Package: TExPosition (via r-universe)

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Type Package

Title Two-Table ExPosition

Version 2.6.10.1

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Description An extension of ExPosition for two table analyses,
specifically, discriminant analyses.

License GPL-2

Depends prettyGraphs (>= 2.1.4), ExPosition (>= 2.0.0)

BugReports http://code.google.com/p/exposition-family/issues/list

NeedsCompilation no

Repository CRAN

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Contents

`TExPosition-package` *TExPosition: Two-table analyses with via ExPosition.*

Description

TExPosition is two-table `ExPosition` and includes discriminant methods of the singular value decomposition (SVD). The core of TExPosition is `ExPosition` and the `svd`.

Details

Package:	TExPosition
Type:	Package
Version:	2.6.10
Date:	2013-12-00
Depends:	R (>=2.15.0), prettyGraphs (>= 2.1.4), ExPosition (>= 2.0.0)
License:	GPL-2
URL:	http://www.utdallas.edu/~derekbeaton/software/ExPosition

Author(s)

Questions, comments, compliments, and complaints go to Derek Beaton `<exposition.software@gmail.com>`.

The following people are authors or contributors to TExPosition code, data, or examples:
Derek Beaton, Jenny Rieck, Cherise Chin-Fatt, Francesca Filbey, and Hervé Abdi.

References

Abdi, H., and Williams, L.J. (2010). Principal component analysis. *Wiley Interdisciplinary Reviews: Computational Statistics*, 2, 433-459.
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Abdi, H. & Williams, L.J. (2010). Barycentric discriminant analysis (BADIA). In N.J. Salkind, D.M., Dougherty, & B. Frey (Eds.): *Encyclopedia of Research Design*. Thousand Oaks (CA): Sage. pp. 64-75.
Abdi, H. (2007). Discriminant correspondence analysis. In N.J. Salkind (Ed.): *Encyclopedia of Measurement and Statistics*. Thousand Oaks (CA): Sage. pp. 270-275. Krishnan, A., Williams, L. J., McIntosh, A. R., & Abdi, H. (2011). Partial Least Squares (PLS) methods for neuroimaging: A tutorial and review. *NeuroImage*, *56*(**2**), 455 – 475.
McIntosh, A. R., & Lobaugh, N. J. (2004). Partial least squares analysis of neuroimaging data: applications and advances. *Neuroimage*, *23*, S250–S263.

See Also

`tepBADA`, `tepPLS`, `tepGPLS`, `tepDICA`, `tepPLSCA`

Examples

```
#For more examples, see each individual function (as noted above).
```

---

calculateLVConstraints

calculateLVConstraints

Description

Calculates constraints for plotting latent variables.

Usage

```
calculateLVConstraints(results,x_axis=1,y_axis=2,constraints=NULL)
```

Arguments

`results`	results (with $lx and $ly) from TExPosition (i.e., $TExPosition.Data)
`x_axis`	which component should be on the x axis?
`y_axis`	which component should be on the y axis?
`constraints`	if available, axis constraints for the plots (determines end points of the plots).

Value

Returns a list with the following items:

`$constraints`	axis constraints for the plots (determines end points of the plots).

Author(s)

Derek Beaton

fastEucCalc *fastEucCalc*

Description

Fast Euclidean distance calculations.

Usage

```
fastEucCalc(x, c)
```

Arguments

x	a set of points.
c	a set of centers.

Details

This function is especially useful for discriminant analyses. The distance from each point in `x` to each point in `c` is computed and returned as a `nrow(x)` x `nrow(c)` matrix.

Value

`a distance matrix`
Euclidean distances of each point to each center are returned.

Author(s)

Hervé Abdi, Derek Beaton

fii2fi *fii2fi: individuals to centers*

Description

All computations between individual factor scores (fii) and group factor scores (fi).

