

Package ‘pcaL1’

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Title L1-Norm PCA Methods

License GPL (>= 3)

Description Implementations of several methods for principal component analysis using the L1 norm. The package depends on COIN-OR Clp version >= 1.17.4. The methods implemented are
PCA-L1 (Kwak 2008) <[DOI:10.1109/TPAMI.2008.114](https://doi.org/10.1109/TPAMI.2008.114)>,
L1-PCA (Ke and Kanade 2003, 2005) <[DOI:10.1109/CVPR.2005.309](https://doi.org/10.1109/CVPR.2005.309)>,
L1-PCA* (Brooks, Dula, and Boone 2013) <[DOI:10.1016/j.csda.2012.11.007](https://doi.org/10.1016/j.csda.2012.11.007)>,
L1-PCAhp (Visentin, Prestwich and Armagan 2016) <[DOI:10.1007/978-3-319-46227-1_37](https://doi.org/10.1007/978-3-319-46227-1_37)>,
wPCA (Park and Klabjan 2016) <[DOI:10.1109/ICDM.2016.0054](https://doi.org/10.1109/ICDM.2016.0054)>,
awPCA (Park and Klabjan 2016) <[DOI:10.1109/ICDM.2016.0054](https://doi.org/10.1109/ICDM.2016.0054)>,
PCA-Lp (Kwak 2014) <[DOI:10.1109/TCYB.2013.2262936](https://doi.org/10.1109/TCYB.2013.2262936)>, and
SharpE11-PCA (Brooks and Dula, submitted).

SystemRequirements COIN-OR Clp (>= 1.17.4)

NeedsCompilation yes

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Description

This package contains implementations of six principal component analysis methods using the L1 norm. The package depends on COIN-OR Clp version $\geq 1.17.4$. The methods implemented are PCA-L1 (Kwak 2008), L1-PCA (Ke and Kanade 2003, 2005), L1-PCA* (Brooks, Dula, and Boone 2013), L1-PCAhp (Visentin, Prestwich and Armagan 2016), wPCA (Park and Klabjan 2016), and awPCA (Park and Klabjan 2016).

Details

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SystemRequirements:	COIN-OR Clp ($\geq 1.17.4$)

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References

1. Brooks and Dula (2017) Estimating L1-Norm Best-Fit Lines, submitted
2. Brooks J.P., Dula J.H., and Boone E.L. (2013) A Pure L1-Norm Principal Component Analysis, *Computational Statistics & Data Analysis*, 61:83-98. DOI:10.1016/j.csda.2012.11.007
3. Ke Q. and Kanade T. (2005) Robust L1 Norm Factorization in the Presence of Outliers and Missing Data by Alternative Convex Programming, *IEEE Conference on Computer Vision and Pattern Recognition*. DOI:10.1109/CVPR.2005.309
4. Kwak N. (2008) Principal Component Analysis Based on L1-Norm Maximization, *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 30: 1672-1680. DOI:10.1109/TPAMI.2008.114
5. Kwak N. (2014) Principal Component Analysis by L_p-Norm Maximization, *IEEE Transactions on Cybernetics*, 44:594-609. DOI:10.1109/TCYB.2013.2262936
6. Park, Y.W. and Klabjan, D. (2016) Iteratively Reweighted Least Squares Algorithms for L1-Norm Principal Component Analysis, *IEEE International Conference on Data Mining (ICDM)*. DOI: 10.1109/ICDM.2016.0054
7. Visentin A., Prestwich S., and Armagan S. T. (2016) Robust Principal Component Analysis by Reverse Iterative Linear Programming, *Joint European Conference on Machine Learning and Knowledge Discovery in Databases*, 593-605. DOI:10.1007/978-3-319-46227-1_37

8. Zhou, Y.-H. and Marron, J.S. (2016) Visualization of Robust L1PCA, *Stat*, 5:173-184. DOI:10.1002/sta4.113

awl1pca

awPCA

Description

Performs a principal component analysis using the algorithm awPCA described by Park and Klabjan (2016).

Usage

```
awl1pca(X, projDim=1, center=TRUE, projections="l2",
        tolerance=0.001, iterations=200, beta=0.99, gamma=0.1)
```

Arguments

X	data, must be in matrix or table form.
projDim	number of dimensions to project data into, must be an integer, default is 1.
center	whether to center the data using the mean, default is TRUE.
projections	whether to calculate projections (reconstructions and scores) using the L2 norm ("l2", default) or the L1 norm ("l1").
tolerance	for testing convergence; if the sum of absolute values of loadings vectors is smaller, then the algorithm terminates.
iterations	maximum number of iterations in optimization routine.
beta	algorithm parameter to set up bound for weights.
gamma	algorithm parameter to determine whether to use approximation formula or prcomp function.

Details

The calculation is performed according to the algorithm described by Park and Klabjan (2016). The method is an iteratively reweighted least squares algorithm for L1-norm principal component analysis.

