

# fabia

April 20, 2011

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estimateMode      *Estimation of the modes of the rows of a matrix*

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## Description

estimateMode: R implementation of estimateMode.

## Usage

```
estimateMode(X, maxiter=50, tol=0.001, alpha=0.1, a1=4.0, G1=FALSE)
```

## Arguments

|         |  |
|---------|--|
| X       | matrix of which the modes of the rows are estimated.           |
| maxiter | maximal number of iterations; default = 50.                    |
| tol     | tolerance for stopping; default = 0.001.                       |
| alpha   | learning rate; default = 0.1.                                  |
| a1      | parameter of the width of the given distribution; default = 4. |
| G1      | kind of distribution, TRUE: G1, FALSE: G2; default = FALSE.    |

## Details

The mode is estimated by contrast functions G1

$$(1/a_1) * \ln(\cosh(a_1 * x))$$

or G2

$$-(1/a_1) * \exp(-1/2 * x * x)$$

The estimation is performed by gradient descent initialized by the median.

Implementation in R.

## Value

|    |                                 |
|----|---------------------------------|
| u  | the vector of estimated modes.  |
| xu | $X - u$ the mode centered data. |

**Author(s)**

Sepp Hochreiter

**References**

A. Hyvaerinen, 'Fast and Robust Fixed-Point Algorithms for Independent Component Analysis', IEEE Transactions on Neural Networks 10(3):626-634, 1999.

**See Also**

[fabia](#), [fabias](#), [fabiap](#), [fabi](#), [fabiasp](#), [mfsc](#), [nmfdiv](#), [nmfeu](#), [nmfsc](#), [plot](#), [extractPlot](#), [extractBic](#), [plotBicluster](#), [Factorization](#), [projFuncPos](#), [projFunc](#), [estimateMode](#), [makeFabiaData](#), [makeFabiaDataBlocks](#), [makeFabiaDataPos](#), [makeFabiaDataBlocksPos](#), [matrixImagePlot](#), [summary](#), [show](#), [showSelected](#), [fabiaDemo](#), [fabiaVersion](#)

**Examples**

```
#-----
# DEMO
#-----

dat <- makeFabiaDataBlocksPos(n = 100, l = 50, p = 10, f1 = 5, f2 = 5,
  of1 = 5, of2 = 10, sd_noise = 2.0, sd_z_noise = 0.2, mean_z = 2.0,
  sd_z = 1.0, sd_l_noise = 0.2, mean_l = 3.0, sd_l = 1.0)

X <- dat[[1]]

modes <- estimateMode(X)

modes$u - apply(X, 1, median)
```

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extractBic

*Extraction of Biclusters*

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**Description**

extractBic: R implementation of extractBic.

**Usage**

```
extractBic(fact, thresZ=0.5, thresL=NULL)
```

**Arguments**

|        |  |
|--------|--|
| fact   | object of the class <code>Factorization</code> .                             |
| thresZ | threshold for sample belonging to bicluster; default 0.5.                    |
| thresL | threshold for loading belonging to bicluster (if not given it is estimated). |

## Details

Essentially the model is the sum of outer products of vectors:

$$X = \sum_{i=1}^p \lambda_i z_i^T + U$$

where the number of summands  $p$  is the number of biclusters. The matrix factorization is

$$X = LZ + U$$

Here  $\lambda_i$  are from  $R^n$ ,  $z_i$  from  $R^l$ ,  $L$  from  $R^{n \times p}$ ,  $Z$  from  $R^{p \times l}$ , and  $X, U$  from  $R^{n \times l}$ .

$U$  is the Gaussian noise with a diagonal covariance matrix which entries are given by `psi`.

The  $Z$  is locally approximated by a Gaussian with inverse variance given by `lapla`.

Using these values we can computer for each  $j$  the variance  $z_i$  given  $x_j$ . Here

$$x_j = Lz_j + u_j$$

This variance can be used to determine the information content of a bicluster.

The  $\lambda_i$  and  $z_i$  are used to extract the bicluster  $i$ , where a threshold determines which observations and which samples belong the the bicluster.

In `bic` the biclusters are extracted according to the largest absolute values of the component  $i$ , i.e. the largest values of  $\lambda_i$  and the largest values of  $z_i$ . The factors  $z_i$  are normalized to variance 1.

The components of `bic` are `binp`, `bixv`, `bixn`, `biypv`, and `biypn`.

`binp` give the size of the bicluster: number observations and number samples. `bixv` gives the values of the extracted observations that have absolute values above a threshold. They are sorted. `bixn` gives the extracted observation names (e.g. gene names). `biypv` gives the values of the extracted samples that have absolute values above a threshold. They are sorted. `biypn` gives the names of the extracted samples (e.g. sample names).

In `bicopp` the opposite clusters to the biclusters are given. Opposite means that the negative pattern is present.

The components of opposite clusters `bicopp` are `binn`, `bixv`, `bixn`, `biypnv`, and `biynn`.

`binp` give the size of the opposite bicluster: number observations and number samples. `bixv` gives the values of the extracted observations that have absolute values above a threshold. They are sorted. `bixn` gives the extracted observation names (e.g. gene names). `biypnv` gives the values of the opposite extracted samples that have absolute values above a threshold. They are sorted. `biynn` gives the names of the opposite extracted samples (e.g. sample names).

That means the samples are divided into two groups where one group shows large positive values and the other group has negative values with large absolute values. That means a observation pattern can be switched on or switched off relative to the average value.

`numn` gives the indices of `bic` with components: `numng = bix` and `numnp = biypn`.

`numn` gives the indices of `bicopp` with components: `numng = bix` and `numnn = biynn`.

Implementation in R.

**Value**

|         |  |
|---------|--|
| bic     | extracted biclusters.                          |
| numn    | indexes for the extracted biclusters.          |
| bicopp  | extracted opposite biclusters.                 |
| numnopp | indexes for the extracted opposite biclusters. |
| X       | scaled and centered data matrix.               |
| np      | number of biclusters.                          |

**Author(s)**

Sepp Hochreiter

**See Also**

[fabia](#), [fabias](#), [fabiap](#), [fabi](#), [fabiasp](#), [mfsc](#), [nmfdiv](#), [nmfeu](#), [nmfsc](#), [plot](#), [extractPlot](#), [extractBic](#), [plotBicluster](#), [Factorization](#), [projFuncPos](#), [projFunc](#), [estimateMode](#), [makeFabiaData](#), [makeFabiaDataBlocks](#), [makeFabiaDataPos](#), [makeFabiaDataBlocksPos](#), [matrixImagePlot](#), [summary](#), [show](#), [showSelected](#), [fabiaDemo](#), [fabiaVersion](#)

**Examples**

```
#-----
# TEST
#-----

dat <- makeFabiaDataBlocks(n = 100,l= 50,p = 3,f1 = 5,f2 = 5,
  of1 = 5,of2 = 10,sd_noise = 3.0,sd_z_noise = 0.2,mean_z = 2.0,
  sd_z = 1.0,sd_l_noise = 0.2,mean_l = 3.0,sd_l = 1.0)

X <- dat[[1]]
Y <- dat[[2]]

resEx <- fabia(X,3,0.1,20)

rEx <- extractBic(resEx)

rEx$bic[1,]
rEx$bic[2,]
rEx$bic[3,]

## Not run:
#-----
# DEMO1
#-----

dat <- makeFabiaDataBlocks(n = 1000,l= 100,p = 10,f1 = 5,f2 = 5,
  of1 = 5,of2 = 10,sd_noise = 3.0,sd_z_noise = 0.2,mean_z = 2.0,
  sd_z = 1.0,sd_l_noise = 0.2,mean_l = 3.0,sd_l = 1.0)

X <- dat[[1]]
Y <- dat[[2]]
```

```

resToy <- fabia(X,13,0.1,200)

rToy <- extractBic(resToy)

resToy@avini

rToy$bic[1,]
rToy$bic[2,]
rToy$bic[3,]

#-----
# DEMO2
#-----

avail <- require(fabiaData)

if (!avail) {
  message("")
  message("")
  message("#####")
  message("Package 'fabiaData' is not available: please install.")
  message("#####")
} else {

data(Breast_A)

X <- as.matrix(XBreast)

resBreast <- fabia(X,5,0.1,200)

rBreast <- extractBic(resBreast)

resBreast@avini

rBreast$bic[1,]
rBreast$bic[2,]
rBreast$bic[3,]
}

## End(Not run)

```

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extractPlot

*Plotting of Biclustering Results*


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### Description

extractPlot: R implementation of extractPlot.

