

# Package ‘idm’

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**Title** Incremental Decomposition Methods

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**SystemRequirements** ImageMagick (<http://imagemagick.org>) or GraphicsMagick (<http://www.graphicsmagick.org>)

**Description** Incremental Multiple Correspondence Analysis and Principal Component Analysis.

**License** GPL (>= 2)

**RoxygenNote** 5.0.1

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 idm-package

*Incremental Decomposition Methods*


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### Description

Incremental Multiple Correspondence Analysis and Principal Component Analysis

### Details

Package: idm  
 Type: Package  
 Version: 1.3.1  
 Date: 2016-03-10  
 License: GPL (>=2)

### Author(s)

Alfonso Iodice D'Enza [aut], Angelos Markos [aut, cre], Davide Buttarazzi [ctb]

### References

Hall, P., Marshall, D., & Martin, R. (2002). Adding and subtracting eigenspaces with eigenvalue decomposition and singular value decomposition. *Image and Vision Computing*, 20(13), 1009-1016.

Ross, D. A., Lim, J., Lin, R. S., & Yang, M. H. (2008). Incremental learning for robust visual tracking. *International Journal of Computer Vision*, 77(1-3), 125-141.

Iodice D'Enza, A., & Markos, A. (2015). Low-dimensional tracking of association structures in categorical data, *Statistics and Computing*, 25(5), 1009-1022.

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 add\_es

*Adds two eigenspaces using incremental SVD (with or without mean update)*


---

### Description

This function implements two procedures for updating existing decomposition. When `method="esm"` it adds two eigenspaces using the incremental method of Hall, Marshall & Martin (2002). The results correspond to the eigenspace of the mean-centered and concatenated data. When `method="isvd"` it adds the eigenspace of an incoming data block to an existing eigenspace using the incremental singular value decomposition (SVD) method described by Zha & Simon (1999), Levy and Lindenbaum (2000), Brand (2002) and Baker (2012). New data blocks are added row-wise. The procedure

can optionally keep track of the data mean using the `orgn` argument, as described in Ross et al. (2008) and Iodice D'Enza & Markos (2015).

### Usage

```
add_es(eg, eg2, current_rank, orgn, ff = 0, method=c("esm", "isvd"))
```

### Arguments

<code>eg</code>	A list describing the eigenspace of a data matrix, with components <code>u</code> Left eigenvectors <code>v</code> Right eigenvectors <code>m</code> Number of cases <code>d</code> Eigenvalues <code>orgn</code> Data mean
<code>method</code>	refers to the procedure being implemented: "esm" refers to the eigenspace merge (Hall et al., 2002); "isvd" refers to the incremental SVD method, with or without keeping track of the data mean.
<code>eg2</code>	(*)A list describing the eigenspace of a data matrix, with components <code>u</code> Left eigenvectors <code>v</code> Right eigenvectors <code>m</code> Number of cases <code>d</code> Eigenvalues <code>orgn</code> Data mean
<code>current_rank</code>	(**)Rank of approximation; if empty then rank = 2
<code>orgn</code>	Data mean
<code>ff</code>	(**)Number between 0 and 1 indicating the forgetting factor used to down-weight the contribution of earlier data blocks to the current solution. When <code>ff = 0</code> (default) no forgetting occurs (*) for <code>method="esm"</code> only; (**) for <code>method="isvd"</code> only.

### Value

A list describing the SVD of a data matrix, with components

<code>u</code>	Left singular vectors
<code>d</code>	Singular values
<code>v</code>	Right singular vectors
<code>m</code>	Number of cases
<code>orgn</code>	Data mean; returned only if 'orgn' is given as input

