcor_ijkOLD(gm1, 2, 3)
## End(Not run)#'
```

**parcor_linear**  
*Partial correlation coefficient between $X_i$ and $X_j$ after removing the linear effect of all others.*

**Description**

This function uses a symmetric correlation matrix $R$ as input to compute usual partial correlations between $X_i$ and $X_j$ where $j$ can be any one of the remaining variables. Computation removes the effect of all other variables in the matrix. The user is encouraged to remove all known irrelevant rows and columns from the $R$ matrix before submitting it to this function.

**Usage**

```r
parcor_linear(x, i, j)
```

**Arguments**

- **x**: Input a $p$ by $p$ matrix $R$ of symmetric correlation coefficients.
- **i**: A column number identifying the first variable.
- **j**: A column number identifying the second variable.

**Value**

- **ouij**: Partial correlation $X_i$ with $X_j$ after removing all other $X$’s
- **ouji**: Partial correlation $X_j$ with $X_i$ after removing all other $X$’s
- **myk**: A list of column numbers whose effect has been removed
parcor_ridg

Note
This function calls \texttt{minor}, and \texttt{cofactor}

Author(s)
Prof. H. D. Vinod, Economics Dept., Fordham University, NY.

See Also
See \texttt{parcor_ijk} for generalized partial correlation coefficients useful for causal path determinations.

Examples

```r
## Not run:
set.seed(34); x = matrix(sample(1:600)[1:99], ncol=3)
colnames(x) = c('V1', 'v2', 'V3')
c1 = cor(x)
parcor_linear(c1, 2, 3)
## End(Not run)
```

parcor_ridg  \hspace{1cm} Compute generalized (ridge-adjusted) partial correlation coefficients from matrix R*. (deprecated)

Description
This function calls \texttt{parcor_ijk} function which uses a generalized correlation matrix R* as input to compute generalized partial correlations between $X_i$ and $X_j$ where j can be any one of the remaining variables. Computation removes the effect of all other variables in the matrix. It further adjusts the resulting partial correlation coefficients to be in the appropriate [-1,1] range by using an additive constant in the fashion of ridge regression.

Usage

```r
parcor_ridg(gmc0, dig = 4, idep = 1, verbo = FALSE, incr = 3)
```

Arguments

- \texttt{gmc0}  
  This must be a p by p matrix R* of generalized correlation coefficients.
- \texttt{dig}  
  The number of digits for reporting (=4, default)
- \texttt{idep}  
  The column number of the first variable (=1, default)
- \texttt{verbo}  
  Make this TRUE for detailed printing of computational steps
incremental constant for iteratively adjusting "ridgek" where ridgek is the constant times the identity matrix used to make sure that the gmc0 matrix is positive definite. If not iteratively increas the incr till all partial correlations are within the [-1,1] interval.

**Value**

A five column 'out' matrix containing partials. The first column has the name of the idep variable. The second column has the name of the j variable, while the third column has r*(i,j | k). The 4-th column has r*(j,i | k) (denoted partji), and the 5-th column has rijMrji, that is the difference in absolute values (abs(partij) - abs(partji)).

**Note**

The ridgek constant created by the function during the first round may not be large enough to make sure that that other pairs of r*(i,j | k) are within the [-1,1] interval. The user may have to choose a suitably larger input incr to get all relevant partial correlation coefficients in the correct [-1,1] interval.

**Author(s)**

Prof. H. D. Vinod, Economics Dept., Fordham University, NY.

**References**


**See Also**

See Also `parcor_ijkOLD`.

**Examples**

```r
set.seed(234)
z<-runif(10,2,11)# z is independently created
x<-(1:10)+z/10  # x is partly indep and partly affected by z
y<-(x+z+x+3)*z+rnorm(10)# y depends on x and z not vice versa
mtx<-cbind(x,y,z)
g1=gmcmtx8(mtx)
parcor_ijkOLD(g1,1,2) # ouji> ouij implies i=x is the cause of j=y
parcor_ridg(g1,idep=1)
```

```r
## Not run:
```
**Description**

Maximum entropy bootstrap (meboot) package is used for statistical inference regarding $\delta$ which equals $\text{GMC}(X|Y)-\text{GMC}(Y|X)$ defined by Zheng et al (2012). The bootstrap provides an approximation to chances of correct determination of the causal direction.

**Usage**

```r
pcause(x, y, n999 = 999)
```

**Arguments**

- **x**: Vector of x data
- **y**: Vector of y data
- **n999**: Number of bootstrap replications (default=999)

**Value**

$P(\text{cause})$ the bootstrap proportion of correct causal determinations.

**Note**

'pcause' is computer intensive and generally slow. It is better to use it at a later stage in the investigation when a preliminary causal determination is already made. Its use may slow the exploratory phase. In my experience, if $P(\text{cause})$ is less than 0.55, there is a cause for concern.

**Author(s)**

Prof. H. D. Vinod, Economics Dept., Fordham University, NY
References


Examples

```r
## Not run:
set.seed(34); x = sample(1:10); y = sample(2:11)
pcause(x, y, n999=29)

data('EuroCrime')
attach(EuroCrime)
pcause(crim, off, n999=29)

## End(Not run)
```

---

**prelec2**

Intermediate weighting function giving Non-Expected Utility theory weights.

**Description**

Computes cumulative probabilities and difference between consecutive cumulative probabilities described in Vinod (2008) textbook. This is a simpler version of the version in the book without mapping to non-expected utility theory weights.

**Usage**

`prelec2(n)`

**Arguments**

- `n` A (usually small) integer.

**Value**

- `x` sequence 1:n
- `p` probabilities p = x[i]/n
- `pdif` consecutive differences p[i] - p[i - 1]
probSign

Author(s)
Prof. H. D. Vinod, Economics Dept., Fordham University, NY

References

Examples

```r
## Not run: prelec2(10)
```

```
probSign

| probSign | Compute probability of positive or negative sign from bootPairs output |
```

Description
If there are p columns of data, probSign produces a p-1 by 1 vector of probabilities of correct signs assuming that the mean of n999 values has the correct sign and assuming that m of the ‘sum’ index values inside the range [-tau, tau] are neither positive nor negative but indeterminate or ambiguous (being too close to zero). That is, the denominator of P(+1) or P(-1) is (n999-m) if m signs are too close to zero.

Usage