Usage

```
fii2fi(DESIGN, fii, fi)
```

Arguments

DESIGN	a dummy-coded design matrix
fii	a set of factor scores for individuals (rows)
fi	a set of factor scores for rows

Value

A list of values containing:

`distances`	Euclidean distances of all rows to each category center
`assignments`	an assignment matrix (similar to DESIGN) where each individual is assigned to the closest category center
`confusion`	a confusion matrix of how many items are assigned (and mis-assigned) to each category

Author(s)

Hervé Abdi, Derek Beaton

`print.tepAssign` *Print assignment results*

Description

Print assignment results.

Usage

```
 ## S3 method for class 'tepAssign'
print(x,...)
```

Arguments

`x`	an list that contains items to make into the tepAssign class.
`...`	inherited/passed arguments for S3 print method(s).

Author(s)

Derek Beaton, Cherise Chin-Fatt

print.tepBADA *Print tepBADA results*

Description

Print tepBADA results.

Usage

```
 ## S3 method for class 'tepBADA'
print(x,...)
```

Arguments

`x`	an list that contains items to make into the tepBADA class.
`...`	inherited/passed arguments for S3 print method(s).

Author(s)

Derek Beaton, Cherise Chin-Fatt

print.tepDICA *Print tepDICA results*

Description

Print tepDICA results.

Usage

```
 ## S3 method for class 'tepDICA'
print(x,...)
```

Arguments

`x`	an list that contains items to make into the tepDICA class.
`...`	inherited/passed arguments for S3 print method(s).

Author(s)

Derek Beaton, Cherise Chin-Fatt

print.tepGPLS *Print tepGPLS results*

Description

Print tepGPLS results.

Usage

```
## S3 method for class 'tepGPLS'
print(x,...)
```

Arguments

x	an list that contains items to make into the tepGPLS class.
...	inherited/passed arguments for S3 print method(s).

Author(s)

Derek Beaton, Cherise Chin-Fatt

print.tepGraphs *Print tepGraphs results*

Description

Print tepGraphs results.

Usage

```
## S3 method for class 'tepGraphs'
print(x,...)
```

Arguments

x	an list that contains items to make into the tepGraphs class.
...	inherited/passed arguments for S3 print method(s).

Author(s)

Derek Beaton, Cherise Chin-Fatt

print.tepPLS *Print tepPLS results*

Description

Print tepPLS results.

Usage

```
 ## S3 method for class 'tepPLS'
print(x,...)
```

Arguments

x	an list that contains items to make into the tepPLS class.
...	inherited/passed arguments for S3 print method(s).

Author(s)

Derek Beaton, Cherise Chin-Fatt

print.tepPLSCA *Print tepPLSCA results*

Description

Print tepPLSCA results.

Usage

```
 ## S3 method for class 'tepPLSCA'
print(x,...)
```

Arguments

x	an list that contains items to make into the tepPLSCA class.
...	inherited/passed arguments for S3 print method(s).

Author(s)

Derek Beaton, Cherise Chin-Fatt

print.texpoOutput *Print TExPosition results*

Description

Print TExPosition results.

Usage

```
 ## S3 method for class 'texpoOutput'
print(x,...)
```

Arguments

`x`	an list that contains items to make into the texpoOutput class.
`...`	inherited/passed arguments for S3 print method(s).

Author(s)

Derek Beaton, Cherise Chin-Fatt

R2 *R-squared computations*

Description

A function to compute R-squared for BADA and DICA

Usage

```
R2(group.masses, di, ind.masses = NULL, dii)
```

Arguments

`group.masses`	a masses matrix for the groups
`di`	a set of squared distances of the groups
`ind.masses`	a masses matrix for the individuals
`dii`	a set of squared distances for the individuals

Value

`R2`	An R-squared

Author(s)

Jenny Rieck, Derek Beaton

tepBADA *Barycentric Discriminant Analysis*

Description

Barycentric Discriminant Analysis (BADA) via TExPosition.