**Usage**

```
extractPlot (fact, thresZ=0.5, ti="", thresL=NULL, Y=NULL, which=c(1, 2, 3, 4, 5, 6, 7, 8))
```

**Arguments**

|        |   |
|--------|---|
| fact   | object of the class <code>Factorization</code> .  |
| thresZ | threshold for sample belonging to bicluster; default 0.5.   |
| thresL | threshold for loading belonging to bicluster (estimated if not given).  |
| ti     | plot title; default "".   |
| Y      | noise free data matrix.   |
| which  | which plot is shown: 1=noise free data (if available), 2=data, 3=reconstructed data, 4=error, 5=absolute factors, 6=absolute loadings, 7=reconstructed matrix sorted, 8=original matrix sorted; default c(1,2,3,4,5,6,7,8). |

**Details**

Essentially the model is the sum of outer products of vectors:

$$X = \sum_{i=1}^p \lambda_i z_i^T + U$$

where the number of summands  $p$  is the number of biclusters. The matrix factorization is

$$X = LZ + U$$

Here  $\lambda_i$  are from  $R^n$ ,  $z_i$  from  $R^l$ ,  $L$  from  $R^{n \times p}$ ,  $Z$  from  $R^{p \times l}$ , and  $X, U$  from  $R^{n \times l}$ .

The hidden dimension  $p$  is used for kmeans clustering of  $\lambda_i$  and  $z_i$ .

The  $\lambda_i$  and  $z_i$  are used to extract the bicluster  $i$ , where a threshold determines which observations and which samples belong to the bicluster.

The method produces following plots depending what plots are chosen by the "which" variable:

"Y": noise free data (if available), "X": data, "LZ": reconstructed data, "LZ-X": error, "abs(Z)": absolute factors, "abs(L)": absolute loadings, "pmL\*L\*z\*pmZ": reconstructed matrix sorted, "pmL\*X\*pmZ": original matrix sorted.

For sorting first kmeans is performed on the  $p$  dimensional space and then the vectors which belong to the same cluster are put together.

This sorting is in general not able to visualize all biclusters as blocks if they overlap.

The kmeans clusters are given by `biclust` with components `biclustx` (the clustered observations) and `biclusty` (the clustered samples).

Implementation in R.

**Value**

|         |   |
|---------|---|
| biclust | clusters of kmeans clustering.  |
| pmZ     | permutation matrix of $Z$ from kmeans clustering.                     |
| pmL     | permutation matrix of $L$ from kmeans clustering.                     |
| L       | normalized loadings (left matrix).                                    |
| Z       | normalized factors (right matrix).                                    |
| Xord    | sorted original matrix according to kmeans on $Z$ and kmeans on $L$ . |

**Author(s)**

Sepp Hochreiter

**See Also**

[fabia](#), [fabias](#), [fabiap](#), [fabi](#), [fabiasp](#), [mfsc](#), [nmfdiv](#), [nmfeu](#), [nmfsc](#), [plot](#), [extractPlot](#), [extractBic](#), [plotBicluster](#), [Factorization](#), [projFuncPos](#), [projFunc](#), [estimateMode](#), [makeFabiaData](#), [makeFabiaDataBlocks](#), [makeFabiaDataPos](#), [makeFabiaDataBlocksPos](#), [matrixImagePlot](#), [summary](#), [show](#), [showSelected](#), [fabiaDemo](#), [fabiaVersion](#)

**Examples**

```
#-----
# TEST
#-----

dat <- makeFabiaDataBlocks(n = 100,l= 50,p = 3,f1 = 5,f2 = 5,
  of1 = 5,of2 = 10,sd_noise = 3.0,sd_z_noise = 0.2,mean_z = 2.0,
  sd_z = 1.0,sd_l_noise = 0.2,mean_l = 3.0,sd_l = 1.0)

X <- dat[[1]]
Y <- dat[[2]]

resEx <- fabia(X,3,0.3,20)

rEx <- extractPlot(resEx,ti="FABIA",Y=Y)

## Not run:
#-----
# DEMO1
#-----

dat <- makeFabiaDataBlocks(n = 1000,l= 100,p = 10,f1 = 5,f2 = 5,
  of1 = 5,of2 = 10,sd_noise = 3.0,sd_z_noise = 0.2,mean_z = 2.0,
  sd_z = 1.0,sd_l_noise = 0.2,mean_l = 3.0,sd_l = 1.0)

X <- dat[[1]]
Y <- dat[[2]]

resToy <- fabia(X,13,0.1,200)

rToy <- extractPlot(resToy,ti="FABIA",Y=Y)

#-----
# DEMO2
#-----

avail <- require(fabiaData)

if (!avail) {
  message("")
}
```

```

    message("")
    message("#####")
    message("Package 'fabiaData' is not available: please install.")
    message("#####")
  } else {

data(Breast_A)

X <- as.matrix(XBreast)

resBreast <- fabia(X,5,0.1,200)

rBreast <- extractPlot(resBreast,ti="FABIA Breast cancer(Veer)")

#sorting of predefined labels
CBreast
}

## End(Not run)

```

---

fabiaDemo

*Demos for fabia*


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## Description

fabiaDemo calls the demo codes for fabia.

## Usage

```
fabiaDemo()
```

## Author(s)

Sepp Hochreiter

## See Also

[fabia](#), [fabias](#), [fabiap](#), [fabi](#), [fabiasp](#), [mfsc](#), [nmfdiv](#), [nmfeu](#), [nmfsc](#), [plot](#), [extractPlot](#), [extractBic](#), [plotBicluster](#), [Factorization](#), [projFuncPos](#), [projFunc](#), [estimateMode](#), [makeFabiaData](#), [makeFabiaDataBlocks](#), [makeFabiaDataPos](#), [makeFabiaDataBlocksPos](#), [matrixImagePlot](#), [summary](#), [show](#), [showSelected](#), [fabiaDemo](#), [fabiaVersion](#)

## Examples

```

## Not run:
# interactive
fabiaDemo()

## End(Not run)

```



fabiap

*Factor Analysis for Bicluster Acquisition: Post-Projection (FABIAP)***Description**

fabiap: C implementation of fabiap.

**Usage**

```
fabiap(X, p=5, alpha=0.1, cyc=500, spl=0.5, spz=0.5, sL=0.6, sZ=0.6, random=1.0, center=2
```

**Arguments**

|        |   |
|--------|---|
| X      | the data matrix.  |
| p      | number of hidden factors = number of biclusters; default = 5.   |
| alpha  | sparseness loadings (0.1 - 1.0); default = 0.1.   |
| cyc    | number of iterations; default = 500.  |
| spl    | sparseness prior loadings (0.5 - 2.0); default = 0.5 (Laplace).   |
| spz    | sparseness factors (0.5 - 2.0); default = 0.5 (Laplace).  |
| sL     | final sparseness loadings; default = 0.6.   |
| sZ     | final sparseness factors; default = 0.6.  |
| random | <=0: by SVD, >0: random initialization of loadings in [-random,random]; default = 1.0.                        |
| center | data centering: 1 (mean), 2 (median), > 2 (mode), 0 (no); default = 2.  |
| norm   | data normalization: 1 (0.75-0.25 quantile), >1 (var=1), 0 (no); default = 1.                                  |
| scale  | loading vectors are scaled in each iteration to the given variance. 0.0 indicates non scaling; default = 0.0. |
| lap    | minimal value of the variational parameter; default = 1.0   |

**Details**

Biclusters are found by sparse factor analysis where *both* the factors and the loadings are sparse. Post-processing by projecting the final results to a given sparseness criterion.