```r
probSign(out, tau = 0.476)
```

Arguments

<table>
<thead>
<tr>
<th>Argument</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>out</td>
<td>output from bootPairs with p-1 columns and n999 rows</td>
</tr>
<tr>
<td>tau</td>
<td>threshold to determine what value is too close to zero, default tau=0.476 is equivalent to 15 percent threshold for the unanimity index ui</td>
</tr>
</tbody>
</table>

Value

sgn When mtx has p columns, sgn reports pairwise p-1 signs representing (fixing the first column in each pair) the average sign after averaging the output of of bootPairs(mtx) (a n999 by p-1 matrix) each containing resampled ‘sum’ values summarizing the weighted sums associated with all three criteria from the function silentPairs(mtx) applied to each bootstrap sample separately. #'

Author(s)
Prof. H. D. Vinod, Economics Dept., Fordham University, NY
References


See Also

See Also silentPairs.

Examples

```r
## Not run:
options(np.messages = FALSE)
set.seed(34); x=sample(1:10); y=sample(2:11)
bb=bootPairs(cbind(x,y),n999=29)
probSign(bb,tau=0.476) #gives summary stats for n999 bootstrap sum computations

bb=bootPairs(airquality,n999=999);options(np.messages=FALSE)
probSign(bb,tau=0.476)#signs for n999 bootstrap sum computations

data('EuroCrime')
attach(EuroCrime)
bb=bootPairs(cbind(crim,off),n999=29) #col.1= crim causes off
#hence positive signs are more intuitively meaningful.
#note that n999=29 is too small for real problems, chosen for quickness here.
probSign(bb,tau=0.476)#signs for n999 bootstrap sum computations

## End(Not run)
```

```
  rhs.lag2
  internal rhs.lag2
  
Description

intended for internal use only

Usage

rhs.lag2
```
### rhs1

**internal rhs1**

**Description**
intended for internal use only

**Usage**
```plaintext
rhs1
```

### ridgek

**internal ridgek**

**Description**
intended for internal use only

**Usage**
```plaintext
ridgek
```

### rij

**internal rij**

**Description**
intended for internal use only

**Usage**
```plaintext
rij
```

### rijMrji

**internal rijMrji**

**Description**
intended for internal use only

**Usage**
```plaintext
rijMrji
```
rji  

**Description**
intended for internal use only

**Usage**

rji

rrrij  

**Description**
intended for internal use only

**Usage**

rrrij

rrrji  

**Description**
intended for internal use only

**Usage**

rrrji
rstar

Function to compute generalized correlation coefficients r*(x,y).

Description
Uses Vinod (2015) definition of generalized (asymmetric) correlation coefficients. It requires kernel regression of x on y obtained by using the ‘np’ package. It also reports usual Pearson correlation coefficient r and p-value for testing the null hypothesis that (population r)=0.

Usage
rstar(x, y)

Arguments
x Vector of data on the dependent variable
y Vector of data on the regressor

Value
Four objects created by this function are:
corxy r*x|y or regressing x on y
coryx r*y|x or regressing y on x
pearson.r Pearson’s product moment correlation coefficient
pv The p-value for testing the Pearson r

Note
This function needs the kern function which in turn needs the np package.

Author(s)
Prof. H. D. Vinod, Economics Dept., Fordham University, NY

References


See Also
See Also as gmcmtx0
Examples

\texttt{x=sample(1:30); y=sample(1:30); rstar(x,y)}

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<table>
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<tr>
<th>sales2Lag</th>
<th>internal sales2Lag</th>
</tr>
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Description

intended for internal use only

Usage

sales2Lag

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<table>
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<th>internal salesLag</th>
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</table>

Description

intended for internal use only

Usage

salesLag

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<th>internal seed</th>
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Description

intended for internal use only

Usage

seed
Description

intended for internal use only

Usage

sgn.e0

silentMtx

No-print kernel-causality unanimity score matrix with optional control variables

Description

Allowing input matrix of control variables and missing data, this function produces a p by p matrix summarizing the results, where the estimated signs of stochastic dominance order values (+1, 0, –1) are weighted by wt=c(1.2, 1.1, 1.05, 1) to compute an overall result for all orders of stochastic dominance by a weighted sum for the criteria Cr1 and Cr2 and added to the Cr3 estimate as: (+1, 0, –1). Final weighted index is always in the range [–3.175, 3.175]. It is converted to the more intuitive range [–100, 100].

Usage

silentMtx(mtx, ctrl = 0, dig = 6, wt = c(1.2, 1.1, 1.05, 1), sumwt = 4)

Arguments

mtx The data matrix with p columns. Denote x1 as the first column which is fixed and then paired with all other columns, say: x2, x3, ..., xp, one by one for the purpose of flipping with x1. p must be 2 or more
ctrl data matrix for designated control variable(s) outside causal paths
dig Number of digits for reporting (default dig=6).
wt Allows user to choose a vector of four alternative weights for SD1 to SD4.
sumwt Sum of weights can be changed here =4(default).

Details

The reason for slightly declining weights on the signs from SD1 to SD4 is simply that the local mean comparisons implicit in SD1 are known to be more reliable than local variance implicit in SD2, local skewness implicit in SD3 and local kurtosis implicit in SD4. Why are higher moment estimates less reliable? The higher power of the deviations from the mean needed in their computations lead to greater sampling variability. The summary results for all three criteria are reported in a vector of numbers internally called crall:
Value