Usage

```
tepBADA(DATA, scale = TRUE, center = TRUE, DESIGN = NULL, make_design_nominal = TRUE,
 group.masses = NULL, weights = NULL, graphs = TRUE, k = 0)
```

Arguments

DATA	original data to perform a BADA on.
scale	a boolean, vector, or string. See expo.scale for details.
center	a boolean, vector, or string. See expo.scale for details.
DESIGN	a design matrix to indicate if rows belong to groups. Required for BADA.
make_design_nominal	a boolean. If TRUE (default), DESIGN is a vector that indicates groups (and will be dummy-coded). If FALSE, DESIGN is a dummy-coded matrix.
group.masses	a diagonal matrix or column-vector of masses for the groups.
weights	a diagonal matrix or column-vector of weights for the column items.
graphs	a boolean. If TRUE (default), graphs and plots are provided (via tepGraphs)
k	number of components to return.

Details

Note: BADA is a special case of PLS (tepPLS,tepGPLS) wherein DATA1 are data and DATA2 are a group-coded disjunctive matrix. This is also called mean-centered PLS (Krishnan et al., 2011).

Value

See epGPCA (and also corePCA) for details on what is returned. In addition to the values returned:

fii	factor scores computed for supplemental observations
dii	squared distances for supplemental observations
rii	cosines for supplemental observations
assign	a list of assignment data. See fii2fi and R2
lx	latent variables from DATA1 computed for observations
ly	latent variables from DATA2 computed for observations

Author(s)

Derek Beaton

References

Abdi, H., and Williams, L.J. (2010). Principal component analysis. *Wiley Interdisciplinary Reviews: Computational Statistics*, 2, 433-459.
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Abdi, H., Williams, L.J., Beaton, D., Posamentier, M., Harris, T.S., Krishnan, A., & Devous, M.D. (in press, 2012). Analysis of regional cerebral blood flow data to discriminate among Alzheimer's disease, fronto-temporal dementia, and elderly controls: A multi-block barycentric discriminant analysis (MUBADA) methodology. *Journal of Alzheimer Disease*, , -. Abdi, H., Williams, L.J., Connolly, A.C., Gobbini, M.I., Dunlop, J.P., & Haxby, J.V. (2012). Multiple Subject Barycentric Discriminant Analysis (MUSUBADA): How to assign scans to categories without using spatial normalization. *Computational and Mathematical Methods in Medicine*, 2012, 1-15. doi:10.1155/2012/634165.
Krishnan, A., Williams, L. J., McIntosh, A. R., & Abdi, H. (2011). Partial Least Squares (PLS) methods for neuroimaging: A tutorial and review. *NeuroImage*, *56*(**2**), 455 – 475.

See Also

corePCA, epPCA, epGPCA, epMDS
For MatLab code: http://utd.edu/~derekbeaton/attachments/Software/matlab/MuSuBADA_V3.zip

Examples

```
data(bada.wine)
bada.res <- tepBADA(bada.wine$data,scale=FALSE,DESIGN=bada.wine$design,make_design_nominal=FALSE)
```

---

tepDICA *Discriminant Correspondence Analysis*

Description

Discriminant Correspondence Analysis (DICA) via TExPosition.

Usage

```
tepDICA(DATA, make_data_nominal = FALSE, DESIGN = NULL, make_design_nominal = TRUE,
group.masses = NULL, weights = NULL, symmetric = TRUE, graphs = TRUE, k = 0)
```

Arguments

`DATA`	original data to perform a DICA on. Data can be contingency (like CA) or categorical (like MCA).
`make_data_nominal`	a boolean. If TRUE (default), DATA is recoded as a dummy-coded matrix. If FALSE, DATA is a dummy-coded matrix.
`DESIGN`	a design matrix to indicate if rows belong to groups. Required for DICA.
`make_design_nominal`	a boolean. If TRUE (default), DESIGN is a vector that indicates groups (and will be dummy-coded). If FALSE, DESIGN is a dummy-coded matrix.
`group.masses`	a diagonal matrix or column-vector of masses for the groups.
`weights`	a diagonal matrix or column-vector of weights for the column it
`symmetric`	a boolean. If TRUE (default) symmetric factor scores for rows.
`graphs`	a boolean. If TRUE (default), graphs and plots are provided (via `tepGraphs`)
`k`	number of components to return.

Details

If you use Hellinger distance, it is best to set `symmetric` to FALSE.

