

# Package ‘whitening’

March 6, 2018

**Version** 1.0.0

**Date** 2018-03-05

**Title** Whitening and High-Dimensional Canonical Correlation Analysis

**Author** Korbinian Strimmer, Takoua Jendoubi, Agnan Kessy, Alex Lewin

**Maintainer** Korbinian Strimmer <strimmerlab@gmail.com>

**Depends** R (>= 3.0.2), corpcor (>= 1.6.9)

**Imports** stats

## Suggests

**Description** Implements the whitening methods (ZCA, PCA, Cholesky, ZCA-cor, and PCA-cor) discussed in Kessy, Lewin, and Strimmer (2018) “Optimal whitening and decorrelation”, *The American Statistician*, <doi:10.1080/00031305.2016.1277159>, as well as the whitening approach to Canonical Correlation Analysis allowing negative canonical correlations described in Jendoubi and Strimmer (2018) “Probabilistic canonical correlation analysis: a whitening approach”, <arXiv:1802.03490>.

**License** GPL (>= 3)

**URL** <http://strimmerlab.org/software/whitening/>

**NeedsCompilation** no

**Repository** CRAN

**Date/Publication** 2018-03-06 18:51:10 UTC

## R topics documented:

whitening-package	2
scca	2
whiteningMatrix	5

<b>Index</b>	<b>7</b>
--------------	----------

---

whitening-package      *The whitening Package*

---

### Description

The "whitening" package implements the whitening methods (ZCA, PCA, Cholesky, ZCA-cor, and PCA-cor) discussed in Kessy, Lewin, and Strimmer (2018) as well as the whitening approach to Canonical Correlation Analysis allowing negative canonical correlations described in Jendoubi and Strimmer (2018).

### Author(s)

Korbinian Strimmer (<http://strimmerlab.org/>) with Takoua Jendoubi, Agnan Kessy, and Alex Lewin.

### References

Kessy, A., A. Lewin, and K. Strimmer. 2018. Optimal whitening and decorrelation. *The American Statistician*. <https://doi.org/10.1080/00031305.2016.1277159>

Jendoubi, T., and K. Strimmer 2018. Probabilistic canonical correlation analysis: a whitening approach. <https://arxiv.org/abs/1802.03490>

Website: <http://strimmerlab.org/software/whitening/>

### See Also

[whiteningMatrix](#), [whiten](#), [cca](#), and [scca](#).

---

scca      *Estimate Canonical Correlations and Directions (Shrinkage and Empirical Estimates)*

---

### Description

scca computes canonical correlations and directions using a shrinkage estimate of the joint correlation matrix of  $X$  and  $Y$ .

cca computes canonical correlations and directions based on empirical correlations.

### Usage

```
scca(X, Y, lambda.cor, scale=TRUE, verbose=TRUE)
cca(X, Y, scale=TRUE)
```

**Arguments**

<code>X</code>	First data matrix, with samples in rows and variables in columns.
<code>Y</code>	Second data matrix, with samples in rows and variables in columns.
<code>lambda.cor</code>	Shrinkage intensity for estimating the joint correlation matrix - see <a href="#">cor.shrink</a> . If not specified this will be estimated from the data.
<code>scale</code>	Determines whether canonical directions are computed for standardized or raw data. Note that if data are not standardized the canonical directions contain the scale of the variables.
<code>verbose</code>	Report shrinkage intensities-

**Details**

The canonical directions in this function are scaled in such a way that they correspond to whitening matrices - see Jendoubi and Strimmer (2018) for details. Note that the sign convention for the canonical directions employed here allows purposely for both positive and negative canonical correlations.

The function `scca` uses some clever matrix algebra to avoid computation of full correlation matrices, and hence can be applied to high-dimensional data sets - see Jendoubi and Strimmer (2018) for details.

`cca` it is a shortcut for running `scca` with `lambda.cor=0` and `verbose=FALSE`.

If `scale=FALSE` the standard deviations needed for the canonical directions are estimated by `apply(X, 2, sd)` and `apply(Y, 2, sd)`.

If `X` or `Y` contains only a single variable the correlation-adjusted cross-correlations  $K$  reduce to the CAR score (see [carscore](#)) described in Strimmer and Zuber (2011).

**Value**

`scca` and `cca` return a list with the following components:

`K` - the correlation-adjusted cross-correlations.

`lambda` - the canonical correlations.

`WX` - the whitening matrix for `X`, with canonical directions in the rows.

`WY` - the whitening matrix for `Y`, with canonical directions in the rows.

`scale` - whether data was standardized (if `codescale=FALSE` then canonical directions include scale of the data).

`scca` additionally returns the shrinkage intensity in the variable `lambda.cor` where `lambda.cor.estimated` indicates whether it was specified or estimated.

**Author(s)**

Korbinian Strimmer (<http://strimmerlab.org>) with Takoua Jendoubi.