Essentially the model is the sum of outer products of vectors:

$$X = \sum_{i=1}^p \lambda_i z_i^T + U$$

where the number of summands  $p$  is the number of biclusters. The matrix factorization is

$$X = LZ + U$$

Here  $\lambda_i$  are from  $R^n$ ,  $z_i$  from  $R^l$ ,  $L$  from  $R^{n \times p}$ ,  $Z$  from  $R^{p \times l}$ , and  $X, U$  from  $R^{n \times l}$ .

If the nonzero components of the sparse vectors are grouped together then the outer product results in a matrix with a nonzero block and zeros elsewhere.

The model selection is performed by a variational approach according to Girolami 2001 and Palmer et al. 2006.

We included a prior on the parameters and minimize a lower bound on the posterior of the parameters given the data. The update of the loadings includes an additive term which pushes the loadings toward zero (Gaussian prior leads to an multiplicative factor).

**Post-processing:** The final results of the loadings and the factors are projected to a sparse vector according to Hoyer, 2004: given an  $l_1$ -norm and an  $l_2$ -norm minimize the Euclidean distance to the original vector (currently the  $l_2$ -norm is fixed to 1). The projection is a convex quadratic problem which is solved iteratively where at each iteration at least one component is set to zero. Instead of the  $l_1$ -norm a sparseness measurement is used which relates the  $l_1$ -norm to the  $l_2$ -norm:

The code is implemented in C using the Rcpp package. The projection is implemented in R.

## Value

object of the class `Factorization`. Containing `LZ` (estimated noise free data  $LZ$ ), `L` (loadings  $L$ ), `Z` (factors  $Z$ ), `U` (noise  $X - LZ$ ), `center` (centering vector), `scaleData` (scaling vector), `X` (centered and scaled data  $X$ ), `Psi` (noise variance  $\sigma$ ), `lapla` (variational parameter), `avini` (the information which the factor  $z_{ij}$  contains about  $x_j$  averaged over  $j$ ) `xavini` (the information which the factor  $z_j$  contains about  $x_j$ ) `ini` (for each  $j$  the information which the factor  $z_{ij}$  contains about  $x_j$ ).

## Author(s)

Sepp Hochreiter

## References

- S. Hochreiter et al., ‘FABIA: Factor Analysis for Bicluster Acquisition’, *Bioinformatics* 26(12):1520-1527, 2010. <http://bioinformatics.oxfordjournals.org/cgi/content/abstract/btq227>
- Mark Girolami, ‘A Variational Method for Learning Sparse and Overcomplete Representations’, *Neural Computation* 13(11): 2517-2532, 2001.
- J. Palmer, D. Wipf, K. Kreutz-Delgado, B. Rao, ‘Variational EM algorithms for non-Gaussian latent variable models’, *Advances in Neural Information Processing Systems* 18, pp. 1059-1066, 2006.
- Patrik O. Hoyer, ‘Non-negative Matrix Factorization with Sparseness Constraints’, *Journal of Machine Learning Research* 5:1457-1469, 2004.

## See Also

`fabia`, `fabias`, `fabiap`, `fabi`, `fabiasp`, `mfsc`, `nmfdiiv`, `nmfeu`, `nmfsc`, `plot`, `extractPlot`, `extractBic`, `plotBicluster`, `Factorization`, `projFuncPos`, `projFunc`, `estimateMode`, `makeFabiaData`, `makeFabiaDataBlocks`, `makeFabiaDataPos`, `makeFabiaDataBlocksPos`, `matrixImagePlot`, `summary`, `show`, `showSelected`, `fabiaDemo`, `fabiaVersion`

## Examples

```
#-----
# TEST
#-----

dat <- makeFabiaDataBlocks(n = 100, l = 50, p = 3, f1 = 5, f2 = 5,
```

```

of1 = 5,of2 = 10,sd_noise = 3.0,sd_z_noise = 0.2,mean_z = 2.0,
sd_z = 1.0,sd_l_noise = 0.2,mean_l = 3.0,sd_l = 1.0)

X <- dat[[1]]
Y <- dat[[2]]

resEx <- fabiap(X,3,0.1,50)

## Not run:

#-----
# DEMO1: Toy Data
#-----

n = 1000
l= 100
p = 10

dat <- makeFabiaDataBlocks(n = n,l= l,p = p,f1 = 5,f2 = 5,
  of1 = 5,of2 = 10,sd_noise = 3.0,sd_z_noise = 0.2,mean_z = 2.0,
  sd_z = 1.0,sd_l_noise = 0.2,mean_l = 3.0,sd_l = 1.0)

X <- dat[[1]]
Y <- dat[[2]]
ZC <- dat[[3]]
LC <- dat[[4]]

gclab <- rep.int(0,l)
gllab <- rep.int(0,n)
clab <- as.character(1:l)
llab <- as.character(1:n)
for (i in 1:p){
  for (j in ZC[i]){
    clab[j] <- paste(as.character(i), "_",clab[j],sep="")
  }
  for (j in LC[i]){
    llab[j] <- paste(as.character(i), "_",llab[j],sep="")
  }
  gclab[unlist(ZC[i])] <- gclab[unlist(ZC[i])] + p^i
  gllab[unlist(LC[i])] <- gllab[unlist(LC[i])] + p^i
}

groups <- gclab

#### FABIAP

resToy3 <- fabiap(X,13,0.1,400)

rToy3 <- extractPlot(resToy3,ti="FABIAP",Y=Y)

raToy3 <- extractBic(resToy3)

if ((raToy3$bic[[1]][1]>1) && (raToy3$bic[[1]][2]>1) {
  plotBicluster(raToy3,1)
}

```

```

if ((raToy3$bic[[2]][1]>1) && (raToy3$bic[[2]][2]>1) {
  plotBicluster(raToy3,2)
}
if ((raToy3$bic[[3]][1]>1) && (raToy3$bic[[3]][2]>1) {
  plotBicluster(raToy3,3)
}
if ((raToy3$bic[[4]][1]>1) && (raToy3$bic[[4]][2]>1) {
  plotBicluster(raToy3,4)
}

colnames(resToy3@X) <- clab

rownames(resToy3@X) <- llab

plot(resToy3,dim=c(1,2),label.tol=0.1,col.group = groups,lab.size=0.6)
plot(resToy3,dim=c(1,3),label.tol=0.1,col.group = groups,lab.size=0.6)
plot(resToy3,dim=c(2,3),label.tol=0.1,col.group = groups,lab.size=0.6)

#-----
# DEMO2: Laura van't Veer's gene expression
#       data set for breast cancer
#-----

avail <- require(fabiaData)

if (!avail) {
  message("")
  message("")
  message("#####")
  message("Package 'fabiaData' is not available: please install.")
  message("#####")
} else {

data(Breast_A)

X <- as.matrix(XBreast)

resBreast3 <- fabiap(X,5,0.1,400)

rBreast3 <- extractPlot(resBreast3,ti="FABIAP Breast cancer (Veer)")

raBreast3 <- extractBic(resBreast3)

if ((raBreast3$bic[[1]][1]>1) && (raBreast3$bic[[1]][2]>1) {
  plotBicluster(raBreast3,1)
}
if ((raBreast3$bic[[2]][1]>1) && (raBreast3$bic[[2]][2]>1) {
  plotBicluster(raBreast3,2)
}
if ((raBreast3$bic[[3]][1]>1) && (raBreast3$bic[[3]][2]>1) {
  plotBicluster(raBreast3,3)
}
if ((raBreast3$bic[[4]][1]>1) && (raBreast3$bic[[4]][2]>1) {