Note: DICA is a special case of PLS-CA (`tepPLSCA`) wherein DATA1 are data and DATA2 are a group-coded disjunctive matrix.

Value

See `epCA` (and also `coreCA`) for details on what is returned. In addition to the values returned:

`fii`	factor scores computed for supplemental observations
`dii`	squared distances for supplemental observations
`rii`	cosines for supplemental observations
`assign`	a list of assignment data. See `fii2fi` and `R2`
`lx`	latent variables from DATA1 computed for observations
`ly`	latent variables from DATA2 computed for observations

Author(s)

Derek Beaton, Hervé Abdi

References

Abdi, H., and Williams, L.J. (2010). Principal component analysis. *Wiley Interdisciplinary Reviews: Computational Statistics*, 2, 433-459.
Abdi, H. and Williams, L.J. (2010). Correspondence analysis. In N.J. Salkind, D.M., Dougherty, & B. Frey (Eds.): *Encyclopedia of Research Design*. Thousand Oaks (CA): Sage. pp. 267-278.

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Williams, L.J., Abdi, H., French, R., & Orange, J.B. (2010). A tutorial on Multi-Block Discriminant Correspondence Analysis (MUDICA): A new method for analyzing discourse data from clinical populations. *Journal of Speech Language and Hearing Research*, 53, 1372-1393.
Williams, L.J., Dunlop, J.P., & Abdi, H. (2012). Effect of age on the variability in the production of text-based global inferences. *PLoS One*, 7(5): e36161. doi:10.1371/ journal.pone.0036161 (pp.1-9)

See Also

`coreCA`, `epCA`, `epMCA`
For MatLab code: http://utd.edu/~herve/HerveAbdi_MatlabPrograms4MUDICA.zip For additional R code (with inference tests): http://utdallas.edu/~dfb090020/attachments/MuDiCA.zip

Examples

```
data(dica.wine)
dica.res <- tepDICA(dica.wine$data,DESIGN=dica.wine$design,make_design_nominal=FALSE)
```

`tepGPLS` *Generalized Partial Least Squares*

Description

Generalized Partial Least Squares (GPLS) via TExPosition. GPLS is to PLS (`tepPLS`) as PCA `epPCA` is to GPCA `epGPCA`. The major difference between PLS and GPLS is that GPLS allows the use of weights for the columns of each data set (just like GPCA).

Usage

```
tepGPLS(DATA1, DATA2,
center1 = TRUE, scale1 = "SS1",
center2 = TRUE, scale2 = "SS1",
DESIGN = NULL, make_design_nominal = TRUE,
weights1 = NULL, weights2 = NULL,
graphs = TRUE, k = 0)
```

Arguments

`DATA1`	Data matrix 1 (X)
`DATA2`	Data matrix 2 (Y)

center1	a boolean, vector, or string to center DATA1. See expo.scale for details.
scale1	a boolean, vector, or string to scale DATA1. See expo.scale for details.
center2	a boolean, vector, or string to center DATA2. See expo.scale for details.
scale2	a boolean, vector, or string to scale DATA2. See expo.scale for details.
DESIGN	a design matrix to indicate if rows belong to groups.
make_design_nominal	a boolean. If TRUE (default), DESIGN is a vector that indicates groups (and will be dummy-coded). If FALSE, DESIGN is a dummy-coded matrix.
weights1	a weight vector (or diag matrix) for the columns of DATA1.
weights2	a weight vector (or diag matrix) for the columns of DATA2.
graphs	a boolean. If TRUE (default), graphs and plots are provided (via tepGraphs)
k	number of components to return.

Details

This implementation of Partial Least Squares is a symmetric analysis. It was first described by Tucker (1958), again by Bookstein (1994), and has gained notoriety in Neuroimaging from McIntosh et al., (1996). This particular implementation allows the user to provide weights for the columns of both DATA1 and DATA2.