With p columns in mtx argument to this function, x1 can be paired with a total of p-1 columns (x2, x3, ..., xp). Note we never flip any of the control variables with x1. This function produces i=1,2,...,p-1 numbers representing the summary sign, or 'sum' from the signs sg1 to sg3 associated with the three criteria: Cr1, Cr2 and Cr3. Note that sg1 and sg2 themselves are weighted signs using weighted sum of signs from four orders of stochastic dominance. In general, a positive sign in the i-th location of the 'sum' output of this function means that x1 is the kernel cause while the variable in (i+1)-th column of mtx is the 'effect' or 'response' or 'endogenous.' The magnitude represents the strength (unanimity) of the evidence for a particular sign. Conversely a negative sign in the i-th location of the 'sum' output of this function means that that the first variable listed as the input to this function is the 'effect,' while the variable in (i+1)-th column of mtx is the exogenous kernel cause. This function is a summary of someCPairs allowing for control variables.

Note

The European Crime data has all three criteria correctly suggesting that high crime rate kernel causes the deployment of a large number of police officers. The command attach(EuroCrime); silentPairs(cbind(crimLoffII returns only one number: 3.175, implying a high unanimity strength. The index 3.175 is the highest. The positive sign of the index suggests that 'crim' variable in the first column of the matrix input to this function kernel causes 'off' in the second column of the matrix argument mtx to this function.

Interpretation of the output matrix produced by this function is as follows. A negative index means the variable named in the column kernel-causes the variable named in the row. A positive index means the row name variable kernel-causes the column name variable. The abs(index) measures unanimity by three criteria, Cr1 to Cr3 representing the strength of evidence for the identified causal path.

Author(s)

Prof. H. D. Vinod, Economics Dept., Fordham University, NY.

References


See Also

See silentPairs.

See someCPairs, some0Pairs

Examples

## Not run:
silentMtx0

### Description

Allowing input matrix of control variables and missing data, this function produces a p by p matrix summarizing the results, where the estimated signs of stochastic dominance order values (+1, 0, –1) are weighted by \( wt = c(1.2, 1.1, 1.05, 1) \) to compute an overall result for all orders of stochastic dominance by a weighted sum for the criteria Cr1 and Cr2 and added to the Cr3 estimate as: (+1, 0, –1). Final weighted index is always in the range \([-3.175, 3.175]\). It is converted to the more intuitive range \([-100, 100]\).

### Usage

\[
\text{silentMtx0}(\text{mtx}, \text{ctrl} = 0, \text{dig} = 6, \text{wt} = c(1.2, 1.1, 1.05, 1), \text{sumwt} = 4)
\]

### Arguments

- **mtx**: The data matrix with p columns. Denote \( x_1 \) as the first column which is fixed and then paired with all other columns, say: \( x_2, x_3, \ldots, x_p \), one by one for the purpose of flipping with \( x_1 \). p must be 2 or more.
- **ctrl**: data matrix for designated control variable(s) outside causal paths
- **dig**: Number of digits for reporting (default \( \text{dig} = 6 \)).
- **wt**: Allows user to choose a vector of four alternative weights for SD1 to SD4.
- **sumwt**: Sum of weights can be changed here =4(default).
Details

The reason for slightly declining weights on the signs from SD1 to SD4 is simply that the local mean comparisons implicit in SD1 are known to be more reliable than local variance implicit in SD2, local skewness implicit in SD3 and local kurtosis implicit in SD4. Why are higher moment estimates less reliable? The higher power of the deviations from the mean needed in their computations lead to greater sampling variability. The summary results for all three criteria are reported in a vector of numbers internally called \texttt{crall}:

Value

With \( p \) columns in \( \texttt{mtx} \) argument to this function, \( x_1 \) can be paired with a total of \( p-1 \) columns \((x_2, x_3, \ldots, x_p)\). Note we never flip any of the control variables with \( x_1 \). This function produces \( i=1,2,\ldots,p-1 \) numbers representing the summary sign, or ‘sum’ from the signs \( \text{sg}_1 \) to \( \text{sg}_3 \) associated with the three criteria: \( \text{Cr}_1, \text{Cr}_2 \) and \( \text{Cr}_3 \). Note that \( \text{sg}_1 \) and \( \text{sg}_2 \) themselves are weighted signs using weighted sum of signs from four orders of stochastic dominance. In general, a positive sign in the \( i \)-th location of the ‘sum’ output of this function means that \( x_1 \) is the kernel cause while the variable in \((i+1)\)-th column of \( \texttt{mtx} \) is the ‘effect’ or ‘response’ or ‘endogenous.’ The magnitude represents the strength (unanimity) of the evidence for a particular sign. Conversely a negative sign in the \( i \)-th location of the ‘sum’ output of this function means that the first variable listed as the input to this function is the ‘effect,’ while the variable in \((i+1)\)-th column of \( \texttt{mtx} \) is the exogenous kernel cause. This function allows for control variables.

Note

The European Crime data has all three criteria correctly suggesting that high crime rate kernel causes the deployment of a large number of police officers. The command \texttt{attach(eurocrimeI[ silentPairs(cbind(crimLoffII returns only one number: 3.175, implying a high unanimity strength. The index 3.175 is the highest. The positive sign of the index suggests that ‘crim’ variable in the first column of the matrix input to this function kernel causes ‘off’ in the second column of the matrix argument \( \texttt{mtx} \) to this function.

Interpretation of the output matrix produced by this function is as follows. A negative index means the variable named in the column kernel-causes the variable named in the row. A positive index means the row name variable kernel-causes the column name variable. The abs(index) measures unanimity by three criteria, \( \text{Cr}_1 \) to \( \text{Cr}_3 \) representing the strength of evidence for the identified causal path.

Author(s)

Prof. H. D. Vinod, Economics Dept., Fordham University, NY.

References

H. D. Vinod ‘Generalized Correlation and Kernel Causality with Applications in Development Economics’ in Communications in Statistics -Simulation and Computation, 2015, \url{http://dx.doi.org/10.1080/03610918.2015.1122048}

silentPairs

See Also

See `silentPairs0` using older Cr1 criterion based on kernel regression local gradients.

See `someCPairs, some0Pairs`

Examples