## References

- Zha, H., & Simon, H. D. (1999). On updating problems in latent semantic indexing. *SIAM Journal on Scientific Computing*, 21(2), 782-791.
- Levy, A., & Lindenbaum, M. (2000). Sequential Karhunen-Loeve basis extraction and its application to images. *IEEE Transactions on Image Processing*, 9(8), 1371-1374.
- Brand, M. (2002). Incremental singular value decomposition of uncertain data with missing values. In *Computer Vision-ECCV 2002* (pp. 707-720). Springer Berlin Heidelberg.
- Ross, D. A., Lim, J., Lin, R. S., & Yang, M. H. (2008). Incremental learning for robust visual tracking. *International Journal of Computer Vision*, 77(1-3), 125-141.
- Baker, C. G., Gallivan, K. A., & Van Dooren, P. (2012). Low-rank incremental methods for computing dominant singular subspaces. *Linear Algebra and its Applications*, 436(8), 2866-2888.
- Iodice D'Enza, A., & Markos, A. (2015). Low-dimensional tracking of association structures in categorical data, *Statistics and Computing*, 25(5), 1009-1022.

## See Also

[do\\_es](#), [i\\_pca](#), [i\\_mca](#), [update.i\\_pca](#), [update.i\\_mca](#)

## Examples

```
## Example 1 - eigenspace merge (Hall et al., 2002)
#Iris species
data("iris", package = "datasets")
X = iris[,-5]
#obtain two eigenspaces
eg = do_es(X[1:50,])
eg2 = do_es(X[c(51:150),])
#add the two eigenspaces keeping track of the data mean
eg12 = add_es(method = "esm", eg, eg2)
#similar to PCA on the covariance matrix of X (SVD of the mean-centered data)

## Example 2 - incremental SVD with mean update, full rank (Ross et al., 2008)
data("iris", package = "datasets")
# obtain the eigenspace of the first 50 Iris species
X = iris[,-5]
eg = do_es(X[1:50,])
#update the eigenspace of the remaining species to
eg_new = add_es(method = "isvd",eg,data.matrix(X[c(51:150),]),orgn = eg$orgn)
#similar to PCA on the covariance matrix of X (SVD of the mean-centered data)

##Example 3 - incremental SVD with mean update, 2d approximation (Ross et al., 2008)
data("iris", package = "datasets")
# obtain the eigenspace of the first 50 Iris species
X = iris[,-5]
```

```
eg = do_es(X[1:50,])
#update the eigenspace of the remaining species to
eg = add_es(method = "isvd",eg,data.matrix(X[c(51:150),]),orgn = eg$orgn)
#similar to PCA on the covariance matrix of X (SVD of the mean-centered data)

##Example 4 - incremental SVD, full rank (Ross et al., 2008)
data("iris", package = "datasets")
#obtain the SVD of the first 50 Iris species
X = iris[,-5]
eg = svd(X[1:50,])
#update the eigenspace of the remaining species to
eg = add_es(method = "isvd",eg,data.matrix(X[c(51:150),]))
#similar results to svd(X)
```

---

do\_es

*Computes the eigenspace of a data matrix*

---

## Description

This function computes the eigenspace of a mean-centered data matrix

## Usage

```
do_es(data)
```

## Arguments

data            a matrix or data frame

## Value

A list describing the eigenspace of a data matrix, with components

u	Left eigenvectors
v	Right eigenvectors
m	Number of cases
d	Eigenvalues
orgn	Data mean
smfq	...

## See Also

[add\\_es](#), [update.i\\_pca](#), [i\\_pca](#)

**Examples**

```
#Iris species
data("iris", package = "datasets")
eg = do_es(iris[,-5])
#corresponds to the SVD of the centered data matrix
```

i\_mca

*Incremental Multiple Correspondence Analysis (MCA)***Description**

This function computes the Multiple Correspondence Analysis (MCA) solution on the indicator matrix using two incremental methods described in Iodice D'Enza & Markos (2015)