Value

See epGPCA (and also corePCA) for details on what is returned. In addition to the values returned:

lx	latent variables from DATA1 computed for observations
ly	latent variables from DATA2 computed for observations
data1.norm	center and scale information for DATA1
data1.norm	center and scale information for DATA2

Author(s)

Derek Beaton

References

Tucker, L. R. (1958). An inter-battery method of factor analysis. *Psychometrika*, *23*(2), 111–136.
Bookstein, F., (1994). Partial least squares: a dose–response model for measurement in the behavioral and brain sciences. *Psycoloquy 5* (23)
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Krishnan, A., Williams, L. J., McIntosh, A. R., & Abdi, H. (2011). Partial Least Squares (PLS) methods for neuroimaging: A tutorial and review. *NeuroImage*, *56*(**2**), 455 – 475.
McIntosh, A. R., & Lobaugh, N. J. (2004). Partial least squares analysis of neuroimaging data: applications and advances. *Neuroimage*, *23*, S250–S263.

See Also

corePCA, epPCA, epGPCA, tepPLS, tepPLSCA, tepBADA, tepDICA

Examples

```
data(beer.tasting.notes)
data1<-beer.tasting.notes$data[,1:8]
data2<-beer.tasting.notes$data[,9:16]
gpls.res <- tepGPLS(data1,data2)
```

---

tepGraphs *tepGraphs: TExPosition plotting function*

Description

TExPosition plotting function which is an interface to prettyGraphs.

Usage

```
tepGraphs(res, x_axis = 1, y_axis = 2,
 tepPlotInfo = NULL, DESIGN = NULL,
 fi.col = NULL, fi.pch = NULL, fii.col = NULL, fii.pch = NULL,
 fj.col = NULL, fj.pch = NULL, col.offset = NULL,
 constraints = NULL, lv.constraints = NULL,
 xlab = NULL, ylab = NULL, main = NULL,
 lvPlots = TRUE, lvAgainst = TRUE,
 contributionPlots = TRUE, correlationPlotter = TRUE,
 showHulls = 1, biplots = FALSE, graphs = TRUE)
```

Arguments

res	results from TExPosition
x_axis	which component should be on the x axis?
y_axis	which component should be on the y axis?
tepPlotInfo	A list ($Plotting.Data) from tepGraphs or TExPosition.
DESIGN	A design matrix to apply colors (by pallete selection) to row items
fi.col	A matrix of colors for the group items. If NULL, colors will be selected.
fi.pch	A matrix of pch values for the group items. If NULL, pch values are all 21.
fii.col	A matrix of colors for the row items (observations). If NULL, colors will be selected.
fii.pch	A matrix of pch values for the row items (observations). If NULL, pch values are all 21.
fj.col	A matrix of colors for the column items. If NULL, colors will be selected.
fj.pch	A matrix of pch values for the column items. If NULL, pch values are all 21.

col.offset — A numeric offset value. Is passed to createColorVectorsByDesign.

constraints — Plot constraints as returned from prettyPlot. If NULL, constraints are selected.

lv.constraints — Plot constraints for latent variables. If NULL, constraints are selected.

xlab — x axis label

ylab — y axis label

main — main label for the graph window

lvPlots — a boolean. If TRUE, latent variables (X, Y) are plotted. If FALSE, latent variables are not plotted.

lvAgainst — a boolean. If TRUE, latent variables (X, Y) are plotted against each other. If FALSE, latent variables are plotted like factor scores.

contributionPlots — a boolean. If TRUE (default), contribution bar plots will be created.

correlationPlotter — a boolean. If TRUE (default), a correlation circle plot will be created. Applies to PCA family of methods (CA is excluded for now).

showHulls — a value between 0 and 1 to make a peeled hull at that percentage. All values outside of 0-1 will not plot any hulls.

biplots — a boolean. If FALSE (default), separate plots are made for row items ($fii and $fi) and column items ($fj). If TRUE, row ($fii and $fi) and column ($fj) items will be on the same plot.

graphs — a boolean. If TRUE, graphs are created. If FALSE, only data associated to plotting (e.g., constraints, colors) are returned.

Details

tepGraphs is an interface between TExPosition and prettyGraphs.