Value

'awl1pca' returns a list with class "awl1pca" containing the following components:

loadings	the matrix of variable loadings. The matrix has dimension ncol(X) x projDim. The columns define the projected subspace.
scores	the matrix of projected points. The matrix has dimension nrow(X) x projDim.
projPoints	the matrix of L2-norm projections of points on the fitted subspace in terms of the original coordinates. The matrix has dimension nrow(X) x ncol(X).
L1error	sum of the L1 norm of reconstruction errors.
nIter	number of iterations.
ElapsedTime	elapsed time.

References

Park, Y.W. and Klabjan, D. (2016) Iteratively Reweighted Least Squares Algorithms for L1-Norm Principal Component Analysis, *IEEE International Conference on Data Mining (ICDM)*, 2016. DOI: 10.1109/ICDM.2016.0054

Examples

```
##for 100x10 data matrix X,
## lying (mostly) in the subspace defined by the first 2 unit vectors,
## projects data into 1 dimension.
X <- matrix(c(runif(100*2, -10, 10), rep(0,100*8)),nrow=100) +
           matrix(c(rep(0,100*2),rnorm(100*8,0,0.1)),ncol=10)
myawl1pca <- awl1pca(X)

##projects data into 2 dimensions.
myawl1pca <- awl1pca(X, projDim=2, center=FALSE)

## plot first two scores
plot(myawl1pca$scores)
```

l1pca

L1-PCA

Description

Performs a principal component analysis using the algorithm L1-PCA given by Ke and Kanade (2005).

Usage

```
l1pca(X, projDim=1, center=TRUE, projections="l1",
      initialize="l2pca", tolerance=0.0001, iterations=10)
```

Arguments

X	data, must be in matrix or table form.
projDim	number of dimensions to project data into, must be an integer, default is 1.
center	whether to center the data using the median, default is TRUE.
projections	Whether to calculate reconstructions and scores using the L1 ("l1", default) or L2 ("l2") norm.
initialize	initial guess for loadings matrix. Options are: "l2pca" - use traditional PCA/SVD, "random" - use a randomly-generated matrix. The user can also provide a matrix as an initial guess.
tolerance	sets the convergence tolerance for the algorithm, default is 0.0001.
iterations	sets the number of iterations to run before returning the result, default is 10.

Details

The calculation is performed according to the linear programming-based algorithm described by Ke and Kanade (2005). The method is a locally-convergent algorithm for finding the L1-norm best-fit subspace by alternatively optimizing the scores and the loadings matrix at each iteration. Linear programming instances are solved using Clp (<http://www.coin-or.org>)

Value

'l1pca' returns a list with class "l1pca" containing the following components:

loadings	the matrix of variable loadings. The matrix has dimension $\text{ncol}(X) \times \text{projDim}$. The columns defined the projected subspace.
scores	the matrix of projected points. The matrix has dimension $\text{nrow}(X) \times \text{projDim}$.
dispExp	the proportion of L1 dispersion explained by the loadings vectors. Calculated as the L1 dispersion of the score on each component divided by the L1 dispersion in the original data.
projPoints	the matrix of projected points in terms of the original coordinates (reconstructions). The matrix has dimension $\text{nrow}(X) \times \text{ncol}(X)$.

References

Ke Q. and Kanade T. (2005) Robust L1 norm factorization in the presence of outliers and missing data by alternative convex programming, *IEEE Conference on Computer Vision and Pattern Recognition*. DOI:10.1109/CVPR.2005.309

Examples

```
##for 100x10 data matrix X,
## lying (mostly) in the subspace defined by the first 2 unit vectors,
## projects data into 1 dimension.
X <- matrix(c(runif(100*2, -10, 10), rep(0,100*8)),nrow=100) +
           matrix(c(rep(0,100*2),rnorm(100*8,0,0.1)),ncol=10)
myl1pca <- l1pca(X)

##projects data into 2 dimensions.
myl1pca <- l1pca(X, projDim=2, center=FALSE,
               tolerance=0.00001, iterations=20)

## plot first two scores
plot(myl1pca$scores)
```

l1pcahp

L1-PCAhp

Description

Performs a principal component analysis using the algorithm L1-PCAhp described by Visentin, Prestwich and Armagan (2016)

Usage

```
l1pcahp(X, projDim=1, center=TRUE, projections="none",
        initialize="l2pca", threshold=0.0001)
```

Arguments

X	data, must be in matrix or table form.
projDim	number of dimensions to project data into, must be an integer, default is 1.
center	whether to center the data using the median, default is TRUE.
projections	whether to calculate reconstructions and scores using the L1 norm ("l1") the L2 norm ("l2") or not at all ("none", default).
initialize	method for initial guess for loadings matrix. Options are: "l2pca" - use traditional PCA/SVD, "random" - use a randomly-generated matrix.
threshold	sets the convergence threshold for the algorithm, default is 0.001.

Details

The calculation is performed according to the algorithm described by Visentin, Prestwich and Armagan (2016). The algorithm computes components iteratively in reverse, using a new heuristic based on Linear Programming. Linear programming instances are solved using Clp (<http://www.coin-or.org>).