**Usage**

```
i_mca(data1, data2, method=c("exact","live"), nchunk = 2, current_rank, ff = 0,
disk=FALSE)
```

**Arguments**

data1	Matrix or data frame of starting data or full data if data2 = NULL
data2	Matrix or data frame of incoming data
method	String specifying the type of implementation: "exact" or "live". "exact" refers to the case when all the data is available from the start and dimension reduction is based on the method of Hall et al. (2002). "live" refers to the case when new data comes in as data flows and dimension reduction is based on the method of Ross et al. (2008). The main difference between the two approaches lies in the calculation of the column margins of the input matrix. For the "exact" approach, the analysis is based on the "global" margins, that is, the margins of the whole indicator matrix, which is available in advance. For the "live" approach, the whole matrix is unknown and the global margins are approximated by the "local" margins, that is, the average margins of the data analysed insofar. A detailed description of the two implementations is provided in Iodice D'Enza & Markos (2015).
nchunk	Number of incoming data chunks (equal splits of 'data2') or a Vector with the row size of each incoming data chunk
current_rank	Rank of approximation; if empty then full rank is used
ff	Number between 0 and 1 indicating the "forgetting factor" used to down-weight the contribution of earlier data blocks to the current solution. When ff = 0 (default) no forgetting occurs; applicable only when method = "live"
disk	Logical indicating whether then output is saved to hard disk

**Value**

rowpcoord	Row principal coordinates
colpcoord	Column principal coordinates
rowcoord	Row standard coordinates
colcoord	Column standard coordinates
levelnames	Column labels
colctr	Column contributions
colcor	Column squared correlations
rowctr	Row contributions
rowcor	Row squared correlations
sv	Singular values
rowmass	Row masses
colmass	Column masses
inertia_e	Percentages of explained (adjusted) inertia
nchunk	Number of incoming data chunks
disk	Logical indicating whether then output is saved to hard disk
allrowcoords	A list containing the row scores on the principal components produced after each data chunk is analyzed; applicable only when disk = FALSE
ff	Number between 0 and 1 indicating the "forgetting factor" used to down-weight the contribution of earlier data blocks to the current solution; applicable only when method = "live"
allcolcoords	A list containing the variable loadings on the principal components produced after each data chunk is analyzed; applicable only when disk = FALSE
allcolctr	A list containing the column contributions after each data chunk is analyzed; applicable only when disk = FALSE
allcolcor	A list containing the column squared correlations produced after each data chunk is analyzed; applicable only when disk = FALSE
allrowctr	A list containing the row contributions after each data chunk is analyzed; applicable only when disk = FALSE
allrowcor	A list containing the row squared correlations produced after each data chunk is analyzed; applicable only when disk = FALSE

**References**

- Hall, P., Marshall, D., & Martin, R. (2002). Adding and subtracting eigenspaces with eigenvalue decomposition and singular value decomposition. *Image and Vision Computing*, 20(13), 1009-1016.
- Ross, D. A., Lim, J., Lin, R. S., & Yang, M. H. (2008). Incremental learning for robust visual tracking. *International Journal of Computer Vision*, 77(1-3), 125-141.
- Iodice D'Enza, A., & Markos, A. (2015). Low-dimensional tracking of association structures in categorical data, *Statistics and Computing*, 25(5), 1009-1022.

**See Also**

[update.i\\_mca](#), [i\\_pca](#), [update.i\\_pca](#), [add\\_es](#)

**Examples**

```
##Example 1 - Exact case
data("women", package = "idm")
nc = 5 # number of chunks
res_iMCAh = i_mca(data1 = women[1:300,1:7], data2 = women[301:2107,1:7]
,method = "exact", nchunk = nc)
#static MCA plot of attributes on axes 2 and 3
plot(x = res_iMCAh, dim = c(2,3), what = c(FALSE,TRUE), animation = FALSE)

#\donttest is used here because the code calls the saveGIF function of the animation package
#which requires ImageMagick or GraphicsMagick to be installed in your system
#See help(im.convert) for details on the configuration of ImageMagick or GraphicsMagick.
#Creates animated GIF movies for objects and variables
plot(res_iMCAh, animation = TRUE, frames = 10)

##Example 2 - Live case
data("tweet", package = "idm")
nc = 5
#provide attributes with custom labels
labels = c("HLTN", "ICN", "MRT", "BWN", "SWD", "HYT", "CH", "-", "-/+", "+", "++", "Low", "Med", "High")
#mimics the 'live' MCA implementation
res_iMCA1 = i_mca(data1 = tweet[1:100,], data2 = tweet[101:1000,],
method="live", nchunk = nc, current_rank=2)

#\donttest is used here because the code calls the saveGIF function of the animation package
#which requires ImageMagick or GraphicsMagick to be installed in your system
#See help(im.convert) for details on the configuration of ImageMagick or GraphicsMagick.
#Creates animated GIF movies for objects and variables
plot(res_iMCA1, labels = labels, animation = TRUE, frames = 10)
```

---

i\_pca

---

*Incremental Principal Component Analysis (PCA)*


---

**Description**

This function computes the Principal Component Analysis (PCA) solution on the covariance matrix using the incremental method of Hall, Marshall & Martin (2002).