Value

The following items are bundled inside of $Plotting.Data:

$fii.col — the colors that are associated to the individuals (row items; $fii).

$fii.pch — the pch values associated to the individuals (row items; $fii).

$fi.col — the colors that are associated to the groups ($fi).

$fi.pch — the pch values associated to the groups ($fi).

$fj.col — the colors that are associated to the column items ($fj).

$fj.pch — the pch values associated to the column items ($fj).

$constraints — axis constraints for the plots (determines end points of the plots).

Author(s)

Derek Beaton

See Also

prettyGraphs

Examples

```
#this is for TExPosition's iris data
data(ep.iris)
bada.iris <- tepBADA(ep.iris$data,DESIGN=ep.iris$design,make_design_nominal=FALSE)
#there are only 2 components, not 3.
bada.iris.plotting.data.biplot <- tepGraphs(bada.iris,x_axis=1,y_axis=2,biplots=TRUE)
```

---

tepPLS *Partial Least Squares*

Description

Partial Least Squares (PLS) via TExPosition.

Usage

```
tepPLS(DATA1, DATA2,
center1 = TRUE, scale1 = "SS1", center2 = TRUE, scale2 = "SS1",
DESIGN = NULL, make_design_nominal = TRUE,
graphs = TRUE, k = 0)
```

Arguments

DATA1	Data matrix 1 (X)
DATA2	Data matrix 2 (Y)
center1	a boolean, vector, or string to center DATA1. See expo.scale for details.
scale1	a boolean, vector, or string to scale DATA1. See expo.scale for details.
center2	a boolean, vector, or string to center DATA2. See expo.scale for details.
scale2	a boolean, vector, or string to scale DATA2. See expo.scale for details.
DESIGN	a design matrix to indicate if rows belong to groups.
make_design_nominal	a boolean. If TRUE (default), DESIGN is a vector that indicates groups (and will be dummy-coded). If FALSE, DESIGN is a dummy-coded matrix.
graphs	a boolean. If TRUE (default), graphs and plots are provided (via tepGraphs)
k	number of components to return.

Details

This implementation of Partial Least Squares is a symmetric analysis. It was first described by Tucker (1958), again by Bookstein (1994), and has gained notoriety in Neuroimaging from McIntosh et al., (1996).

Value

See epGPCA (and also corePCA) for details on what is returned. In addition to the values returned:

`lx`	latent variables from DATA1 computed for observations
`ly`	latent variables from DATA2 computed for observations
`data1.norm`	center and scale information for DATA1
`data1.norm`	center and scale information for DATA2

Author(s)

Derek Beaton

References

Tucker, L. R. (1958). An inter-battery method of factor analysis. *Psychometrika*, *23*(2), 111–136.
Bookstein, F., (1994). Partial least squares: a dose–response model for measurement in the behavioral and brain sciences. *Psycoloquy 5* (23)
McIntosh, A. R., Bookstein, F. L., Haxby, J. V., & Grady, C. L. (1996). Spatial Pattern Analysis of Functional Brain Images Using Partial Least Squares. *NeuroImage*, *3*(3), 143–157.

Krishnan, A., Williams, L. J., McIntosh, A. R., & Abdi, H. (2011). Partial Least Squares (PLS) methods for neuroimaging: A tutorial and review. *NeuroImage*, *56*(**2**), 455 – 475.
McIntosh, A. R., & Lobaugh, N. J. (2004). Partial least squares analysis of neuroimaging data: applications and advances. *Neuroimage*, *23*, S250–S263.

See Also

corePCA, epPCA, epGPCA, tepBADA, tepGPLS, tepPLSCA

Examples

```
data(beer.tasting.notes)
data1<-beer.tasting.notes$data[,1:8]
data2<-beer.tasting.notes$data[,9:16]
pls.res <- tepPLS(data1,data2)
```

---

tepPLSCA *Partial Least Squares-Correspondence Analysis*

Description

Partial Least Squares-Correspondence Analysis (PLSCA) via TExPosition.