Value

'l1pcahp' returns a list with class "l1pcahp" containing the following components:

loadings	the matrix of variable loadings. The matrix has dimension $\text{ncol}(X) \times \text{ncol}(X)$. The columns define the projected subspace.
scores	the matrix of projected points. The matrix has dimension $\text{nrow}(X) \times \text{projDim}$.
dispExp	the proportion of L1 dispersion explained by the loadings vectors. Calculated as the L1 dispersion of the score on each component divided by the L1 dispersion in the original data.
projPoints	the matrix of projected points in terms of the original coordinates. The matrix has dimension $\text{nrow}(X) \times \text{ncol}(X)$.

References

Visentin A., Prestwich S., and Armagan S. T. (2016) Robust Principal Component Analysis by Reverse Iterative Linear Programming, *Joint European Conference on Machine Learning and Knowledge Discovery in Databases*, 593-605. DOI:10.1007/978-3-319-46227-1_37

Examples

```
##for a 100x10 data matrix X,
## lying (mostly) in the subspace defined by the first 2 unit vectors,
## projects data into 1 dimension.
X <- matrix(c(runif(100*2, -10, 10), rep(0,100*8)),nrow=100) +
```

```

matrix(c(rep(0,100*2),rnorm(100*8,0,0.1)),ncol=10)
myl1pcahp <- l1pcahp(X)

##projects data into 2 dimensions.
myl1pcahp <- l1pcahp(X, projDim=2, center=FALSE, projections="l1")

## plot first two scores
plot(myl1pcahp$scores)

```

l1pcastar

*L1-PCA**

Description

Performs a principal component analysis using the algorithm L1-PCA* described by Brooks, Dula, and Boone (2013)

Usage

```
l1pcastar(X, projDim=1, center=TRUE, projections="none")
```

Arguments

<code>X</code>	data, must be in matrix or table form
<code>projDim</code>	number of dimensions to project data into, must be an integer, default is 1
<code>center</code>	whether to center the data using the median, default is TRUE
<code>projections</code>	whether to calculate reconstructions and scores using the L1 norm ("l1") the L2 norm ("l2") or not at all ("none", default)

Details

The calculation is performed according to the algorithm described by Brooks, Dula, and Boone (2013). The algorithm finds successive directions of minimum dispersion in the data by finding the L1-norm best-fit hyperplane at each iteration. Linear programming instances are solved using Clp (<http://www.coin-or.org>)

Value

'l1pcastar' returns a list with class "l1pcastar" containing the following components:

<code>loadings</code>	the matrix of variable loadings. The matrix has dimension $\text{ncol}(X) \times \text{ncol}(X)$. The columns define the projected subspace.
<code>scores</code>	the matrix of projected points. The matrix has dimension $\text{nrow}(X) \times \text{projDim}$.
<code>dispExp</code>	the proportion of L1 dispersion explained by the loadings vectors. Calculated as the L1 dispersion of the score on each component divided by the L1 dispersion in the original data.
<code>projPoints</code>	the matrix of projected points in terms of the original coordinates. The matrix has dimension $\text{nrow}(X) \times \text{ncol}(X)$.

References

1. Brooks J.P., Dula J.H., and Boone E.L. (2013) A Pure L1-Norm Principal Component Analysis, *Computational Statistics & Data Analysis*, 61:83-98. DOI:10.1016/j.csda.2012.11.007
2. Zhou, Y.-H. and Marron, J.S. (2016) Visualization of Robust L1PCA, *Stat*, 5:173-184. DOI:10.1002/sta4.113

Examples

```
##for a 100x10 data matrix X,
## lying (mostly) in the subspace defined by the first 2 unit vectors,
## projects data into 1 dimension.
X <- matrix(c(runif(100*2, -10, 10), rep(0,100*8)),nrow=100) +
           matrix(c(rep(0,100*2),rnorm(100*8,0,0.1)),ncol=10)
myl1pcastar <- l1pcastar(X)

##projects data into 2 dimensions.
myl1pcastar <- l1pcastar(X, projDim=2, center=FALSE, projections="l1")

## plot first two scores
plot(myl1pcastar$scores)
```

l1projection

L1 Projection

Description

Provides the L1-norm projection of points on a subspace, including both scores and reconstructions.

Usage

```
l1projection(X, loadings)
```

Arguments

X	data, in matrix or table form
loadings	an orthonormal matrix of loadings vectors

Details

The scores and reconstructions are calculated by solving a linear program.

Value

'l1projection' returns a list containing the following components:

scores	the matrix of projected points
projPoints	the matrix of projected points in terms of the original coordinates (reconstructions)

L2PCA_approx

L2PCA_approx

Description

Provides an approximation of traditional PCA described by Park and Klabjan (2016) as a subroutine for `awl1pca`.

Usage

```
L2PCA_approx(ev.prev, pc.prev, projDim, X.diff)
```

Arguments

<code>ev.prev</code>	matrix of principal component loadings from a previous iteration of <code>awl1pca</code>
<code>pc.prev</code>	vector of eigenvalues from previous iteration of <code>awl1pca</code>
<code>projDim</code>	number of dimensions to project data into, must be an integer
<code>X.diff</code>	The difference between the current weighted matrix estimate and the estimate from the previous iteration

Details

The calculation is performed according to equations (11) and (12) in Park and Klabjan (2016). The method is an approximation for traditional principal component analysis.