```r
## Not run:
options(np.messages=FALSE)
colnames(mtcars[2:ncol(mtcars)])
silentMtx0(mtcars[,1:3],ctrl=mtcars[,4:5]) # mpg paired with others

## End(Not run)

options(np.messages=FALSE)
set.seed(234)
z=runif(10,2,11)# z is independently created
x=sample(1:10)+z/10 # x is somewhat indep and affected by z
y=1+2*x+3*x+z+runif(10)
w=runif(10)
x2=x;x2[4]=NA;y2=y;y2[8]=NA;w2=w;w2[4]=NA
silentMtx0(mtx=cbind(x2,y2), ctrl=cbind(z,w2))
```

silentPairs  

No-print kernel causality scores with control variables Hausman-Wu Criterion 1

Description

Allowing input matrix of control variables and missing data, this function produces a 3 column matrix summarizing the results where the estimated signs of stochastic dominance order values (+1, 0, -1) are weighted by wt=c(1.2, 1.1, 1.05, 1) to compute an overall result for all orders of stochastic dominance by a weighted sum for the criteria Cr1 and Cr2 and added to the Cr3 estimate as: (+1, 0, -1), always in the range [-3.175, 3.175].

Usage

```r
silentPairs(mtx, ctrl = 0, dig = 6, wt = c(1.2, 1.1, 1.05, 1),
sumwt = 4)
```

Arguments

- `mtx` The data matrix with p columns. Denote x1 as the first column which is fixed and then paired with all other columns, say: x2, x3, ... xp, one by one for the purpose of flipping with x1. p must be 2 or more.
**silentPairs**

- **ctrl**: Data matrix for designated control variable(s) outside causal paths default ctrl=0 which means that there are no control variables used.
- **dig**: Number of digits for reporting (default dig=6).
- **wt**: Allows user to choose a vector of four alternative weights for SD1 to SD4.
- **sumwt**: Sum of weights can be changed here =4 (default).

**Details**

The reason for slightly declining weights on the signs from SD1 to SD4 is simply that the local mean comparisons implicit in SD1 are known to be more reliable than local variance implicit in SD2, local skewness implicit in SD3 and local kurtosis implicit in SD4. The source of slightly declining sampling unreliability of higher moments is the higher power of the deviations from the mean needed in their computations. The summary results for all three criteria are reported in a vector of numbers internally called `crall1`:

**Value**

With p columns in `mtx` argument to this function, x1 can be paired with a total of p-1 columns (x2, x3, ..., xp). Note we never flip any of the control variables with x1. This function produces i=1,2,...,p-1 numbers representing the summary sign, or ‘sum’ from the signs sg1 to sg3 associated with the three criteria: Cr1, Cr2 and Cr3. Note that sg1 and sg2 themselves are weighted signs using weighted sum of signs from four orders of stochastic dominance. In general, a positive sign in the i-th location of the ‘sum’ output of this function means that x1 is the kernel cause while the variable in (i+1)-th column of `mtx` is the ‘effect’ or ‘response’ or ‘endogenous.’ The magnitude represents the strength (unanimity) of the evidence for a particular sign. Conversely a negative sign in the i-th location of the ‘sum’ output of this function means that the first variable listed as the input to this function is the ‘effect,’ while the variable in (i+1)-th column of `mtx` is the exogenous kernel cause.

**Note**

The European Crime data has all three criteria correctly suggesting that high crime rate kernel causes the deployment of a large number of police officers. The command `attach(eurocrimeI); silentPairs(cbind(crimLoffII)` returns only one number: 3.175, implying the highest unanimity strength index, with the positive sign suggesting ‘crim’ in the first column kernel causes ‘off’ in the second column of the argument `mtx` to this function.

**Author(s)**

Prof. H. D. Vinod, Economics Dept., Fordham University, NY.

**References**


silentPairs0

See Also
See bootPairs, silentMtx
See someCPairs, some0Pairs

Examples

```r
## Not run:
options(np.messages=FALSE)
colnames(mtcars[2:ncol(mtcars)])
silentPairs(mtcars[,1:3],ctrl=mtcars[,4:5]) # mpg paired with others

## End(Not run)
options(np.messages=FALSE)
set.seed(234)
z=runif(10,2,11)# z is independently created
x=sample(1:10)+z/10 # x is somewhat indep and affected by z
y=1+2*x+3*x+rnorm(10)
w=runif(10)
x2=x;x2[4]=NA;y2=y;y2[8]=NA;w2=w;w2[4]=NA
silentPairs(mtx=cbind(x2,y2), ctrl=cbind(z,w2))
```

silentPairs0

Older version, kernel causality weighted sum allowing control variables

Description

Allowing input matrix of control variables and missing data, this function produces a 3 column matrix summarizing the results where the estimated signs of stochastic dominance order values (+1, 0, -1) are weighted by \( wt = c(1.2, 1.1, 1.05, 1) \) to compute an overall result for all orders of stochastic dominance by a weighted sum for the criteria Cr1 and Cr2 and added to the Cr3 estimate as: (+1, 0, -1), always in the range \([-3.175, 3.175]\).

Usage

```r
silentPairs0(mtx, ctrl = 0, dig = 6, wt = c(1.2, 1.1, 1.05, 1),
             sumwt = 4)
```

Arguments

- `mtx` The data matrix with \( p \) columns. Denote \( x1 \) as the first column which is fixed and then paired with all other columns, say: \( x2, x3, \ldots, xp \), one by one for the purpose of flipping with \( x1 \). \( p \) must be 2 or more.
ctrl  data matrix for designated control variable(s) outside causal paths default ctrl=0 which means that there are no control variables used.
dig  Number of digits for reporting (default dig=6).
wt  Allows user to choose a vector of four alternative weights for SD1 to SD4.
sumwt  Sum of weights can be changed here =4(default).

details
This uses an older version of the first criterion Cr1 based on absolute values of local gradients of kernel regressions, not absolute Hausman-Wu statistic (RHS variable times kernel residuals). It calls abs_stdapd and abs_stdapdc The reason for slightly declining weights on the signs from SD1 to SD4 is simply that the local mean comparisons implicit in SD1 are known to be more reliable than local variance implicit in SD2, local skewness implicit in SD3 and local kurtosis implicit in SD4. The source of slightly declining sampling unreliability of higher moments is the higher power of the deviations from the mean needed in their computations. The summary results for all three criteria are reported in a vector of numbers internally called crall:

value
With p columns in mtx argument to this function, x1 can be paired with a total of p-1 columns (x2, x3, .., xp). Note we never flip any of the control variables with x1. This function produces i=1,2,...,p-1 numbers representing the summary sign, or 'sum' from the signs sg1 to sg3 associated with the three criteria: Cr1, Cr2 and Cr3. Note that sg1 and sg2 themselves are weighted signs using weighted sum of signs from four orders of stochastic dominance. In general, a positive sign in the i-th location of the 'sum' output of this function means that x1 is the kernel cause while the variable in (i+1)-th column of mtx is the 'effect' or 'response' or 'endogenous.' The magnitude represents the strength (unanimity) of the evidence for a particular sign. Conversely a negative sign in the i-th location of the 'sum' output of this function means that that the first variable listed as the input to this function is the 'effect,' while the variable in (i+1)-th column of mtx is the exogenous kernel cause. This function is a summary of someCPairs allowing for control variables.

note
The European Crime data has all three criteria correctly suggesting that high crime rate kernel causes the deployment of a large number of police officers. The command attach(EuroCrime); silentPairs(cbind(crimLoffII returns only one number: 3.175, implying the highest unanimity strength index, with the positive sign suggesting 'crim' in the first column kernel causes 'off' in the second column of the argument mtx to this function.

author(s)
Prof. H. D. Vinod, Economics Dept., Fordham University, NY.

references
some0Pairs


See Also

See bootPairs, silentMtx
See someCPairs, some0Pairs
See silentPairs for newer version using more direct Hausman-Wu exogeneity test statistic.

Examples