**Usage**

```
i_pca(data1, data2, nchunk = 2, disk = FALSE)
```



**Arguments**

data1	Matrix or data frame of starting data, or full data if data2 = NULL
data2	Matrix or data frame of incoming data; omitted when full data is given in data1
nchunk	Number of incoming data chunks (equal splits of 'data2') or a Vector with the row size of each incoming data chunk
disk	Logical indicating whether then output is saved to hard disk

**Value**

rowcoord	Row scores on the principal components
colpcoord	Variable loadings
eg	A list describing the eigenspace of a data matrix, with components u Left eigenvectors v Right eigenvectors m Number of cases d Eigenvalues or gn Data mean
inertia_e	Percentage of explained variance
sv	Singular values
levelnames	Column labels
rowctr	Row contributions
colctr	Column contributions
rowcor	Row squared correlations
colcor	Column squared correlations
nchunk	Number of incoming data chunks
disk	Logical indicating whether the output is saved to hard disk
allrowcoords	A list containing the row scores on the principal components produced after each data chunk is analyzed; applicable only when disk = FALSE
allcolcoords	A list containing the variable loadings on the principal components produced after each data chunk is analyzed; applicable only when disk = FALSE
allrowctr	A list containing the row contributions after each data chunk is analyzed; applicable only when disk = FALSE
allrowcor	A list containing the row squared correlations produced after each data chunk is analyzed; applicable only when disk = FALSE

**References**

Hall, P., Marshall, D., & Martin, R. (2002). Adding and subtracting eigenspaces with eigenvalue decomposition and singular value decomposition. *Image and Vision Computing*, 20(13), 1009-1016.

Iodice D'Enza, A., & Markos, A. (2015). Low-dimensional tracking of association structures in categorical data, *Statistics and Computing*, 25(5), 1009-1022.

**See Also**

[update.i\\_pca](#), [i\\_mca](#), [update.i\\_mca](#), [add\\_es](#)

**Examples**

```
#Iris Species
data("iris", package = "datasets")
X = scale(iris[, -5])
res_iPCA = i_pca(data1 = X[1:50,], data2 = X[51:150,], nchunk = 2)
#static plot
plot(res_iPCA, animation = FALSE)

#\donttest is used here because the code calls the saveGIF function of the animation package
#which requires ImageMagick or GraphicsMagick to be installed in your system
#See help(im.convert) for details on the configuration of ImageMagick or GraphicsMagick.
#Creates animated GIF movies for objects and variables
plot(res_iPCA, animation = TRUE, frames = 10)

#Daily Closing Prices of Major European Stock Indices, 1991-1998
data("EuStockMarkets", package = "datasets")
res_iPCA = i_pca(data1 = EuStockMarkets[1:50,], data2 = EuStockMarkets[51:1860,], nchunk = 5)

#\donttest is used here because the code calls the saveGIF function of the animation package
#which requires ImageMagick or GraphicsMagick to be installed in your system
#See help(im.convert) for details on the configuration of ImageMagick or GraphicsMagick.
#Creates animated GIF movies for objects and variables
plot(res_iPCA, animation = TRUE, frames = 10)
```

---

plot.i\_mca

*Plotting 2D maps in Multiple Correspondence Analysis*

---

**Description**

Graphical display of Multiple Correspondence Analysis results in two dimensions

**Usage**

```
## S3 method for class 'i_mca'
plot(x, dims=c(1,2), what=c(TRUE,TRUE),
     contrib="none", dataname=NULL, labels=NULL, animation=TRUE, frames=10,
     zoom=TRUE,...)
```