```

```

    plotBiclust3(raBreast3,4)
  }

plot(resBreast3,dim=c(1,2),label.tol=0.03,col.group=CBreast,lab.size=0.6)
plot(resBreast3,dim=c(1,3),label.tol=0.03,col.group=CBreast,lab.size=0.6)
plot(resBreast3,dim=c(1,4),label.tol=0.03,col.group=CBreast,lab.size=0.6)
plot(resBreast3,dim=c(1,5),label.tol=0.03,col.group=CBreast,lab.size=0.6)
plot(resBreast3,dim=c(2,3),label.tol=0.03,col.group=CBreast,lab.size=0.6)
plot(resBreast3,dim=c(2,4),label.tol=0.03,col.group=CBreast,lab.size=0.6)
plot(resBreast3,dim=c(2,5),label.tol=0.03,col.group=CBreast,lab.size=0.6)
plot(resBreast3,dim=c(3,4),label.tol=0.03,col.group=CBreast,lab.size=0.6)
plot(resBreast3,dim=c(3,5),label.tol=0.03,col.group=CBreast,lab.size=0.6)
plot(resBreast3,dim=c(4,5),label.tol=0.03,col.group=CBreast,lab.size=0.6)

}

#-----
# DEMO3: Su's multiple tissue types
#       gene expression data set
#-----

avail <- require(fabiaData)

if (!avail) {
  message("")
  message("")
  message("#####")
  message("Package 'fabiaData' is not available: please install.")
  message("#####")
} else {

data(Multi_A)

X <- as.matrix(XMulti)

resMulti3 <- fabiap(X,5,0.1,300)

rMulti3 <- extractPlot(resMulti3,ti="FABIAP Multiple tissues(Su)")

raMulti3 <- extractBic(resMulti3)

if ((raMulti3$bic[[1]][1]>1) && (raMulti3$bic[[1]][2]>1) {
  plotBiclust3(raMulti3,1)
}
if ((raMulti3$bic[[2]][1]>1) && (raMulti3$bic[[2]][2]>1) {
  plotBiclust3(raMulti3,2)
}
if ((raMulti3$bic[[3]][1]>1) && (raMulti3$bic[[3]][2]>1) {
  plotBiclust3(raMulti3,3)
}
if ((raMulti3$bic[[4]][1]>1) && (raMulti3$bic[[4]][2]>1) {
  plotBiclust3(raMulti3,4)
}
}

```

```

plot(resMulti3,dim=c(1,2),label.tol=0.01,col.group=CMulti,lab.size=0.6)
plot(resMulti3,dim=c(1,3),label.tol=0.01,col.group=CMulti,lab.size=0.6)
plot(resMulti3,dim=c(1,4),label.tol=0.01,col.group=CMulti,lab.size=0.6)
plot(resMulti3,dim=c(1,5),label.tol=0.01,col.group=CMulti,lab.size=0.6)
plot(resMulti3,dim=c(2,3),label.tol=0.01,col.group=CMulti,lab.size=0.6)
plot(resMulti3,dim=c(2,4),label.tol=0.01,col.group=CMulti,lab.size=0.6)
plot(resMulti3,dim=c(2,5),label.tol=0.01,col.group=CMulti,lab.size=0.6)
plot(resMulti3,dim=c(3,4),label.tol=0.01,col.group=CMulti,lab.size=0.6)
plot(resMulti3,dim=c(3,5),label.tol=0.01,col.group=CMulti,lab.size=0.6)
plot(resMulti3,dim=c(4,5),label.tol=0.01,col.group=CMulti,lab.size=0.6)

}

#-----
# DEMO4: Rosenwald's diffuse large-B-cell
#       lymphoma gene expression data set
#-----

avail <- require(fabiaData)

if (!avail) {
  message("")
  message("")
  message("#####")
  message("Package 'fabiaData' is not available: please install.")
  message("#####")
} else {

data(DLBCL_B)

X <- as.matrix(XDLBCL)

resDLBCL3 <- fabiap(X,5,0.1,400)

rDLBCL3 <- extractPlot(resDLBCL3,ti="FABIAP Lymphoma (Rosenwald)")
raDLBCL3 <- extractBic(resDLBCL3)

if ((raDLBCL3$bic[[1]][1]>1) && (raDLBCL3$bic[[1]][2]>1) {
  plotBicluster(raDLBCL3,1)
}
if ((raDLBCL3$bic[[2]][1]>1) && (raDLBCL3$bic[[2]][2]>1) {
  plotBicluster(raDLBCL3,2)
}
if ((raDLBCL3$bic[[3]][1]>1) && (raDLBCL3$bic[[3]][2]>1) {
  plotBicluster(raDLBCL3,3)
}
if ((raDLBCL3$bic[[4]][1]>1) && (raDLBCL3$bic[[4]][2]>1) {
  plotBicluster(raDLBCL3,4)
}

plot(resDLBCL3,dim=c(1,2),label.tol=0.03,col.group=CDLBCL,lab.size=0.6)
plot(resDLBCL3,dim=c(1,3),label.tol=0.03,col.group=CDLBCL,lab.size=0.6)
plot(resDLBCL3,dim=c(1,4),label.tol=0.03,col.group=CDLBCL,lab.size=0.6)
plot(resDLBCL3,dim=c(1,5),label.tol=0.03,col.group=CDLBCL,lab.size=0.6)

```

```

plot(resDLBCL3,dim=c(2,3),label.tol=0.03,col.group=CDLBCL,lab.size=0.6)
plot(resDLBCL3,dim=c(2,4),label.tol=0.03,col.group=CDLBCL,lab.size=0.6)
plot(resDLBCL3,dim=c(2,5),label.tol=0.03,col.group=CDLBCL,lab.size=0.6)
plot(resDLBCL3,dim=c(3,4),label.tol=0.03,col.group=CDLBCL,lab.size=0.6)
plot(resDLBCL3,dim=c(3,5),label.tol=0.03,col.group=CDLBCL,lab.size=0.6)
plot(resDLBCL3,dim=c(4,5),label.tol=0.03,col.group=CDLBCL,lab.size=0.6)

}

## End(Not run)

```

fabia

*Factor Analysis for Bicluster Acquisition: Laplace Prior (FABIA)***Description**

fabia: C implementation of fabia.

**Usage**

```
fabia(X,p=5,alpha=0.1,cyc=500,spl=0.5,spz=0.5,random=1.0,center=2,norm=1,scale=0
```

**Arguments**

|        |   |
|--------|---|
| X      | the data matrix.  |
| p      | number of hidden factors = number of biclusters; default = 5.   |
| alpha  | sparseness loadings (0.1 - 1.0); default = 0.1.   |
| cyc    | number of iterations; default = 500.  |
| spl    | sparseness prior loadings (0.5 - 2.0); default = 0.5 (Laplace).   |
| spz    | sparseness factors (0.5 - 2.0); default = 0.5 (Laplace).  |
| random | <=0: by SVD, >0: random initialization of loadings in [-random,random]; default = 1.0.                        |
| center | data centering: 1 (mean), 2 (median), > 2 (mode), 0 (no); default = 2.  |
| norm   | data normalization: 1 (0.75-0.25 quantile), >1 (var=1), 0 (no); default = 1.                                  |
| scale  | loading vectors are scaled in each iteration to the given variance. 0.0 indicates non scaling; default = 0.0. |
| lap    | minimal value of the variational parameter; default = 1.0   |

**Details**

Biclusters are found by sparse factor analysis where *both* the factors and the loadings are sparse.

Essentially the model is the sum of outer products of vectors:

$$X = \sum_{i=1}^p \lambda_i z_i^T + U$$

where the number of summands  $p$  is the number of biclusters. The matrix factorization is

$$X = LZ + U$$

Here  $\lambda_i$  are from  $R^n$ ,  $z_i$  from  $R^l$ ,  $L$  from  $R^{n \times p}$ ,  $Z$  from  $R^{p \times l}$ , and  $X, U$  from  $R^{n \times l}$ .

If the nonzero components of the sparse vectors are grouped together then the outer product results in a matrix with a nonzero block and zeros elsewhere.

The model selection is performed by a variational approach according to Girolami 2001 and Palmer et al. 2006.

We included a prior on the parameters and minimize a lower bound on the posterior of the parameters given the data. The update of the loadings includes an additive term which pushes the loadings toward zero (Gaussian prior leads to a multiplicative factor).

The code is implemented in C using the Rcpp package.