Value

'L2PCA_approx' returns a list containing the following components:

<code>eigenvalues</code>	Estimate of eigenvalues of the covariance matrix.
<code>eigenvectors</code>	Estimate of eigenvectors of the covariance matrix.

References

Park, Y.W. and Klabjan, D. (2016) Iteratively Reweighted Least Squares Algorithms for L1-Norm Principal Component Analysis, *IEEE International Conference on Data Mining (ICDM)*, 2016.

See Also

[awl1pca](#)

l2projection

L2 Projection

Description

Provides the L2-norm projection of points on a subspace, including both scores and reconstructions.

Usage

```
l2projection(X, loadings)
```

Arguments

X	data, in matrix or table form
loadings	an orthonormal matrix of loadings vectors

Details

The scores and reconstructions are calculated by solving a linear program.

Value

'l2projection' returns a list containing the following components:

scores	the matrix of projected points
projPoints	the matrix of projected points in terms of the original coordinates (reconstructions)

pcal1

PCA-L1

Description

Performs a principal component analysis using the algorithm PCA-L1 given by Kwak (2008).

Usage

```
pcal1(X, projDim=1, center=TRUE, projections="none", initialize="l2pca")
```

Arguments

<code>X</code>	data, must be in matrix or table form.
<code>projDim</code>	number of dimensions to project data into, must be an integer, default is 1.
<code>center</code>	whether to center the data using the median, default is TRUE.
<code>projections</code>	whether to calculate reconstructions and scores using the L1 norm ("l1") the L2 norm ("l2") or not at all ("none", default).
<code>initialize</code>	initial guess for first component. Options are: "l2pca" - use traditional PCA/SVD, "maxx" - use the point with the largest norm, "random" - use a random vector. The user can also provide a vector as the initial guess.

Details

The calculation is performed according to the algorithm described by Kwak (2008). The method is a locally-convergent algorithm for finding successive directions of maximum L1 dispersion.

Value

'pcal1' returns a list with class "pcal1" containing the following components:

<code>loadings</code>	the matrix of variable loadings. The matrix has dimension $\text{ncol}(X) \times \text{projDim}$. The columns define the projected subspace.
<code>scores</code>	the matrix of projected points. The matrix has dimension $\text{nrow}(X) \times \text{projDim}$.
<code>dispExp</code>	the proportion of L1 dispersion explained by the loadings vectors. Calculated as the L1 dispersion of the score on each component divided by the L1 dispersion in the original data.
<code>projPoints</code>	the matrix of projected points in terms of the original coordinates (reconstructions). The matrix has dimension $\text{nrow}(X) \times \text{ncol}(X)$.

References

Kwak N. (2008) Principal component analysis based on L1-norm maximization, *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 30: 1672-1680. DOI:10.1109/TPAMI.2008.114

Examples

```
##for 100x10 data matrix X,
## lying (mostly) in the subspace defined by the first 2 unit vectors,
## projects data into 1 dimension.
X <- matrix(c(runif(100*2, -10, 10), rep(0,100*8)),nrow=100) +
           matrix(c(rep(0,100*2),rnorm(100*8,0,0.1)),ncol=10)
mypcal1 <- pcal1(X)

##projects data into 2 dimensions.
mypcal1 <- pcal1(X, projDim=2, center=FALSE, projections="l1")

## plot first two scores
plot(mypcal1$scores)
```

pcalp *PCA-Lp*

Description

Performs a principal component analysis using the greedy algorithms PCA-Lp(G) and PCA-Lp(L) given by Kwak (2014).

Usage

```
pcalp(X, projDim=1, p = 1.0, center=TRUE, projections="none",
      initialize="l2pca", solution = "L",
      epsilon = 0.000000001, lratio = 0.02)
```

Arguments

X	data, must be in matrix or table form.
projDim	number of dimensions to project data into, must be an integer, default is 1.
p	p-norm use to measure the distance between points.
center	whether to center the data using the median, default is TRUE.
projections	whether to calculate reconstructions and scores using the L1 norm ("l1") the L2 norm ("l2") or not at all ("none", default).
initialize	method for initial guess for component. Options are: "l2pca" - use traditional PCA/SVD, "maxx" - use the point with the largest norm, "random" - use a random vector.
solution	method projection vector update. Options are: "G" - PCA-Lp(G) implementation: Gradient search, "L" - PCA-Lp(L) implementation: Lagrangian (default).
epsilon	for checking convergence.
lratio	learning ratio, default is 0.02. Suggested value 1/(nr. instances).

Details

The calculation is performed according to the algorithm described by Kwak (2014), an extension of the original Kwak(2008). The method is a greedy locally-convergent algorithm for finding successive directions of maximum Lp dispersion.

Value

'pcalp' returns a list with class "pcalp" containing the following components:

loadings	the matrix of variable loadings. The matrix has dimension ncol(X) x projDim. The columns define the projected subspace.
scores	the matrix of projected points. The matrix has dimension nrow(X) x projDim.

dispExp	the proportion of L1 dispersion explained by the loadings vectors. Calculated as the L1 dispersion of the score on each component divided by the L1 dispersion in the original data.
projPoints	the matrix of projected points in terms of the original coordinates. The matrix has dimension nrow(X) x ncol(X).