**Arguments**

x Multiple correspondence analysis object returned by [i\\_mca](#)

dims	Numerical vector of length 2 indicating the dimensions to plot on horizontal and vertical axes respectively; default is first dimension horizontal and second dimension vertical
what	Vector of two logicals specifying the contents of the plot(s). First entry indicates if the rows (objects) are displayed and the second entry if the columns (attributes) are displayed
contrib	Vector of two character strings specifying if attribute contributions should be represented by different label size. Available options are "none" (contributions are not indicated in the plot) "cor" (relative contributions are indicated by label size) "ctr" (absolute contributions are indicated by label size) The higher the contribution of a point, the larger its label size. Default is "none"
dataname	String prefix used for custom naming of output files; default is the name of the output object
labels	String vector of variable labels
animation	Logical indicating whether animated GIF files are created and saved to the hard drive or a static plot is obtained
frames	Number of animation frames shown per iteration; applicable only when animation = TRUE
zoom	Logical indicating whether axis limits change during the animation creating a zooming effect; applicable only when animation = TRUE
...	Further arguments passed to <code>plot</code> and <code>points</code>

### Details

The function `plot.i_mca` makes a two-dimensional map of the object created by `i_mca` with respect to two selected dimensions. In this map both the row and column points are scaled to have inertias (weighted variances) equal to the principal inertia (eigenvalue or squared singular value) along the principal axes, that is both rows and columns are in principal coordinates.

### References

Greenacre, M.J. (1993) *Correspondence Analysis in Practice*. London: Academic Press.  
Greenacre, M.J. (1993) Biplots in Correspondence Analysis, *Journal of Applied Statistics*, 20, 251 - 269.  
ImageMagick: <http://www.imagemagick.org>; GraphicsMagick: <http://www.graphicsmagick.org>

### See Also

[plot.i\\_pca](#)

### Examples

```
data("women", package="idm")
nc = 4 # number of chunks
### Different approaches to incremental MCA:
```

```
# Live case
res_iMCA1 = i_mca(data1 = women[1:50,1:4],data2 = women[51:300,1:4],method = "live",nchunk = nc)
#static plot, final solution
plot(res_iMCA1, contrib="ctr", animation = FALSE)

#\donttest is used here because the code calls the saveGIF function of the animation package
#which requires ImageMagick or GraphicsMagick to be installed in your system
#See help(im.convert) for details on the configuration of ImageMagick or GraphicsMagick.
#Creates animated GIF movies for objects and variables
plot(res_iMCA1, contrib = "ctr", animation = TRUE, frames = 10)
```

---

plot.i\_pca

*Plotting 2D maps in Principal Component Analysis*


---

### Description

Graphical display of Principal Component Analysis results in two dimensions

### Usage

```
## S3 method for class 'i_pca'
plot(x, dims = c(1,2), what = c(TRUE,TRUE),
      dataname = NULL, labels = NULL, animation = TRUE, frames = 10, zoom = TRUE, ...)
```

### Arguments

x	Principal component analysis object returned by <a href="#">i_pca</a>
dims	Numerical vector of length 2 indicating the dimensions to plot on horizontal and vertical axes respectively; default is first dimension horizontal and second dimension vertical
what	Vector of two logicals specifying the contents of the plot(s). First entry indicates if the rows (objects) are displayed and the second entry if the columns (attributes) are displayed
dataname	String prefix used for custom naming of output files; default is the name of the output object
labels	String vector of variable labels
animation	Logical indicating whether animated GIF files are created and saved to the hard drive or a static plot is obtained
frames	Number of animation frames shown per iteration; applicable only when animation = TRUE
zoom	Logical indicating whether axis limits change during the animation creating a zooming effect; applicable only when animation = TRUE
...	Further arguments passed to <a href="#">plot</a> and <a href="#">points</a>

## Details

The function `plot.i_pca` makes a two-dimensional map of the object created by `i_pca` with respect to two selected dimensions.