## Value

object of the class `Factorization`. Containing `LZ` (estimated noise free data  $LZ$ ), `L` (loadings  $L$ ), `Z` (factors  $Z$ ), `U` (noise:  $X - LZ$ ), `center` (centering vector), `scaleData` (scaling vector), `X` (centered and scaled data  $X$ ), `Psi` (noise variance  $\sigma$ ), `lapla` (variational parameter), `avini` (the information which the factor  $z_{ij}$  contains about  $x_j$  averaged over  $j$ ) `xavini` (the information which the factor  $z_j$  contains about  $x_j$ ) `ini` (for each  $j$  the information which the factor  $z_{ij}$  contains about  $x_j$ ).

## Author(s)

Sepp Hochreiter

## References

S. Hochreiter et al., 'FABIA: Factor Analysis for Bicluster Acquisition', *Bioinformatics* 26(12):1520-1527, 2010. <http://bioinformatics.oxfordjournals.org/cgi/content/abstract/btq227>

Mark Girolami, 'A Variational Method for Learning Sparse and Overcomplete Representations', *Neural Computation* 13(11): 2517-2532, 2001.

J. Palmer, D. Wipf, K. Kreutz-Delgado, B. Rao, 'Variational EM algorithms for non-Gaussian latent variable models', *Advances in Neural Information Processing Systems* 18, pp. 1059-1066, 2006.

## See Also

`fabia`, `fabias`, `fabiap`, `fabi`, `fabiasp`, `mfsc`, `nmfdiv`, `nmfeu`, `nmfsc`, `plot`, `extractPlot`, `extractBic`, `plotBicluster`, `Factorization`, `projFuncPos`, `projFunc`, `estimateMode`, `makeFabiaData`, `makeFabiaDataBlocks`, `makeFabiaDataPos`, `makeFabiaDataBlocksPos`, `matrixImagePlot`, `summary`, `show`, `showSelected`, `fabiaDemo`, `fabiaVersion`

## Examples

```
#-----
# TEST
#-----

dat <- makeFabiaDataBlocks(n = 100, l = 50, p = 3, f1 = 5, f2 = 5,
```



```

of1 = 5,of2 = 10,sd_noise = 3.0,sd_z_noise = 0.2,mean_z = 2.0,
sd_z = 1.0,sd_l_noise = 0.2,mean_l = 3.0,sd_l = 1.0)

X <- dat[[1]]
Y <- dat[[2]]

resEx <- fabia(X,3,0.1,50)

## Not run:
#-----
# DEMO1: Toy Data
#-----

n = 1000
l= 100
p = 10

dat <- makeFabiaDataBlocks(n = n,l= l,p = p,f1 = 5,f2 = 5,
  of1 = 5,of2 = 10,sd_noise = 3.0,sd_z_noise = 0.2,mean_z = 2.0,
  sd_z = 1.0,sd_l_noise = 0.2,mean_l = 3.0,sd_l = 1.0)

X <- dat[[1]]
Y <- dat[[2]]
ZC <- dat[[3]]
LC <- dat[[4]]

gclab <- rep.int(0,l)
gllab <- rep.int(0,n)
clab <- as.character(1:l)
llab <- as.character(1:n)
for (i in 1:p){
  for (j in ZC[i]){
    clab[j] <- paste(as.character(i), "_",clab[j],sep="")
  }
  for (j in LC[i]){
    llab[j] <- paste(as.character(i), "_",llab[j],sep="")
  }
  gclab[unlist(ZC[i])] <- gclab[unlist(ZC[i])] + p^i
  gllab[unlist(LC[i])] <- gllab[unlist(LC[i])] + p^i
}

groups <- gclab

#### FABIA

resToy1 <- fabia(X,13,0.1,400)

rToy1 <- extractPlot(resToy1,ti="FABIA",Y=Y)

raToy1 <- extractBic(resToy1)

if ((raToy1$bic[[1]][1]>1) && (raToy1$bic[[1]][2]>1) {

```

```

    plotBicluster(raToy1,1)
  }
  if ((raToy1$bic[[2]][1]>1) && (raToy1$bic[[2]][2]>1) {
    plotBicluster(raToy1,2)
  }
  if ((raToy1$bic[[3]][1]>1) && (raToy1$bic[[3]][2]>1) {
    plotBicluster(raToy1,3)
  }
  if ((raToy1$bic[[4]][1]>1) && (raToy1$bic[[4]][2]>1) {
    plotBicluster(raToy1,4)
  }
}

colnames(resToy1@X) <- clab

rownames(resToy1@X) <- llab

plot(resToy1,dim=c(1,2),label.tol=0.1,col.group = groups,lab.size=0.6)
plot(resToy1,dim=c(1,3),label.tol=0.1,col.group = groups,lab.size=0.6)
plot(resToy1,dim=c(2,3),label.tol=0.1,col.group = groups,lab.size=0.6)

#-----
# DEMO2: Laura van't Veer's gene expression
#       data set for breast cancer
#-----

avail <- require(fabiaData)

if (!avail) {
  message("")
  message("")
  message("#####")
  message("Package 'fabiaData' is not available: please install.")
  message("#####")
} else {

data(Breast_A)

X <- as.matrix(XBreast)

resBreast1 <- fabia(X,5,0.1,400)

rBreast1 <- extractPlot(resBreast1,ti="FABIA Breast cancer (Veer)")

raBreast1 <- extractBic(resBreast1)

if ((raBreast1$bic[[1]][1]>1) && (raBreast1$bic[[1]][2]>1) {
  plotBicluster(raBreast1,1)
}
if ((raBreast1$bic[[2]][1]>1) && (raBreast1$bic[[2]][2]>1) {
  plotBicluster(raBreast1,2)
}
}

```

```

}
if ((raBreast1$bic[[3]][1]>1) && (raBreast1$bic[[3]][2]>1) {
  plotBicluster(raBreast1,3)
}
if ((raBreast1$bic[[4]][1]>1) && (raBreast1$bic[[4]][2]>1) {
  plotBicluster(raBreast1,4)
}

plot(resBreast1,dim=c(1,2),label.tol=0.03,col.group=CBreast,lab.size=0.6)
plot(resBreast1,dim=c(1,3),label.tol=0.03,col.group=CBreast,lab.size=0.6)
plot(resBreast1,dim=c(1,4),label.tol=0.03,col.group=CBreast,lab.size=0.6)
plot(resBreast1,dim=c(1,5),label.tol=0.03,col.group=CBreast,lab.size=0.6)
plot(resBreast1,dim=c(2,3),label.tol=0.03,col.group=CBreast,lab.size=0.6)
plot(resBreast1,dim=c(2,4),label.tol=0.03,col.group=CBreast,lab.size=0.6)
plot(resBreast1,dim=c(2,5),label.tol=0.03,col.group=CBreast,lab.size=0.6)
plot(resBreast1,dim=c(3,4),label.tol=0.03,col.group=CBreast,lab.size=0.6)
plot(resBreast1,dim=c(3,5),label.tol=0.03,col.group=CBreast,lab.size=0.6)
plot(resBreast1,dim=c(4,5),label.tol=0.03,col.group=CBreast,lab.size=0.6)

}

#-----
# DEMO3: Su's multiple tissue types
#       gene expression data set
#-----

avail <- require(fabiaData)

if (!avail) {
  message("")
  message("")
  message("#####")
  message("Package 'fabiaData' is not available: please install.")
  message("#####")
} else {

data(Multi_A)

X <- as.matrix(XMulti)

resMultil <- fabia(X,5,0.1,300)

rMultil <- extractPlot(resMultil,ti="FABIA Multiple tissues(Su)")

raMultil <- extractBic(resMultil)

if ((raMultil$bic[[1]][1]>1) && (raMultil$bic[[1]][2]>1) {
  plotBicluster(raMultil,1)
}
if ((raMultil$bic[[2]][1]>1) && (raMultil$bic[[2]][2]>1) {
  plotBicluster(raMultil,2)
}
if ((raMultil$bic[[3]][1]>1) && (raMultil$bic[[3]][2]>1) {