References

Kwak N. (2008) Principal component analysis based on L1-norm maximization, *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 30: 1672-1680. DOI:10.1109/TPAMI.2008.114

Kwak N. (2014). Principal component analysis by Lp-norm maximization. *IEEE transactions on cybernetics*, 44(5), 594-609. DOI: 10.1109/TCYB.2013.2262936

Examples

```
##for 100x10 data matrix X,
## lying (mostly) in the subspace defined by the first 2 unit vectors,
## projects data into 1 dimension.
X <- matrix(c(runif(100*2, -10, 10), rep(0,100*8)),nrow=100)
      + matrix(c(rep(0,100*2),rnorm(100*8,0,0.1)),ncol=10)
mypcalp <- pcalp(X, p = 1.5)

##projects data into 2 dimensions.
mypcalp <- pcalp(X, projDim=2, p = 1.5, center=FALSE, projections="l1")

## plot first two scores
plot(mypcalp$scores)
```

plot.awl1pca

Plot an awl1pca Object

Description

Plots the scores on the first two principal components.

Usage

```
## S3 method for class 'awl1pca'
plot(x, ...)
```

Arguments

x	an object of class awl1pca with scores for at least the first two dimensions
...	arguments to be passed to or from other methods.

Details

This function is a method for the generic function plot, for objects of class awl1pca.

See Also[l1pcastar](#)**Examples**

```
##for a 100x10 data matrix X,  
## lying (mostly) in the subspace defined by the first 2 unit vectors,  
## projects data into 1 dimension.  
X <- matrix(c(runif(100*2, -10, 10), rep(0,100*8)),nrow=100)  
          + matrix(c(rep(0,100*2),rnorm(100*8,0,0.1)),ncol=10)  
myawl1pca <- awl1pca(X)  
  
##projects data into 2 dimensions.  
myawl1pca <- awl1pca(X, projDim=2, center=FALSE)  
  
## plot first two scores  
plot(myawl1pca$scores)
```

plot.l1pca

Plot an L1pca Object

Description

Plots the scores on the first two principal components.

Usage

```
## S3 method for class 'l1pca'  
plot(x, ...)
```

Arguments

x an object of class l1pca with scores for at least the first two dimensions
... arguments to be passed to or from other methods.

Details

This function is a method for the generic function plot, for objects of class l1pca.

See Also[l1pca](#)

Examples

```
##for a 100x10 data matrix X,
## lying (mostly) in the subspace defined by the first 2 unit vectors,
## projects data into 1 dimension.
X <- matrix(c(runif(100*2, -10, 10), rep(0,100*8)),nrow=100)
      + matrix(c(rep(0,100*2),rnorm(100*8,0,0.1)),ncol=10)
myl1pca <- l1pca(X)

##projects data into 2 dimensions.
myl1pca <- l1pca(X, projDim=2, center=FALSE)

## plot first two scores
plot(myl1pca$scores)
```

plot.l1pcahp

Plot an L1PCAhp Object

Description

Plots the scores on the first two principal components.

Usage

```
## S3 method for class 'l1pcahp'
plot(x, ...)
```

Arguments

x an object of class l1pcahp with scores for at least the first two dimensions
... arguments to be passed to or from other methods.

Details

This function is a method for the generic function plot, for objects of class l1pcahp.

See Also

[l1pcastar](#)

Examples

```
##for a 100x10 data matrix X,
## lying (mostly) in the subspace defined by the first 2 unit vectors,
## projects data into 1 dimension.
X <- matrix(c(runif(100*2, -10, 10), rep(0,100*8)),nrow=100)
      + matrix(c(rep(0,100*2),rnorm(100*8,0,0.1)),ncol=10)
myl1pcahp <- l1pcahp(X)

##projects data into 2 dimensions.
```

```
myl1pcahp <- l1pcahp(X, projDim=2, center=FALSE, projections="l1")

## plot first two scores
plot(myl1pcahp$scores)
```

plot.l1pcastar *Plot an L1pcastar Object*

Description

Plots the scores on the first two principal components.

Usage

```
## S3 method for class 'l1pcastar'
plot(x, ...)
```

Arguments

x an object of class l1pcastar with scores for at least the first two dimensions
... arguments to be passed to or from other methods.

Details

This function is a method for the generic function plot, for objects of class l1pcastar.

See Also

[l1pcastar](#)

Examples

```
##for a 100x10 data matrix X,
## lying (mostly) in the subspace defined by the first 2 unit vectors,
## projects data into 1 dimension.
X <- matrix(c(runif(100*2, -10, 10), rep(0,100*8)),nrow=100)
          + matrix(c(rep(0,100*2),rnorm(100*8,0,0.1)),ncol=10)
myl1pcastar <- l1pcastar(X)

##projects data into 2 dimensions.
myl1pcastar <- l1pcastar(X, projDim=2, center=FALSE, projections="l1")

## plot first two scores
plot(myl1pcastar$scores)
```

plot.pcal1	<i>Plot a Pcal1 Object</i>
------------	----------------------------

Description

Plots the scores on the first two principal components.