## References

ImageMagick: <http://www.imagemagick.org>; GraphicsMagick: <http://www.graphicsmagick.org>

## See Also

[plot.i\\_mca](#)

## Examples

```
data("iris", package = "datasets")
#Iris species
X = scale(iris[, -5])
res_iPCA = i_pca(data1 = X[1:50, -5], data2 = X[51:150, -5], nchunk = c(50, 50))
#static plot, final solution
plot(res_iPCA, animation = FALSE)

##\donttest is used here because the code calls the saveGIF function of the animation package
##which requires ImageMagick or GraphicsMagick to be installed in your system
##See help(im.convert) for details on the configuration of ImageMagick or GraphicsMagick.
##Creates animated GIF movies for objects and variables
plot(res_iPCA, animation = TRUE, frames = 10)
```

---

tweet

*twitter data set*

---

## Description

The data set refers to a small corpus of messages or tweets mentioning seven major hotel brands. It was gathered by continuously querying and archiving the Twitter Streaming API service, using the `twitter` package in R. A total of 7,296 tweets were extracted within a time period of 6 days, from June 23th to June 28th 2013. Only tweets in the English language were considered. A sentiment polarity variable was calculated, indicating the sentiment value of each message and a third variable, user visibility or popularity, as measured by the number of followers each user had, was also included in the dataset

## Usage

```
data("tweet")
```

**Format**

A data frame with the following variables:

Brand The hotel brand mentioned in the tweet: 1=Hilton, 2=Intercontinental, 3=Marriott, 4=Bestwestern, 5=Starwood, 6=Hyatt, 7=Choice

Sentiment Sentiment for each tweet: 1=negative (-), 2=mixed (+/-), 3=positive (+), 4=very positive (++)

UserVis User popularity/visibility in Twitter: 1=low, 2=medium, 3=high

**References**

Iodice D' Enza, A., & Markos, A. (2015). Low-dimensional tracking of association structures in categorical data, *Statistics and Computing*, 25(5), 1009-1022.

**Examples**

```
data(tweet)
```

---

```
update.i_mca
```

*Updates a Multiple Correspondence Analysis solution*

---

**Description**

This function updates the Multiple Correspondence Analysis (MCA) solution on the indicator matrix using the incremental method of Ross et al. (2008)

**Usage**

```
## S3 method for class 'i_mca'
update(object, incdata, current_rank, ff = 0, nchunk = 1, ...)
```

**Arguments**

object	object of class 'i_mca'
incdata	Matrix of incoming data
current_rank	Rank of approximation; if empty then full rank is used
ff	Number between 0 and 1 indicating the "forgetting factor"
nchunk	Number of blocks processed up to that point; default is 1
...	Further arguments passed to <a href="#">update</a>

**Value**

indmat	Indicator matrix
colcoord	Column standard coordinates
rowcoord	Row standard coordinates
colpcoord	Column principal coordinates
rowpcoord	Row principal coordinates
colctr	Column contributions
colcor	Column squared correlations
rowctr	Row contributions
rowcor	Row squared correlations
sv	Singular values
rowmass	Row masses
colmass	Column masses
levelnames	Attribute names
m	Number of cases processed up to this point
inertia_e	Percentages of explained (adjusted) inertia

**References**

Ross, D. A., Lim, J., Lin, R. S., & Yang, M. H. (2008). Incremental learning for robust visual tracking. *International Journal of Computer Vision*, 77(1-3), 125-141.

Iodice D'Enza, A., & Markos, A. (2015). Low-dimensional tracking of association structures in categorical data, *Statistics and Computing*, 25(5), 1009-1022.