```

```

    plotBicluster(raMultil,3)
  }
  if ((raMultil$bic[[4]][1]>1) && (raMultil$bic[[4]][2]>1) {
    plotBicluster(raMultil,4)
  }

  plot(resMultil,dim=c(1,2),label.tol=0.01,col.group=CMulti,lab.size=0.6)
  plot(resMultil,dim=c(1,3),label.tol=0.01,col.group=CMulti,lab.size=0.6)
  plot(resMultil,dim=c(1,4),label.tol=0.01,col.group=CMulti,lab.size=0.6)
  plot(resMultil,dim=c(1,5),label.tol=0.01,col.group=CMulti,lab.size=0.6)
  plot(resMultil,dim=c(2,3),label.tol=0.01,col.group=CMulti,lab.size=0.6)
  plot(resMultil,dim=c(2,4),label.tol=0.01,col.group=CMulti,lab.size=0.6)
  plot(resMultil,dim=c(2,5),label.tol=0.01,col.group=CMulti,lab.size=0.6)
  plot(resMultil,dim=c(3,4),label.tol=0.01,col.group=CMulti,lab.size=0.6)
  plot(resMultil,dim=c(3,5),label.tol=0.01,col.group=CMulti,lab.size=0.6)
  plot(resMultil,dim=c(4,5),label.tol=0.01,col.group=CMulti,lab.size=0.6)

}

#-----
# DEMO4: Rosenwald's diffuse large-B-cell
#       lymphoma gene expression data set
#-----

avail <- require(fabiaData)

if (!avail) {
  message("")
  message("")
  message("#####")
  message("Package 'fabiaData' is not available: please install.")
  message("#####")
} else {

  data(DLBCL_B)

  X <- as.matrix(XDLBCL)

  resDLBCL1 <- fabia(X,5,0.1,400)

  rDLBCL1 <- extractPlot(resDLBCL1,ti="FABIA Lymphoma (Rosenwald)")

  raDLBCL1 <- extractBic(resDLBCL1)

  if ((raDLBCL1$bic[[1]][1]>1) && (raDLBCL1$bic[[1]][2]>1) {
    plotBicluster(raDLBCL1,1)
  }
  if ((raDLBCL1$bic[[2]][1]>1) && (raDLBCL1$bic[[2]][2]>1) {
    plotBicluster(raDLBCL1,2)
  }
  if ((raDLBCL1$bic[[3]][1]>1) && (raDLBCL1$bic[[3]][2]>1) {
    plotBicluster(raDLBCL1,3)
  }
  if ((raDLBCL1$bic[[4]][1]>1) && (raDLBCL1$bic[[4]][2]>1) {

```

```

    plotBicluster (raDLBCL1, 4)
  }

  plot (resDLBCL1, dim=c (1, 2), label.tol=0.03, col.group=CDLBCL, lab.size=0.6)
  plot (resDLBCL1, dim=c (1, 3), label.tol=0.03, col.group=CDLBCL, lab.size=0.6)
  plot (resDLBCL1, dim=c (1, 4), label.tol=0.03, col.group=CDLBCL, lab.size=0.6)
  plot (resDLBCL1, dim=c (1, 5), label.tol=0.03, col.group=CDLBCL, lab.size=0.6)
  plot (resDLBCL1, dim=c (2, 3), label.tol=0.03, col.group=CDLBCL, lab.size=0.6)
  plot (resDLBCL1, dim=c (2, 4), label.tol=0.03, col.group=CDLBCL, lab.size=0.6)
  plot (resDLBCL1, dim=c (2, 5), label.tol=0.03, col.group=CDLBCL, lab.size=0.6)
  plot (resDLBCL1, dim=c (3, 4), label.tol=0.03, col.group=CDLBCL, lab.size=0.6)
  plot (resDLBCL1, dim=c (3, 5), label.tol=0.03, col.group=CDLBCL, lab.size=0.6)
  plot (resDLBCL1, dim=c (4, 5), label.tol=0.03, col.group=CDLBCL, lab.size=0.6)

}

## End (Not run)

```

fabiasp

*Factor Analysis for Bicluster Acquisition: Sparseness Projection (FABIASP)*

## Description

fabiasp: R implementation of fabias, therefore it is **slow**.

## Usage

```
fabiasp(X, p=5, alpha=0.6, cyc=500, spz=0.5, center=2, norm=1)
```

## Arguments

|        |  |
|--------|--|
| X      | the data matrix.   |
| p      | number of hidden factors = number of biclusters; default = 5.                |
| alpha  | sparseness loadings (0.1 - 1.0); default = 0.1.                              |
| cyc    | number of iterations; default = 500.   |
| spz    | sparseness factors (0.5 - 2.0); default = 0.5 (Laplace).                     |
| center | data centering: 1 (mean), 2 (median), > 2 (mode), 0 (no); default = 2.       |
| norm   | data normalization: 1 (0.75-0.25 quantile), >1 (var=1), 0 (no); default = 1. |

## Details

Biclusters are found by sparse factor analysis where *both* the factors and the loadings are sparse. Essentially the model is the sum of outer products of vectors:

$$X = \sum_{i=1}^p \lambda_i z_i^T + U$$

where the number of summands  $p$  is the number of biclusters. The matrix factorization is

$$X = LZ + U$$

Here  $\lambda_i$  are from  $R^n$ ,  $z_i$  from  $R^l$ ,  $L$  from  $R^{n \times p}$ ,  $Z$  from  $R^{p \times l}$ , and  $X, U$  from  $R^{n \times l}$ .

If the nonzero components of the sparse vectors are grouped together then the outer product results in a matrix with a nonzero block and zeros elsewhere.

The model selection is performed by a variational approach according to Girolami 2001 and Palmer et al. 2006.

The prior has finite support, therefore after each update of the loadings they are projected to the finite support. The projection is done according to Hoyer, 2004: given an  $l_1$ -norm and an  $l_2$ -norm minimize the Euclidean distance to the original vector (currently the  $l_2$ -norm is fixed to 1). The projection is a convex quadratic problem which is solved iteratively where at each iteration at least one component is set to zero. Instead of the  $l_1$ -norm a sparseness measurement is used which relates the  $l_1$ -norm to the  $l_2$ -norm.

The code is implemented in R, therefore it is **slow**.

## Value

object of the class `Factorization`. Containing `LZ` (estimated noise free data  $LZ$ ), `L` (loadings  $L$ ), `Z` (factors  $Z$ ), `U` (noise  $X - LZ$ ), `center` (centering vector), `scaleData` (scaling vector), `X` (centered and scaled data  $X$ ), `Psi` (noise variance  $\sigma$ ), `lapla` (variational parameter), `avini` (the information which the factor  $z_{ij}$  contains about  $x_j$  averaged over  $j$ ) `xavini` (the information which the factor  $z_j$  contains about  $x_j$ ) `ini` (for each  $j$  the information which the factor  $z_{ij}$  contains about  $x_j$ ).

## Author(s)

Sepp Hochreiter

## References

- S. Hochreiter et al., 'FABIA: Factor Analysis for Bicluster Acquisition', *Bioinformatics* 26(12):1520-1527, 2010. <http://bioinformatics.oxfordjournals.org/cgi/content/abstract/btq227>
- Mark Girolami, 'A Variational Method for Learning Sparse and Overcomplete Representations', *Neural Computation* 13(11): 2517-2532, 2001.
- J. Palmer, D. Wipf, K. Kreutz-Delgado, B. Rao, 'Variational EM algorithms for non-Gaussian latent variable models', *Advances in Neural Information Processing Systems* 18, pp. 1059-1066, 2006.
- Patrik O. Hoyer, 'Non-negative Matrix Factorization with Sparseness Constraints', *Journal of Machine Learning Research* 5:1457-1469, 2004.