```r
## Not run:
options(np.messages=FALSE)
colnames(mtcars[2:ncol(mtcars)])
silentPairs0(mtcars[,1:3],ctrl=mtcars[,4:5]) # mpg paired with others
## End(Not run)

options(np.messages=FALSE)
set.seed(234)
z=runif(10,2,11)# z is independently created
x=sample(1:10+z/10 # x is somewhat indep and affected by z
y=1+2*x^3*z+rnorm(10)
w=runif(10)
x2=x;x2[4]=NA;y2=y;y2[8]=NA;w2=w;w2[4]=NA
silentPairs0(mtx=cbind(x2,y2), ctrl=cbind(z,w2))
```

some0Pairs

Function reporting kernel causality results as a detailed 7-column matrix

Description

The seven columns produced by this function summarize the results where the signs of stochastic dominance order values (+1 or -1) are weighted by wt=c(1.2,1.1, 1.05, 1) to compute an overall result for all orders of stochastic dominance by a weighted sum for the criteria Cr1 and Cr2. The weighting is obviously not needed for the third criterion Cr3.

Usage

```r
some0Pairs(mtx, dig = 6, verbo = TRUE, rnam = FALSE, wt = c(1.2, 1.1, 1.05, 1), sumwt = 4)
```
Arguments

- **mtx**: The data matrix in the first column is paired with all others.
- **dig**: Number of digits for reporting (default dig=6).
- **verbo**: Make verbo= TRUE for printing detailed steps.
- **rnam**: Make rnam= TRUE if cleverly created row-names are desired.
- **wt**: Allows user to choose a vector of four alternative weights for SD1 to SD4.
- **sumwt**: Sum of weights can be changed here =4(default).

Details

The reason for slightly declining weights on the signs from SD1 to SD4 is simply that the local mean comparisons implicit in SD1 are known to be more reliable than local variance implicit in SD2, local skewness implicit in SD3 and local kurtosis implicit in SD4. The source of slightly declining sampling unreliability of higher moments is the higher power of the deviations from the mean needed in their computations. The summary results for all three criteria are reported in one matrix called outVote:

- **typ=1** reports ('Y', 'X', 'Cause', 'SD1apd', 'SD2apd', 'SD3apd', 'SD4apd') naming variables identifying 'cause' and measures of stochastic dominance using absolute values of kernel regression gradients (or amorphous partial derivatives, apd-s) being minimized by the kernel regression algorithm while comparing the kernel regression of X on Y with that of Y on X.
- **typ=2** reports ('Y', 'X', 'Cause', 'SD1res', 'SD2res', 'SD3res', 'SD4res') and measures of stochastic dominance using absolute values of kernel regression residuals comparing regression of X on Y with that of Y on X.
- **typ=3** reports ('Y', 'X', 'Cause', 'r*x|y', 'r*y|x', 'r', 'p-val') containing generalized correlation coefficients r*, 'r' refers to. Pearson correlation coefficient p-val is the p-value for testing the significance of 'r'.

Value

Prints three matrices detailing results for Cr1, Cr2 and Cr3. It also returns a grand summary matrix called ‘outVote’ which summarizes all three criteria. In general, a positive sign for weighted sum reported in the column ‘sum’ means that the first variable listed as the input to this function is the ‘kernel cause.’ For example, crime ‘kernel causes’ police officer deployment (not vice versa) is indicated by the positive sign of ‘sum’ (=3.175) reported for that example included in this package.

Note

The output matrix last column for ‘mtcars’ example has the sum of the scores by the three criteria combined. If ‘sum’ is positive, then variable X (mpg) is more likely to have been engineered to kernel cause the response variable Y, rather than vice versa.

The European Crime data has all three criteria correctly suggesting that high crime rate kernel causes the deployment of a large number of police officers.

Author(s)

Prof. H. D. Vinod, Economics Dept., Fordham University, NY.
someCPairs

References


See Also

See Also somePairs

Examples

```r
## Not run:
someCPairs(mtcars) # first variable is mpg and effect on mpg is of interest
## End(Not run)

## Not run:
data(EuroCrime)
attach(EuroCrime)
someCPairs(cbind(crim,off))
## End(Not run)
```

---

**someCPairs**

*Kernel causality computations admitting control variables reporting a 7-column matrix (has older Cr1)*

**Description**

Allowing input matrix of control variables, produce 7 column matrix summarizing the results where the signs of stochastic dominance order values (+1 or -1) are weighted by wt=c(1.2, 1.1, 1.05, 1) to compute an overall result for all orders of stochastic dominance by a weighted sum for the criteria Cr1 and Cr2. The weighting is obviously not needed for the third criterion Cr3.

**Usage**

```r
someCPairs(mtx, ctrl, dig = 6, verbo = TRUE, rnam = FALSE, wt = c(1.2, 1.1, 1.05, 1), sumwt = 4)
```

**Arguments**

- **mtx**: The data matrix with many columns where the first column is fixed and then paired with all other columns, one by one.
- **ctrl**: data matrix for designated control variable(s) outside causal paths
dig  Number of digits for reporting (default dig=6).
verbo  Make verbo= TRUE for printing detailed steps.
rnam  Make rnam= TRUE if cleverly created rownames are desired.
wt  Allows user to choose a vector of four alternative weights for SD1 to SD4.
sumwt  Sum of weights can be changed here =4(default).

Details

The reason for slightly declining weights on the signs from SD1 to SD4 is simply that the local mean comparisons implicit in SD1 are known to be more reliable than local variance implicit in SD2, local skewness implicit in SD3 and local kurtosis implicit in SD4. The source of slightly declining sampling unreliability of higher moments is the higher power of the deviations from the mean needed in their computations. The summary results for all three criteria are reported in one matrix called outVote:

- **typ=1** reports ('Y', 'X', 'Cause', 'SD1apdC', 'SD2apdC', 'SD3apdC', 'SD4apdC') naming variables identifying 'cause' and measures of stochastic dominance using absolute values of kernel regression gradients (or amorphous partial derivatives, apd-s) being minimized by the kernel regression algorithm while comparing the kernel regression of X on Y with that of Y on X. The letter C in the titles reminds presence of control variable(s).

- **typ=2** reports ('Y', 'X', 'Cause', 'SD1resC', 'SD2resC', 'SD3resC', 'SD4resC') and measures of stochastic dominance using absolute values of kernel regression residuals comparing regression of X on Y with that of Y on X.

- **typ=3** reports ('Y', 'X', 'Cause', 'r*xyC', 'r+y|xC', 'r', 'p-val') containing generalized correlation coefficients r*, 'r' refers to. Pearson correlation coefficient p-val is the p-value for testing the significance of 'r'. The letter C in the titles reminds the presence of control variable(s).

Value

Prints three matrices detailing results for Cr1, Cr2 and Cr3. It also returns a grand summary matrix called ‘outVote’ which summarizes all three criteria. In general, a positive sign for weighted sum reported in the column ‘sum’ means that the first variable listed as the input to this function is the ‘kernel cause.’ This function is an extension of someCPairs to allow for control variables. For example, crime ‘kernel causes’ police officer deployment (not vice versa) is indicated by the positive sign of ‘sum’ (=3.175) reported for that example included in this package.

Note

The output matrix last column for ‘mtcars’ example has the sum of the scores by the three criteria combined. If ‘sum’ is positive, then variable X (mpg) is more likely to have been engineered to kernel cause the response variable Y, rather than vice versa.

The European Crime data has all three criteria correctly suggesting that high crime rate kernel causes the deployment of a large number of police officers.

Author(s)

Prof. H. D. Vinod, Economics Dept., Fordham University, NY.
someCPairs2

References


See Also

See Also somePairs, some0Pairs

Examples