**See Also**

[add\\_es](#), [i\\_mca](#), [plot.i\\_mca](#)

**Examples**

```
data(women, package = "idm")
dat = women[,c(1:4)]
res_mca = i_mca(dat[1:300,])
nchunk = seq(301,2107,258)
for (k in c(1:(length(nchunk)-1)))
{
  res_mca = update(res_mca, dat[c((nchunk[k]+1):nchunk[k+1]),], nchunk=k+1)
}
plot(res_mca, what=c(FALSE, TRUE), animation = FALSE)
```

---

update.i_pca	<i>Updates a Principal Component Analysis solution</i>
--------------	--

---

### Description

This function updates the Principal Component Analysis (PCA) solution on the covariance matrix using the incremental method of Hall, Marshall & Martin (2002)

### Usage

```
## S3 method for class 'i_pca'
update(object, incdata, ...)
```

### Arguments

object	object of class 'i_pca'
incdata	matrix of incoming data
...	Further arguments passed to <a href="#">update</a>

### Value

rowpcoord	Row scores on the principal components
colpcoord	Variable loadings
eg	A list describing the eigenspace of a data matrix, with components u Left eigenvectors v Right eigenvectors m Number of cases d Eigenvalues orgn Data mean
inertia_e	Percentages of explained variance
sv	Singular values
levelnames	Column names
rowctr	Row contributions
rowcor	Row squared correlations
colctr	Column contributions
colcor	Column squared correlations

### References

Hall, P., Marshall, D., & Martin, R. (2002). Adding and subtracting eigenspaces with eigenvalue decomposition and singular value decomposition. *Image and Vision Computing*, 20(13), 1009-1016.

Iodice D'Enza, A., & Markos, A. (2015). Low-dimensional tracking of association structures in categorical data, *Statistics and Computing*, 25(5), 1009-1022.



**See Also**

[update.i\\_mca, i\\_pca, i\\_mca, add\\_es](#)

**Examples**

```
data(iris, package="datasets")
dat = scale(iris[, -5])
res_pca = i_pca(dat[1:50, -5])
aa = seq(50, 150, 50)
for (k in c(1:2)) {
  res_pca = update(res_pca, dat[c((aa[k]+1):aa[k+1]),])
}
plot(res_pca, animation = FALSE)
```

---

women

*women data set*

---

**Description**

The data are from the third Family and Changing Gender Roles survey conducted in 2002. The questions retained are those related to working women in Spain and the effect on the family. A total of 2,107 respondents answered eight questions on a 5-point Likert scale, as well as four demographic variables (gender, marital status, education and age). There are no cases with missing data.

**Usage**

```
data("women")
```

**Format**

A data frame with the following variables:

- A "a working mother can establish a warm relationship with her child"  
1=strongly agree, 2=agree, 3=neither agree or disagree, 4=disagree, 5=strongly disagree
- B "a pre-school child suffers if his or her mother works"  
1=strongly agree, 2=agree, 3=neither agree or disagree, 4=disagree, 5=strongly disagree
- C "when a woman works the family life suffers"  
1=strongly agree, 2=agree, 3=neither agree or disagree, 4=disagree, 5=strongly disagree
- D "what women really want is a home and kids"  
1=strongly agree, 2=agree, 3=neither agree or disagree, 4=disagree, 5=strongly agree

- E "running a household is just as satisfying as a paid job"  
1=strongly agree, 2=agree, 3=neither agree or disagree, 4=disagree, 5=strongly disagree
- F "work is best for a woman's independence"  
1=strongly agree, 2=agree, 3=neither agree or disagree, 4=disagree, 5=strongly disagree
- G "a man's job is to work; a woman's job is the household"  
1=strongly agree, 2=agree, 3=neither agree or disagree, 4=disagree, 5=strongly disagree
- H "working women should get paid maternity leave"  
1=strongly agree, 2=agree, 3=neither agree or disagree, 4=disagree, 5=strongly disagree
- g gender: 1=male, 2=female
- m marital status: 1=married/living as married, 2=widowed, 3=divorced, 4=separated, but married, 5=single, never married
- e education: 1=no formal education, 2=lowest education, 3=above lowest education, 4=highest secondary completed, 5=above higher secondary level, below full university, 6=university degree completed
- a age: 1=16-25 years, 2=26-35, 3=36-45, 4=46-55, 5=56-65, 6=66 and older

### Source

[http://www.econ.upf.edu/~michael/women\\_Spain2002\\_original.xls](http://www.econ.upf.edu/~michael/women_Spain2002_original.xls)

### References

Greenacre, M. J. (2010). *Biplots in practice*. Fundacion BBVA.

### Examples

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