## See Also

[fabia](#), [fabias](#), [fabiap](#), [fabi](#), [fabiasp](#), [mfsc](#), [nmfdiv](#), [nmfeu](#), [nmfsc](#), [plot](#), [extractPlot](#), [extractBic](#), [plotBicluster](#), [Factorization](#), [projFuncPos](#), [projFunc](#), [estimateMode](#), [makeFabiaData](#), [makeFabiaDataBlocks](#), [makeFabiaDataPos](#), [makeFabiaDataBlocksPos](#), [matrixImagePlot](#), [summary](#), [show](#), [showSelected](#), [fabiaDemo](#), [fabiaVersion](#)

**Examples**

```

#-----
# TEST
#-----

dat <- makeFabiaDataBlocks(n = 100,l= 50,p = 3,f1 = 5,f2 = 5,
  of1 = 5,of2 = 10,sd_noise = 3.0,sd_z_noise = 0.2,mean_z = 2.0,
  sd_z = 1.0,sd_l_noise = 0.2,mean_l = 3.0,sd_l = 1.0)

X <- dat[[1]]
Y <- dat[[2]]

resEx <- fabiasp(X,3,0.6,50)

## Not run:
#-----
# DEMO1
#-----

dat <- makeFabiaDataBlocks(n = 1000,l= 100,p = 10,f1 = 5,f2 = 5,
  of1 = 5,of2 = 10,sd_noise = 3.0,sd_z_noise = 0.2,mean_z = 2.0,
  sd_z = 1.0,sd_l_noise = 0.2,mean_l = 3.0,sd_l = 1.0)

X <- dat[[1]]
Y <- dat[[2]]

resToy <- fabiasp(X,13,0.6,200)

rToy <- extractPlot(resToy,"ti=FABIASP",Y=Y)

#-----
# DEMO2
#-----

avail <- require(fabiaData)

if (!avail) {
  message("")
  message("")
  message("#####")
  message("Package 'fabiaData' is not available: please install.")
  message("#####")
} else {

data(Breast_A)

X <- as.matrix(XBreast)

resBreast <- fabiasp(X,5,0.6,200)

```

```

rBreast <- extractPlot(resBreast,ti="FABIASP Breast cancer(Veer)")

#sorting of predefined labels
CBreast

}

#-----
# DEMO3
#-----

avail <- require(fabiaData)

if (!avail) {
  message("")
  message("")
  message("#####")
  message("Package 'fabiaData' is not available: please install.")
  message("#####")
} else {

data(Multi_A)

X <- as.matrix(XMulti)

resMulti <- fabiasp(X,5,0.6,200)

rMulti <- extractPlot(resMulti,"ti=FABIASP Multiple tissues(Su)")

#sorting of predefined labels
CMulti

}

#-----
# DEMO4
#-----

avail <- require(fabiaData)

if (!avail) {
  message("")
  message("")
  message("#####")
  message("Package 'fabiaData' is not available: please install.")
  message("#####")
} else {

data(DLBCL_B)

X <- as.matrix(XDLBCL)

```



```

resDLBCL <- fabiasp(X,5,0.6,200)

rDLBCL <- extractPlot(resDLBCL,ti="FABIASP Lymphoma (Rosenwald) ")

#sorting of predefined labels
CDLBCL
}

## End(Not run)

```

---

|        |  |
|--------|--|
| fabias | <i>Factor Analysis for Bicluster Acquisition: Sparseness Projection (FABIAS)</i> |
|--------|--|

---

## Description

fabias: C implementation of fabias.

## Usage

```
fabias(X, p=5, alpha=0.6, cyc=500, spz=0.5, random=1.0, center=2, norm=1, lap=1.0)
```

## Arguments

|        |  |
|--------|--|
| X      | the data matrix.   |
| p      | number of hidden factors = number of biclusters; default = 5.                          |
| alpha  | sparseness loadings (0.1 - 1.0); default = 0.1.  |
| cyc    | number of iterations; default = 500.   |
| spz    | sparseness factors (0.5 - 2.0); default = 0.5 (Laplace).                               |
| random | <=0: by SVD, >0: random initialization of loadings in [-random,random]; default = 1.0. |
| center | data centering: 1 (mean), 2 (median), > 2 (mode), 0 (no); default = 2.                 |
| norm   | data normalization: 1 (0.75-0.25 quantile), >1 (var=1), 0 (no); default = 1.           |
| lap    | minimal value of the variational parameter; default = 1.0                              |

## Details

Biclusters are found by sparse factor analysis where *both* the factors and the loadings are sparse. Essentially the model is the sum of outer products of vectors:

$$X = \sum_{i=1}^p \lambda_i z_i^T + U$$

where the number of summands  $p$  is the number of biclusters. The matrix factorization is

$$X = LZ + U$$

Here  $\lambda_i$  are from  $R^n$ ,  $z_i$  from  $R^l$ ,  $L$  from  $R^{n \times p}$ ,  $Z$  from  $R^{p \times l}$ , and  $X, U$  from  $R^{n \times l}$ .

If the nonzero components of the sparse vectors are grouped together then the outer product results in a matrix with a nonzero block and zeros elsewhere.

The model selection is performed by a variational approach according to Girolami 2001 and Palmer et al. 2006.

The prior has finite support, therefore after each update of the loadings they are projected to the finite support. The projection is done according to Hoyer, 2004: given an  $l_1$ -norm and an  $l_2$ -norm minimize the Euclidean distance to the original vector (currently the  $l_2$ -norm is fixed to 1). The projection is a convex quadratic problem which is solved iteratively where at each iteration at least one component is set to zero. Instead of the  $l_1$ -norm a sparseness measurement is used which relates the  $l_1$ -norm to the  $l_2$ -norm.

The code is implemented in C using the Rcpp package.

## Value

object of the class `Factorization`. Containing `LZ` (estimated noise free data  $LZ$ ), `L` (loadings  $L$ ), `Z` (factors  $Z$ ), `U` (noise  $X - LZ$ ), `center` (centering vector), `scaleData` (scaling vector), `X` (centered and scaled data  $X$ ), `Psi` (noise variance  $\sigma$ ), `lapla` (variational parameter), `avini` (the information which the factor  $z_{ij}$  contains about  $x_j$  averaged over  $j$ ) `xavini` (the information which the factor  $z_j$  contains about  $x_j$ ) `ini` (for each  $j$  the information which the factor  $z_{ij}$  contains about  $x_j$ ).

## Author(s)

Sepp Hochreiter

## References

S. Hochreiter et al., 'FABIA: Factor Analysis for Bicluster Acquisition', *Bioinformatics* 26(12):1520-1527, 2010. <http://bioinformatics.oxfordjournals.org/cgi/content/abstract/btq227>

Mark Girolami, 'A Variational Method for Learning Sparse and Overcomplete Representations', *Neural Computation* 13(11): 2517-2532, 2001.

J. Palmer, D. Wipf, K. Kreutz-Delgado, B. Rao, 'Variational EM algorithms for non-Gaussian latent variable models', *Advances in Neural Information Processing Systems* 18, pp. 1059-1066, 2006.

Patrik O. Hoyer, 'Non-negative Matrix Factorization with Sparseness Constraints', *Journal of Machine Learning Research* 5:1457-1469, 2004.

## See Also

`fabia`, `fabias`, `fabiap`, `fabi`, `fabiasp`, `mfsc`, `nmfdi`, `nmfeu`, `nmfsc`, `plot`, `extractPlot`, `extractBic`, `plotBicluster`, `Factorization`, `projFuncPos`, `projFunc`, `estimateMode`, `makeFabiaData`, `makeFabiaDataBlocks`, `makeFabiaDataPos`, `makeFabiaDataBlocksPos`, `matrixImagePlot`, `summary`, `show`, `showSelected`, `fabiaDemo`, `fabiaVersion`