```r
## Not run:
someCPairs(mtcars[,1:3],ctrl=mtcars[4:5]) # first variable is mpg and effect on mpg is of interest
## End(Not run)

set.seed(234)
z=runif(10,2,11)# z is independently created
x=sample(1:10)+z/10  # x is somewhat indep and affected by z
y=1+2*x+3*z+rnorm(10)
w=runif(10)
x2=x;x2[4]=NA;y2=y;y2[8]=NA;w2=w;w2[4]=NA
someCPairs(cbind(x2,y2), cbind(z,w2)) # yields x2 as correct cause
```

---

**someCPairs2**  
*Kernel causality computations admitting control variables reporting a 7-column matrix, ver. 2*

**Description**

Second version of someCPairs also allows input matrix of control variables, produce 7 column matrix summarizing the results where the signs of stochastic dominance order values (+1 or -1) are weighted by wt=c(1.2,1.1, 1.05, 1) to compute an overall result for all orders of stochastic dominance by a weighted sum for the criteria Cr1 and Cr2. The weighting is obviously not needed for the third criterion Cr3.

**Usage**

```r
someCPairs2(mtx, ctrl, dig = 6, verbo = TRUE, rnam = FALSE, wt = c(1.2, 1.1, 1.05, 1), sumwt = 4)
```
Arguments

\textbf{mtx} \hspace{1cm} The data matrix with many columns where the first column is fixed and then paired with all other columns, one by one.

\textbf{ctrl} \hspace{1cm} data matrix for designated control variable(s) outside causal paths

\textbf{dig} \hspace{1cm} Number of digits for reporting (default dig=6).

\textbf{verbo} \hspace{1cm} Make verbo= TRUE for printing detailed steps.

\textbf{rnam} \hspace{1cm} Make rnam= TRUE if cleverly created rownames are desired.

\textbf{wt} \hspace{1cm} Allows user to choose a vector of four alternative weights for SD1 to SD4.

\textbf{sumwt} \hspace{1cm} Sum of weights can be changed here =4(default).

Details

The reason for slightly declining weights on the signs from SD1 to SD4 is simply that the local mean comparisons implicit in SD1 are known to be more reliable than local variance implicit in SD2, local skewness implicit in SD3 and local kurtosis implicit in SD4. The source of slightly declining sampling unreliability of higher moments is the higher power of the deviations from the mean needed in their computations. The summary results for all three criteria are reported in one matrix called \textit{outVote}:

\( \text{(typ=1) reports ('Y', 'X', 'Cause', 'SD1.rhserr', 'SD2.rhserr', 'SD3.rhserr', 'SD4.rhserr')} \) naming variables identifying the 'cause' and measures of stochastic dominance using absolute values of kernel regression \( \text{abs(RHS first regressor*residual)} \) values comparing flipped regressions X on Y versus Y on X. The letter C in the titles reminds presence of control variable(s).

\( \text{typ=2 reports ('Y', 'X', 'Cause', 'SD1resC', 'SD2resC', 'SD3resC', 'SD4resC')} \) and measures of stochastic dominance using absolute values of kernel regression residuals comparing regression of X on Y with that of Y on X.

\( \text{typ=3 reports ('Y', 'X', 'Cause', 'r*x|yC', 'r*y|xC', 'r', 'p-val')} \) containing generalized correlation coefficients \( r^* \), \( 'r' \) refers to. Pearson correlation coefficient \( p-val \) is the p-value for testing the significance of \( 'r' \). The letter C in the titles reminds the presence of control variable(s).

Value

Prints three matrices detailing results for Cr1, Cr2 and Cr3. It also returns a grand summary matrix called \textit{outVote} which summarizes all three criteria. In general, a positive sign for weighted sum reported in the column 'sum' means that the first variable listed as the input to this function is the 'kernel cause.' This function is an extension of \textit{somePpairs} to allow for control variables. For example, crime 'kernel causes' police officer deployment (not vice versa) is indicated by the positive sign of 'sum' (=3.175) reported for that example included in this package.

Note

The output matrix last column for 'mtcars' example has the sum of the scores by the three criteria combined. If 'sum' is positive, then variable X (mpg) is more likely to have been engineered to kernel cause the response variable Y, rather than vice versa.

The European Crime data has all three criteria correctly suggesting that high crime rate kernel causes the deployment of a large number of police officers.
someMagPairs

Author(s)
Prof. H. D. Vinod, Economics Dept., Fordham University, NY.

References

See Also
See Also somePairs, somePairs

Examples

```r
## Not run:
someCPairs2(mtcars[,1:3],ctrl=mtcars[4:5]) # first variable is mpg and effect on mpg is of interest

## End(Not run)

set.seed(234)
z=runif(10,2,11)# z is independently created
x=sample(1:10)+z/10 #x is somewhat indep and affected by z
y=1+2x+3x^2+z+rnorm(10)
wx=runif(10)
x2=x;x2[4]=NA;y2=y;y2[8]=NA;w2=w;w2[4]=NA
someCPairs2(cbind(x2,y2),cbind(z,w2)) #yields x2 as correct cause
```

somemagpairs

Summary magnitudes after removing control variables in several pairs where dependent variable is fixed.

Description
This builds on the function mag_ctrl, where the input matrix mtx has p columns. The first column is present in each of the (p-1) pairs. Its output is a matrix with four columns containing the names of variables and approximate overall estimates of the magnitudes of partial derivatives (dy/dx) and (dx/dy) for a distinct (x,y) pair in a row. The estimated overall derivatives are not always well-defined, because the real partial derivatives of nonlinear functions are generally distinct for each observation point.

Usage