Usage

```
## S3 method for class 'pcal1'  
plot(x, ...)
```

Arguments

x	an object of class pcal1 with scores for at least the first two dimensions
...	arguments to be passed to or from other methods.

Details

This function is a method for the generic function plot, for objects of class pcal1.

See Also

[pcal1](#)

Examples

```
##for a 100x10 data matrix X,  
## lying (mostly) in the subspace defined by the first 2 unit vectors,  
## projects data into 1 dimension.  
X <- matrix(c(runif(100*2, -10, 10), rep(0,100*8)),nrow=100)  
          + matrix(c(rep(0,100*2),rnorm(100*8,0,0.1)),ncol=10)  
mypcal1 <- pcal1(X)  
  
##projects data into 2 dimensions.  
mypcal1 <- pcal1(X, projDim=2, center=FALSE, projections="l1")  
  
## plot first two scores  
plot(mypcal1$scores)
```

`plot.pcalp`*Plot a Pcalp Object*

Description

Plots the scores on the first two principal components.

Usage

```
## S3 method for class 'pcalp'  
plot(x, ...)
```

Arguments

`x` an object of class `pcalp` with scores for at least the first two dimensions
`...` arguments to be passed to or from other methods.

Details

This function is a method for the generic function `plot`, for objects of class `pcalp`.

See Also

[pcalp](#)

Examples

```
##for a 100x10 data matrix X,  
## lying (mostly) in the subspace defined by the first 2 unit vectors,  
## projects data into 1 dimension.  
X <- matrix(c(runif(100*2, -10, 10), rep(0,100*8)),nrow=100)  
          + matrix(c(rep(0,100*2),rnorm(100*8,0,0.1)),ncol=10)  
mypcalp <- pcalp(X)  
  
##projects data into 2 dimensions.  
mypcalp <- pcalp(X, projDim=2, center=FALSE, projections="l1")  
  
## plot first two scores  
plot(mypcalp$scores)
```

plot.sharpel1pca *Plot a Sharpel1pca Object*

Description

Plots the scores on the first two principal components.

Usage

```
## S3 method for class 'sharpel1pca'  
plot(x, ...)
```

Arguments

x an object of class sharpel1pca with scores for at least the first two dimensions
... arguments to be passed to or from other methods.

Details

This function is a method for the generic function plot, for objects of class sharpel1pca.

See Also

[sharpel1pca](#)

Examples

```
##for a 100x10 data matrix X,  
## lying (mostly) in the subspace defined by the first 2 unit vectors,  
## projects data into 1 dimension.  
X <- matrix(c(runif(100*2, -10, 10), rep(0,100*8)),nrow=100)  
          + matrix(c(rep(0,100*2),rnorm(100*8,0,0.1)),ncol=10)  
mysharpel1pca <- sharpel1pca(X)  
  
##projects data into 2 dimensions.  
mysharpel1pca <- sharpel1pca(X, projDim=2, center=FALSE, projections="l1")  
  
## plot first two scores  
plot(myssharpel1pca$scores)
```

plot.sharpel1rs	<i>Plot a Sharpel1rs Object</i>
-----------------	---------------------------------

Description

Plots the scores on the first two principal components.

Usage

```
## S3 method for class 'sharpel1rs'  
plot(x, ...)
```

Arguments

x	an object of class sharpel1rs with scores for at least the first two dimensions
...	arguments to be passed to or from other methods.

Details

This function is a method for the generic function plot, for objects of class sharpel1rs.

See Also

[sharpel1rs](#)

Examples

```
##for a 100x10 data matrix X,  
## lying (mostly) in the subspace defined by the first 2 unit vectors,  
## projects data into 1 dimension.  
X <- matrix(c(runif(100*2, -10, 10), rep(0,100*8)),nrow=100)  
          + matrix(c(rep(0,100*2),rnorm(100*8,0,0.1)),ncol=10)  
mysharpel1rs <- sharpel1rs(X)  
  
##projects data into 2 dimensions.  
mysharpel1rs <- sharpel1rs(X, projDim=2, center=FALSE, projections="l1")  
  
## plot first two scores  
plot(myssharpel1rs$scores)
```

plot.sparse1pca *Plot a Sparse1pca Object*

Description

Plots the scores on the first two principal components.

Usage

```
## S3 method for class 'sparse1pca'  
plot(x, ...)
```

Arguments

x an object of class sparse1pca with scores for at least the first two dimensions
... arguments to be passed to or from other methods.

Details

This function is a method for the generic function plot, for objects of class sparse1pca.

See Also

[sparse1pca](#)

Examples

```
##for a 100x10 data matrix X,  
## lying (mostly) in the subspace defined by the first 2 unit vectors,  
## projects data into 1 dimension.  
X <- matrix(c(runif(100*2, -10, 10), rep(0,100*8)),nrow=100)  
          + matrix(c(rep(0,100*2),rnorm(100*8,0,0.1)),ncol=10)  
mysparse1pca <- sparse1pca(X)  
  
##projects data into 2 dimensions.  
mysparse1pca <- sparse1pca(X, projDim=2, center=FALSE, projections="l1")  
  
## plot first two scores  
plot(mysparse1pca$scores)
```

plot.w11pca	<i>Plot a W11pca Object</i>
-------------	-----------------------------

Description

Plots the scores on the first two principal components.