Usage

```
tepPLSCA(DATA1, DATA2, make_data1_nominal = FALSE, make_data2_nominal = FALSE,
DESIGN = NULL, make_design_nominal = TRUE,
weights1=NULL, weights2 = NULL,
symmetric = TRUE, graphs = TRUE, k = 0)
```

Arguments

DATA1	Data matrix 1 (X), must be categorical (like MCA) or in disjunctive code see make_data1_nominal.
DATA2	Data matrix 2 (Y), must be categorical (like MCA) or in disjunctive code see make_data2_nominal.
make_data1_nominal	a boolean. If TRUE (default), DATA1 is recoded as a dummy-coded matrix. If FALSE, DATA1 is a dummy-coded matrix.
make_data2_nominal	a boolean. If TRUE (default), DATA2 is recoded as a dummy-coded matrix. If FALSE, DATA2 is a dummy-coded matrix.
DESIGN	a design matrix to indicate if rows belong to groups.
make_design_nominal	a boolean. If TRUE (default), DESIGN is a vector that indicates groups (and will be dummy-coded). If FALSE, DESIGN is a dummy-coded matrix.
weights1	a diagonal matrix or column-vector of weights for the columns of DATA1
weights2	a diagonal matrix or column-vector of weights for the columns of DATA2
symmetric	a boolean. If TRUE (default) symmetric factor scores for rows.
graphs	a boolean. If TRUE (default), graphs and plots are provided (via tepGraphs)
k	number of components to return.

Details

This implementation of Partial Least Squares is for two categorical data sets (Beaton et al., 2013), and based on the PLS method proposed by Tucker (1958) and again by Bookstein (1994).

Value

See epCA (and also coreCA) for details on what is returned. In addition to the values returned:

W1	Weights for columns of DATA1, replaces M from coreCA.
W2	Weights for columns of DATA2, replaces W from coreCA.
lx	latent variables from DATA1 computed for observations
ly	latent variables from DATA2 computed for observations

Author(s)

Derek Beaton, Hervé Abdi

References

Tucker, L. R. (1958). An inter-battery method of factor analysis. *Psychometrika*, *23*(2), 111–136.
Bookstein, F., (1994). Partial least squares: a dose–response model for measurement in the behavioral and brain sciences. *Psycoloquy 5* (23)
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Krishnan, A., Williams, L. J., McIntosh, A. R., & Abdi, H. (2011). Partial Least Squares (PLS) methods for neuroimaging: A tutorial and review. *NeuroImage*, *56*(**2**), 455 – 475.
Beaton, D., Filbey, F., & Abdi H. (in press, 2013). Integrating partial least squares correlation and correspondence analysis for nominal data. In Abdi, H., Chin, W., Esposito Vinzi, V., Russolillo, G., & Trinchera, L. (Eds.), New Perspectives in Partial Least Squares and Related Methods. New York: Springer Verlag.

See Also

coreCA, epCA, epMCA, tepDICA

Examples

```
data(snps.druguse)
plsca.res <- tepPLSCA(snps.druguse$DATA1,snps.druguse$DATA2,
  make_data1_nominal=TRUE,make_data2_nominal=TRUE)
```

---

texpoDesignCheck *texpoDesignCheck*

Description

TExPosition's DESIGN matrix check function. Calls into ExPosition's designCheck.

Usage

```
texpoDesignCheck(DATA = NULL, DESIGN = NULL, make_design_nominal = TRUE, force_bary=FALSE)
```

Arguments

DATA	original data that should be matched to a design matrix
DESIGN	a column vector with levels for observations or a dummy-coded matrix
make_design_nominal	a boolean. Will make DESIGN nominal if TRUE (default).
force_bary	a boolean. If TRUE, it forces the check for barycentric methods (tepDICA, tepBADA). If FALSE, designCheck is performed.

Details

For BADA & DICA, execution stops if:
1. DESIGN has more columns (groups) than observations, 2. DESIGN has only 1 column (group), or 3. DESIGN has at least 1 occurence where an observation is the only observation in a group (i.e., colSums(DESIGN)==1 at least once).

Value

`DESIGN`	dummy-coded design matrix

Author(s)

Derek Beaton

Index