```r
someMagPairs(mtx, ctrl, dig = 6, verbo = TRUE)
```
someMagPairs

Arguments

mtx  The data matrix with many columns where the first column is fixed and then paired with all other columns, one by one.
ctrl  data matrix for designated control variable(s) outside causal paths. A constant vector is not allowed as a control variable.
dig  Number of digits for reporting (default dig=6).
verbo  Make verbo= TRUE for printing detailed steps.

Details

The function mag_ctrl has kernel regressions: \( x \sim y + ctrl \) and \( x \sim ctrl \) to evaluate the 'incremental change' in R-squares. Let \((rxy;ctrl)\) denote the square root of that 'incremental change' after its sign is made the same as that of the Pearson correlation coefficient from \( \text{cor}(x, y) \). One can interpret \((rxy;ctrl)\) as a generalized partial correlation coefficient when \( x \) is regressed on \( y \) after removing the effect of control variable(s) in \( ctrl \). It is more general than the usual partial correlation coefficient, since this one allows for nonlinear relations among variables. Next, the function computes \( 'dxdy' \) obtained by multiplying \((rxy;ctrl)\) by the ratio of standard deviations, \( \text{sd}(x)/\text{sd}(y) \). Now our 'dxdy' approximates the magnitude of the partial derivative \((dx/dy)\) in a causal model where \( y \) is the cause and \( x \) is the effect. The function also reports entirely analogous 'dydx' obtained by interchanging \( x \) and \( y \).

someMegPairs function runs the function mag_ctrl on several column pairs in a matrix input \( mtx \) where the first column is held fixed and all others are changed one by one, reporting two partial derivatives for each row.

Value

Table containing names of \( Xi \) and \( Xj \) and two magnitudes: \((dXidXj, dXjdXi)\). \( dXidXj \) is the magnitude of the effect on \( Xi \) when \( Xi \) is regressed on \( Xj \) (i.e., when \( Xj \) is the cause). The analogous \( dXjdXi \) is the magnitude when \( Xj \) is regressed on \( Xi \).

Note

This function is intended for use only after the causal path direction is already determined by various functions in this package (e.g. someCPairs). That is, after the researcher knows whether \( Xi \) causes \( Xj \) or vice versa. The output of this function is a matrix of 4 columns, where first columns list the names of \( Xi \) and \( Xj \) and the next two numbers in each row are \( dXidXj \), \( dXjdXi \), respectively, representing the magnitude of effect of one variable on the other.

Author(s)

Prof. H. D. Vinod, Economics Dept., Fordham University, NY

References


See Also
See mag_ctrl, someCPairs

Examples

```r
set.seed(34); x = sample(1:10); y = 1 + 2 * x + rnorm(10); z = sample(2:11)
w = runif(10)
ss = someMagPairs(cbind(y, x, z), ctrl = w)
```

### somePairs

**Function reporting kernel causality results as a 7-column matrix.**

**Description**

This function lets the user choose one of three criteria to determine causal direction by setting typ as 1, 2 or 3. This function reports results for only one criterion at a time unlike the function somePpairs which summarizes the resulting causal directions for all criteria with suitable weights. If some variables are ‘control’ variables, use someCPairs, C=control.

**Usage**

```r
somePairs(mtx, dig = 6, verbo = FALSE, typ = 1, rnam = FALSE)
```

**Arguments**

- **mtx**: The data matrix in the first column is paired with all others.
- **dig**: Number of digits for reporting (default dig = 6).
- **verbo**: Make verbo= TRUE for printing detailed steps.
- **typ**: Must be 1 (default), 2 or 3 for the three criteria.
- **rnam**: Make rnam= TRUE if cleverly created rownames are desired.

**Details**

(typ=1) reports (‘Y’, ‘X’, ‘Cause’, ‘SD1apd’, ‘SD2apd’, ‘SD3apd’, ‘SD4apd’) naming variables identifying ‘cause’ and measures of stochastic dominance using absolute values of kernel regression gradients comparing regression of X on Y with that of Y on X.

(typ=2) reports (‘Y’, ‘X’, ‘Cause’, ‘SD1res’, ‘SD2res’, ‘SD3res’, ‘SD4res’) and measures of stochastic dominance using absolute values of kernel regression residuals comparing regression of X on Y with that of Y on X.
somePairs2

(typ=3) reports ('Y', 'X', 'Cause', 'r*Y|X', 'r*X|Y', 'r', 'p-val') containing generalized correlation coefficients r*, 'r' refers to the Pearson correlation coefficient and p-val column has the p-values for testing the significance of Pearson's 'r'.

Value

A matrix containing causal identification results for one criterion. The first column of the input mtx having p columns is paired with (p-1) other columns The output matrix headings are self-explanatory and distinct for each criterion Cr1 to Cr3.

Author(s)

Prof. H. D. Vinod, Economics Dept., Fordham University, NY

References


See Also

The related function some0Pairs may be more useful, since it reports on all three criteria (by choosing typ=1,2,3) and further summarizes their results by weighting to help choose causal paths.

Examples

```r
## Not run:
data(mtcars)
somePairs(mtcars)
## End(Not run)
```

somePairs2  Function reporting kernel causality results as a 7-column matrix, version 2.

Description

This function is an alternative implementation of somePairs which also lets the user choose one of three criteria to determine causal direction by setting typ as 1, 2 or 3. This function reports results for only one criterion at a time unlike the function some0Pairs which summarizes the resulting causal directions for all criteria with suitable weights. If some variables are 'control' variables, use someCPairs, where notation C=control.
somePairs2

Usage

somePairs2(mtx, dig = 6, verbo = FALSE, typ = 1, rnam = FALSE)

Arguments

mtx
The data matrix in the first column is paired with all others.

dig
Number of digits for reporting (default dig = 6).

verbo
Make verbo = TRUE for printing detailed steps.

typ
Must be 1 (default), 2 or 3 for the three criteria.

rnam
Make rnam = TRUE if cleverly created rownames are desired.

Details

(typ = 1) reports ('Y', 'X', 'Cause', 'SD1.rhserr', 'SD2.rhserr', 'SD3.rhserr', 'SD4.rhserr') naming variables identifying the 'cause' and measures of stochastic dominance using absolute values of kernel regression abs(RHS first regressor*residual) comparing flipped regressions X on Y versus Y on X.

(typ = 2) reports ('Y', 'X', 'Cause', 'SD1res', 'SD2res', 'SD3res', 'SD4res') and measures of stochastic dominance using absolute values of kernel regression residuals comparing regression of X on Y with that of Y on X.

(typ = 3) reports ('Y', 'X', 'Cause', 'r*X|Y', 'r*Y|X', 'r', 'p-val') containing generalized correlation coefficients r*, 'r' refers to the Pearson correlation coefficient and p-val column has the p-values for testing the significance of Pearson's 'r'.

Value

A matrix containing causal identification results for one criterion. The first column of the input mtx having p columns is paired with (p-1) other columns. The output matrix headings are self-explanatory and distinct for each criterion Cr1 to Cr3.

Author(s)

Prof. H. D. Vinod, Economics Dept., Fordham University, NY

References


See Also

The related function somePairs may be more useful, since it reports on all three criteria (by choosing typ = 1, 2, 3) and further summarizes their results by weighting to help choose causal paths. Alternative and revised function somePairs2 implements the Cr1 (first criterion) with a direct estimate of the Hausman-Wu statistic for testing exogeneity.
sort_matrix

Sort all columns of matrix x with respect to the j-th column.

Description
This function can use the sort.list function in R. The reason for using it is that one wants the sort to carry along all columns.

Usage
sort_matrix(x, j)

Examples

## Not run:
data(mtcars)
somePairs2(mtcars)

## End(Not run)
stdres

Arguments

x  An input matrix with several columns
j  The column number with reference to which one wants to sort

Value

A sorted matrix

Examples