Usage

```
## S3 method for class 'w11pca'  
plot(x, ...)
```

Arguments

x	an object of class w11pca with scores for at least the first two dimensions
...	arguments to be passed to or from other methods.

Details

This function is a method for the generic function plot, for objects of class w11pca.

See Also

[l1pcastar](#)

Examples

```
##for a 100x10 data matrix X,  
## lying (mostly) in the subspace defined by the first 2 unit vectors,  
## projects data into 1 dimension.  
X <- matrix(c(runif(100*2, -10, 10), rep(0,100*8)),nrow=100)  
          + matrix(c(rep(0,100*2),rnorm(100*8,0,0.1)),ncol=10)  
myw11pca <- w11pca(X)  
  
##projects data into 2 dimensions.  
myw11pca <- w11pca(X, projDim=2, center=FALSE)  
  
## plot first two scores  
plot(myw11pca$scores)
```

sharpe11pca

*SharpE11-PCA***Description**

Performs a principal component analysis using the algorithm SharpE11-PCA described by Brooks and Dula (2017, submitted)

Usage

```
sharpe11pca(X, projDim=1, center=TRUE, projections="none")
```

Arguments

X	data, must be in matrix or table form.
projDim	number of dimensions to project data into, must be an integer, default is 1.
center	whether to center the data using the median, default is TRUE.
projections	whether to calculate reconstructions and scores using the L1 norm ("l1") the L2 norm ("l2") or not at all ("none", default).

Details

The calculation is performed according to the algorithm described by Brooks and Dula (2017, submitted). The algorithm finds successive, orthogonal fitted lines in the data.

Value

'sharpe11pca' returns a list with class "sharpe11pca" containing the following components:

loadings	the matrix of variable loadings. The matrix has dimension ncol(X) x projDim. The columns define the projected subspace.
scores	the matrix of projected points. The matrix has dimension nrow(X) x projDim.
dispExp	the proportion of L1 dispersion explained by the loadings vectors. Calculated as the L1 dispersion of the score on each component divided by the L1 dispersion in the original data.
projPoints	the matrix of projected points in terms of the original coordinates. The matrix has dimension nrow(X) x ncol(X).
minobjectives	the L1 distance of points to their projections in the fitted subspace.

References

Brooks J.P. and Dula J.H. (2017) Estimating L1-Norm Best-Fit Lines, submitted.

Examples

```
##for a 100x10 data matrix X,
## lying (mostly) in the subspace defined by the first 2 unit vectors,
## projects data into 1 dimension.
X <- matrix(c(runif(100*2, -10, 10), rep(0,100*8)),nrow=100) +
           matrix(c(rep(0,100*2),rnorm(100*8,0,0.1)),ncol=10)
mysharpe11pca <- sharpe11pca(X)

##projects data into 2 dimensions.
mysharpe11pca <- sharpe11pca(X, projDim=2, center=FALSE, projections="l1")

## plot first two scores
plot(mysharpe11pca$scores)
```

sharpe11rs

*SharpE11-RS***Description**

Fits a line in the presence of missing data based on an L1-norm criterion.

Usage

```
sharpe11rs(X, projDim=1, center=TRUE, projections="none")
```

Arguments

X	data, must be in matrix or table form.
projDim	number of dimensions to project data into, must be an integer, default is 1.
center	whether to center the data using the median, default is TRUE.
projections	whether to calculate reconstructions and scores using the L1 norm ("l1") the L2 norm ("l2") or not at all ("none", default).

Details

The algorithm finds successive, orthogonal fitted lines in the data.

Value

'sharpe11rs' returns a list with class "sharpe11rs" containing the following components:

loadings	the matrix of variable loadings. The matrix has dimension ncol(X) x projDim. The columns define the projected subspace.
scores	the matrix of projected points. The matrix has dimension nrow(X) x projDim.
dispExp	the proportion of L1 dispersion explained by the loadings vectors. Calculated as the L1 dispersion of the score on each component divided by the L1 dispersion in the original data.

projPoints the matrix of projected points in terms of the original coordinates. The matrix has dimension $nrow(X) \times ncol(X)$.

minobjectives the L1 distance of points to their projections in the fitted subspace.

References

Valizadeh Gamchi, F. and Brooks J.P. (2023), working paper.

Examples

```
##for a 100x10 data matrix X,
## lying (mostly) in the subspace defined by the first 2 unit vectors,
## projects data into 1 dimension.
X <- matrix(c(runif(100*2, -10, 10), rep(0,100*8)),nrow=100) +
           matrix(c(rep(0,100*2),rnorm(100*8,0,0.1)),ncol=10)
mysharpel1rs <- sharpel1rs(X)

##projects data into 2 dimensions.
mysharpel1rs <- sharpel1rs(X, projDim=2, center=FALSE, projections="l1")

## plot first two scores
plot(mysharpel1rs$scores)
```

sparse11pca

SparsE11-PCA

Description

L1-norm line fitting with L1-regularization.