## References

Jendoubi, T., and K. Strimmer 2018. Probabilistic canonical correlation analysis: a whitening approach. <https://arxiv.org/abs/1802.03490>

Zuber, V., and K. Strimmer. 2011. High-dimensional regression and variable selection using CAR scores. *Statist. Appl. Genet. Mol. Biol.* 10: 34. <https://doi.org/10.2202/1544-6115.1730>

## See Also

[cancor](#) and [carscore](#).

## Examples

```
# load whitening library
library("whitening")

# example data set
data(LifeCycleSavings)
X = as.matrix( LifeCycleSavings[, 2:3] )
Y = as.matrix( LifeCycleSavings[, -(2:3)] )
n = nrow(X)
colnames(X) # "pop15" "pop75"
colnames(Y) # "sr" "dpi" "ddpi"

# CCA

cca.out = cca(X, Y, scale=TRUE)
cca.out$lambda # canonical correlations
cca.out$WX # whitening matrix / canonical directions X
cca.out$WY # whitening matrix / canonical directions Y
cca.out$K # correlation-adjusted cross-correlations

# CCA whitened data
CCAX = scale(X)
CCAY = scale(Y)
zapsmall(cov(CCAX))
zapsmall(cov(CCAY))
zapsmall(cov(CCAX,CCAY)) # canonical correlations

# compare with built-in function cancors
# note different signs in correlations and directions!
cancors.out = cancors(scale(X), scale(Y))
cancors.out$cor # canonical correlations
t(cancors.out$xcoef)*sqrt(n-1) # canonical directions X
t(cancors.out$ycoef)*sqrt(n-1) # canonical directions Y

## see "User guides, package vignettes and other documentation"
## for examples with high-dimensional data using the scca function
```

---

whiteningMatrix      *Compute Whitening Matrix and Whiten Data*


---

### Description

whiteningMatrix computes the whitening matrix  $W$  corresponding to the five natural whitening procedures discussed in Kessy, Lewin, and Strimmer (2018).

whiten whitens data  $X$  using the empirical covariance matrix  $cov(X)$  as basis for computing the whitening transformation.

### Usage

```
whiteningMatrix(Sigma, method=c("ZCA", "PCA", "Cholesky",
                                "ZCA-cor", "PCA-cor"))
whiten(X, method=c("ZCA", "PCA", "Cholesky", "ZCA-cor", "PCA-cor"))
```

### Arguments

Sigma	Covariance matrix.
method	Determines the type of whitening.
X	Data matrix, with samples in rows and variables in columns.

### Details

ZCA whitening, or Mahalanobis whitening ensures that the average covariance between whitened and original variables is maximal. Likewise, ZCA-cor whitening leads to whitened variables that are maximally correlated (on average) with the original variables.

In contrast, PCA and PCA-cor whitening lead to maximally compressed whitened variables, as measured by squared covariance and correlation, respectively.

Cholesky whitening is the unique whitening procedure that results from lower-triangular positive diagonal cross-covariance and cross-correlations matrices.

In PCA and PCA-cor eigenvector matrices with positive diagonal are used, in order to resolve the sign-ambiguity and also to make cross-correlations and cross-correlations positive diagonal.

For details see Kessy, Lewin, and Strimmer (2018).

ZCA-cor whitening is implicitly employed in computing CAT and CAR scores (cf. [catscore](#) and [carscore](#)).

Canonical correlation analysis (CCA) can also be understood as a special form form of whitening.

### Value

whiteningMatrix returns a square whitening matrix  $W$ .

whiten returns the whitened data matrix  $Z = XW'$ .

**Author(s)**

Korbinian Strimmer (<http://strimmerlab.org>) with Agnan Kessy and Alex Lewin.

**References**

Kessy, A., A. Lewin, and K. Strimmer. 2018. Optimal whitening and decorrelation. The American Statistician. <https://doi.org/10.1080/00031305.2016.1277159>

**See Also**

[catscore](#) and [carscore](#).

**Examples**

```
# load whitening library
library("whitening")

#####

# example data set
# E. Anderson. 1935. The irises of the Gaspé Peninsula.
# Bull. Am. Iris Soc. 59: 2--5
data("iris")
X = as.matrix(iris[,1:4])
d = ncol(X) # 4
n = nrow(X) # 150
colnames(X) # "Sepal.Length" "Sepal.Width" "Petal.Length" "Petal.Width"

# estimate covariance
S = cov(X)

# ZCA-cor whitening matrix
W.ZCAcor = whiteningMatrix(S, method="ZCA-cor")

# whitened data
Z.ZCAcor.1 = tcrossprod(X, W.ZCAcor)
zapsmall( cov(Z.ZCAcor.1) )

# directly compute whitened data from X
Z.ZCAcor.2 = whiten(X, method="ZCA-cor")
zapsmall( cov(Z.ZCAcor.2) )
```

# Index

## \*Topic **multivariate**

- scca, 2
- whitening-package, 2
- whiteningMatrix, 5

cancor, 4

carscore, 3–6

catscore, 5, 6

cca, 2

cca (scca), 2

cor.shrink, 3

scca, 2, 2

whiten, 2

whiten (whiteningMatrix), 5

whitening-package, 2

whiteningMatrix, 2, 5