```r
set.seed(30)
x = matrix(sample(1:50), ncol=5)
y = sort_matrix(x, 3); y
```

```r
stdres
Residuals of kernel regressions of x on y when both x and y are standardized.
```

Description

1) Standardize the data to force mean zero and variance unity, 2) kernel regress x on y, with the option ‘residuals = TRUE’ and finally 3) compute the residuals.

Usage

`stdres(x, y)`

Arguments

x  vector of data on the dependent variable
y  data on the regressors which can be a matrix

Details

The first argument is assumed to be the dependent variable. If `stdres(x, y)` is used, you are regressing x on y (not the usual y on x). The regressors can be a matrix with 2 or more columns. The missing values are suitably ignored by the standardization.

Value

Kernel regression residuals are returned after standardizing the data on both sides so that the magnitudes of residuals are comparable between regression of x on y on the one hand and regression of y on x on the other.

Author(s)

Prof. H. D. Vinod, Economics Dept., Fordham University, NY
stdz_xy

References


Examples

```r
## Not run:
set.seed(330)
x = sample(20:50)
y = sample(20:50)
stdres(x, y)

## End(Not run)
```

---

stdz_xy

*Standardize x and y vectors to achieve zero mean and unit variance.*

Description

Standardize x and y vectors to achieve zero mean and unit variance.

Usage

```r
stdz_xy(x, y)
```

Arguments

- `x`  Vector of data which can have NA's
- `y`  Vector of data which can have NA's

Value

- `stdx`  standardized values of x
- `stdy`  standardized values of y

Note

This works even if there are missing x or y values.

Author(s)

Prof. H. D. Vinod, Economics Dept., Fordham University, NY
stochdom2

Examples

```r
## Not run:
set.seed(30)
x = sample(20:30)
y = sample(21:31)
std_z_xy(x, y)
## End(Not run)
```

stochdom2  Compute vectors measuring stochastic dominance of four orders.

Description

Stochastic dominance originated as a sophisticated comparison of two distributions of stock market returns. The dominating distribution is superior in terms of local mean, variance, skewness and kurtosis respectively, representing dominance orders 1 to 4, without simply computing the four moment summary measures for the entire data. Vinod (2008, sec. 4.3) explains the details. This function uses the output of ‘wtdpapb’.

Usage

`stochdom2(dj, wpa, wpb)`

Arguments

- `dj`  Vector of (unequal) distances of consecutive intervals defined on common support of two probability distributions being compared
- `wpa`  Vector of the first set of (weighted) probabilities
- `wpb`  Vector of the second set of (weighted) probabilities

Value

- `sd1b`  Vector measuring stochastic dominance of order 1, SD1
- `sd2b`  Vector measuring stochastic dominance of order 2, SD2
- `sd3b`  Vector measuring stochastic dominance of order 3, SD3
- `sd4b`  Vector measuring stochastic dominance of order 4, SD4

Note

The input to this function is the output of the function `wtdpapb`.

Author(s)

Prof. H. D. Vinod, Economics Dept., Fordham University, NY
wtdpapb

References


See Also

See Also wtdpapb

Examples

```r
## Not run:
set.seed(234); x = sample(1:30); y = sample(5:34)
w1 = wtdpapb(x, y) # y should dominate x with mostly positive SDs
stochdom2(w1$dj, w1$wpa, w1$wpb)
## End(Not run)
```

wtdpapb

Creates input for the stochastic dominance function stochdom2

Description

Stochastic dominance is a sophisticated comparison of two distributions of stock market returns. The dominating distribution is superior in terms of mean, variance, skewness and kurtosis respectively, representing dominance orders 1 to 4, without directly computing four moments. Vinod(2008) sec. 4.3 explains the details. The ‘wtdpapb’ function creates the input for stochdom2 which in turn computes the stochastic dominance. See Vinod (2004) for details about quantitative stochastic dominance.

Usage

wtdpapb(xa, xb)

Arguments

xa
  Vector of (excess) returns for the first investment option A or values of any random variable being compared to another.

xb
  Vector of returns for the second option B

Value

wpa
  Weighted vector of probabilities for option A

wpb
  Weighted vector of probabilities for option B

dj
  Vector of interval widths (distances) when both sets of data are forced on a common support
**Note**

Function is needed before using stochastic dominance

In Vinod (2008) where the purpose of wtdpapb is to map from standard 'expected utility theory' weights to more sophisticated 'non-expected utility theory' weights using Prelec's (1998, Econometrica, p. 497) method. These weights are not needed here. Hence we provide the function prelec2 which does not use Prelec weights at all, thereby simplifying and speeding up the R code provided in Vinod (2008). This function avoids sophisticated 'non-expected' utility theory which incorporates commonly observed human behavior favoring loss aversion and other anomalies inconsistent with precepts of the expected utility theory. Such weighting is not needed for our application.

**Author(s)**

Prof. H. D. Vinod, Economics Dept., Fordham University, NY

**References**


**See Also**

See Also `stochdom2`

**Examples**

```r
## Not run:
set.seed(234); x=sample(1:30); y=sample(5:34)
wtdpapb(x,y)
## End(Not run)
```
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