Usage

```
sparse11pca(X, projDim=1, center=TRUE, projections="none", lambda=0)
```

Arguments

X data, must be in matrix or table form.

projDim number of dimensions to project data into, must be an integer, default is 1.

center whether to center the data using the median, default is TRUE.

projections whether to calculate reconstructions and scores using the L1 norm ("l1") the L2 norm ("l2") or not at all ("none", default).

lambda If negative and number of rows is at most 100, calculates all possible breakpoints for the regularization parameter. Otherwise, fits a regularized line with lambda set to that value.

Details

The calculation is performed according to the algorithm described by Ling and Brooks (2023, working paper). The algorithm finds successive, orthogonal fitted lines in the data.

Value

'sparsellpca' returns a list with class "sparsellpca" containing the following components:

loadings	the matrix of variable loadings. The matrix has dimension $\text{ncol}(X) \times \text{projDim}$. The columns define the projected subspace.
scores	the matrix of projected points. The matrix has dimension $\text{nrow}(X) \times \text{projDim}$.
dispExp	the proportion of L1 dispersion explained by the loadings vectors. Calculated as the L1 dispersion of the score on each component divided by the L1 dispersion in the original data.
projPoints	the matrix of projected points in terms of the original coordinates. The matrix has dimension $\text{nrow}(X) \times \text{ncol}(X)$.
minobjectives	the L1 distance of points to their projections in the fitted subspace.

References

Ling, X. and Brooks J.P. (2023) L1-Norm Regularized L1-Norm Best-Fit Lines, working paper.

Examples

```
##for a 100x10 data matrix X,
## lying (mostly) in the subspace defined by the first 2 unit vectors,
## projects data into 1 dimension.
X <- matrix(c(runif(100*2, -10, 10), rep(0,100*8)),nrow=100) +
           matrix(c(rep(0,100*2),rnorm(100*8,0,0.1)),ncol=10)
mysparsellpca <- sparsellpca(X, lambda=0.5)

##projects data into 2 dimensions.
mysparsellpca <- sparsellpca(X, projDim=2, center=FALSE, projections="l1", lambda=0.5)

## plot first two scores
plot(mysparsellpca$scores)
```

weightedL1Distance *Weighted L1 Distance*

Description

Provides the (weighted) L1-norm distances and total distance of points to a subspace.

Usage

```
weightedL1Distance(X, loadings, weights)
```

Arguments

X	data, in <i>matrix</i> or <i>table</i> form
loadings	an orthonormal matrix of loadings vectors
weights	a list of weights for loadings vectors

Details

The reconstructions are calculated by solving a linear program. Then the weights are applied to the distances.

Value

'weightedL1Distance' returns a list containing the following components:

wDistances	list of weighted distances
totalDistance	total distance

w11pca

wPCA

Description

Performs a principal component analysis using the algorithm *wPCA* described by Park and Klabjan (2016).

Usage

```
w11pca(X, projDim=1, center=TRUE, projections="l2",
        tolerance=0.001, iterations=200, beta=0.99)
```

Arguments

X	data, must be in <i>matrix</i> or <i>table</i> form.
projDim	number of dimensions to project data into, must be an integer, default is 1.
center	whether to center the data using the mean, default is TRUE
projections	whether to calculate projections (reconstructions and scores) using the L2 norm ("l2", default) or the L1 norm ("l1").
tolerance	for testing convergence; if the sum of absolute values of loadings vectors is smaller, then the algorithm terminates.
iterations	maximum number of iterations in optimization routine.
beta	algorithm parameter to set up bound for weights.

Details

The calculation is performed according to the algorithm described by Park and Klabjan (2016). The method is an iteratively reweighted least squares algorithm for L1-norm principal component analysis.

Value

'w11pca' returns a list with class "w11pca" containing the following components:

loadings	the matrix of variable loadings. The matrix has dimension $\text{ncol}(X) \times \text{projDim}$. The columns define the projected subspace.
scores	the matrix of projected points. The matrix has dimension $\text{nrow}(X) \times \text{projDim}$.
projPoints	the matrix of L2 projections points on the fitted subspace in terms of the original coordinates. The matrix has dimension $\text{nrow}(X) \times \text{ncol}(X)$.
L1error	sum of the L1 norm of reconstruction errors.
nIter	number of iterations.
ElapsedTime	elapsed time.

References

Park, Y.W. and Klabjan, D. (2016) Iteratively Reweighted Least Squares Algorithms for L1-Norm Principal Component Analysis, *IEEE International Conference on Data Mining (ICDM)*, 2016. DOI: 10.1109/ICDM.2016.0054

Examples

```
##for 100x10 data matrix X,
## lying (mostly) in the subspace defined by the first 2 unit vectors,
## projects data into 1 dimension.
X <- matrix(c(runif(100*2, -10, 10), rep(0,100*8)),nrow=100) +
           matrix(c(rep(0,100*2),rnorm(100*8,0,0.1)),ncol=10)
myw11pca <- w11pca(X)

##projects data into 2 dimensions.
myw11pca <- w11pca(X, projDim=2, center=FALSE)

## plot first two scores
plot(myw11pca$scores)
```

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