## Examples

```
#-----
# TEST
#-----
```

```

dat <- makeFabiaDataBlocks(n = 100,l= 50,p = 3,f1 = 5,f2 = 5,
  of1 = 5,of2 = 10,sd_noise = 3.0,sd_z_noise = 0.2,mean_z = 2.0,
  sd_z = 1.0,sd_l_noise = 0.2,mean_l = 3.0,sd_l = 1.0)

X <- dat[[1]]
Y <- dat[[2]]

resEx <- fabias(X,3,0.6,50)

## Not run:
#-----
# DEMO1: Toy Data
#-----

n = 1000
l= 100
p = 10

dat <- makeFabiaDataBlocks(n = n,l= l,p = p,f1 = 5,f2 = 5,
  of1 = 5,of2 = 10,sd_noise = 3.0,sd_z_noise = 0.2,mean_z = 2.0,
  sd_z = 1.0,sd_l_noise = 0.2,mean_l = 3.0,sd_l = 1.0)

X <- dat[[1]]
Y <- dat[[2]]
ZC <- dat[[3]]
LC <- dat[[4]]

gclab <- rep.int(0,l)
gllab <- rep.int(0,n)
clab <- as.character(1:l)
llab <- as.character(1:n)
for (i in 1:p){
  for (j in ZC[i]){
    clab[j] <- paste(as.character(i), "_", clab[j], sep="")
  }
  for (j in LC[i]){
    llab[j] <- paste(as.character(i), "_", llab[j], sep="")
  }
  gclab[unlist(ZC[i])] <- gclab[unlist(ZC[i])] + p^i
  gllab[unlist(LC[i])] <- gllab[unlist(LC[i])] + p^i
}

groups <- gclab

#### FABIAS

resToy2 <- fabias(X,13,0.6,400)

rToy2 <- extractPlot(resToy2,ti="FABIAS",Y=Y)

raToy2 <- extractBic(resToy2)

```

```

if ((raToy2$bic[[1]][1]>1) && (raToy2$bic[[1]][2]>1) {
  plotBicluster(raToy2,1)
}
if ((raToy2$bic[[2]][1]>1) && (raToy2$bic[[2]][2]>1) {
  plotBicluster(raToy2,2)
}
if ((raToy2$bic[[3]][1]>1) && (raToy2$bic[[3]][2]>1) {
  plotBicluster(raToy2,3)
}
if ((raToy2$bic[[4]][1]>1) && (raToy2$bic[[4]][2]>1) {
  plotBicluster(raToy2,4)
}

colnames(resToy2@X) <- clab

rownames(resToy2@X) <- llab

plot(resToy2,dim=c(1,2),label.tol=0.1,col.group = groups,lab.size=0.6)
plot(resToy2,dim=c(1,3),label.tol=0.1,col.group = groups,lab.size=0.6)
plot(resToy2,dim=c(2,3),label.tol=0.1,col.group = groups,lab.size=0.6)

#-----
# DEMO2: Laura van't Veer's gene expression
#       data set for breast cancer
#-----

avail <- require(fabiaData)

if (!avail) {
  message("")
  message("")
  message("#####")
  message("Package 'fabiaData' is not available: please install.")
  message("#####")
} else {

data(Breast_A)

X <- as.matrix(XBreast)

resBreast2 <- fabias(X,5,0.6,300)

rBreast2 <- extractPlot(resBreast2,ti="FABIAS Breast cancer (Veer)")

raBreast2 <- extractBic(resBreast2)

if ((raBreast2$bic[[1]][1]>1) && (raBreast2$bic[[1]][2]>1) {
  plotBicluster(raBreast2,1)
}
if ((raBreast2$bic[[2]][1]>1) && (raBreast2$bic[[2]][2]>1) {
  plotBicluster(raBreast2,2)
}

```

```

if ((raBreast2$bic[[3]][1]>1) && (raBreast2$bic[[3]][2]>1) {
  plotBicluster(raBreast2,3)
}
if ((raBreast2$bic[[4]][1]>1) && (raBreast2$bic[[4]][2]>1) {
  plotBicluster(raBreast2,4)
}

plot(resBreast2,dim=c(1,2),label.tol=0.03,col.group=CBreast,lab.size=0.6)
plot(resBreast2,dim=c(1,3),label.tol=0.03,col.group=CBreast,lab.size=0.6)
plot(resBreast2,dim=c(1,4),label.tol=0.03,col.group=CBreast,lab.size=0.6)
plot(resBreast2,dim=c(1,5),label.tol=0.03,col.group=CBreast,lab.size=0.6)
plot(resBreast2,dim=c(2,3),label.tol=0.03,col.group=CBreast,lab.size=0.6)
plot(resBreast2,dim=c(2,4),label.tol=0.03,col.group=CBreast,lab.size=0.6)
plot(resBreast2,dim=c(2,5),label.tol=0.03,col.group=CBreast,lab.size=0.6)
plot(resBreast2,dim=c(3,4),label.tol=0.03,col.group=CBreast,lab.size=0.6)
plot(resBreast2,dim=c(3,5),label.tol=0.03,col.group=CBreast,lab.size=0.6)
plot(resBreast2,dim=c(4,5),label.tol=0.03,col.group=CBreast,lab.size=0.6)

}

#-----
# DEMO3: Su's multiple tissue types
#       gene expression data set
#-----

avail <- require(fabiaData)

if (!avail) {
  message("")
  message("")
  message("#####")
  message("Package 'fabiaData' is not available: please install.")
  message("#####")
} else {

data(Multi_A)

X <- as.matrix(XMulti)

resMulti2 <- fabias(X,5,0.6,300)

rMulti2 <- extractPlot(resMulti2,ti="FABIAS Multiple tissues(Su)")

raMulti2 <- extractBic(resMulti2)

if ((raMulti2$bic[[1]][1]>1) && (raMulti2$bic[[1]][2]>1) {
  plotBicluster(raMulti2,1)
}
if ((raMulti2$bic[[2]][1]>1) && (raMulti2$bic[[2]][2]>1) {
  plotBicluster(raMulti2,2)
}
if ((raMulti2$bic[[3]][1]>1) && (raMulti2$bic[[3]][2]>1) {
  plotBicluster(raMulti2,3)
}
if ((raMulti2$bic[[4]][1]>1) && (raMulti2$bic[[4]][2]>1) {
  plotBicluster(raMulti2,4)
}
}

```

```

plot(resMulti2,dim=c(1,2),label.tol=0.01,col.group=CMulti,lab.size=0.6)
plot(resMulti2,dim=c(1,3),label.tol=0.01,col.group=CMulti,lab.size=0.6)
plot(resMulti2,dim=c(1,4),label.tol=0.01,col.group=CMulti,lab.size=0.6)
plot(resMulti2,dim=c(1,5),label.tol=0.01,col.group=CMulti,lab.size=0.6)
plot(resMulti2,dim=c(2,3),label.tol=0.01,col.group=CMulti,lab.size=0.6)
plot(resMulti2,dim=c(2,4),label.tol=0.01,col.group=CMulti,lab.size=0.6)
plot(resMulti2,dim=c(2,5),label.tol=0.01,col.group=CMulti,lab.size=0.6)
plot(resMulti2,dim=c(3,4),label.tol=0.01,col.group=CMulti,lab.size=0.6)
plot(resMulti2,dim=c(3,5),label.tol=0.01,col.group=CMulti,lab.size=0.6)
plot(resMulti2,dim=c(4,5),label.tol=0.01,col.group=CMulti,lab.size=0.6)

}

#-----
# DEMO4: Rosenwald's diffuse large-B-cell
#       lymphoma gene expression data set
#-----

avail <- require(fabiaData)

if (!avail) {
  message("")
  message("")
  message("#####")
  message("Package 'fabiaData' is not available: please install.")
  message("#####")
} else {

data(DLBCL_B)

X <- as.matrix(XDLBCL)

resDLBCL2 <- fabias(X,5,0.6,300)

rDLBCL2 <- extractPlot(resDLBCL2,ti="FABIAS Lymphoma (Rosenwald)")

raDLBCL2 <- extractBic(resDLBCL2)

if ((raDLBCL2$bic[[1]][1]>1) && (raDLBCL2$bic[[1]][2]>1) {
  plotBicluster(raDLBCL2,1)
}
if ((raDLBCL2$bic[[2]][1]>1) && (raDLBCL2$bic[[2]][2]>1) {
  plotBicluster(raDLBCL2,2)
}
if ((raDLBCL2$bic[[3]][1]>1) && (raDLBCL2$bic[[3]][2]>1) {
  plotBicluster(raDLBCL2,3)
}
if ((raDLBCL2$bic[[4]][1]>1) && (raDLBCL2$bic[[4]][2]>1) {
  plotBicluster(raDLBCL2,4)
}

plot(resDLBCL2,dim=c(1,2),label.tol=0.03,col.group=CDLBCL,lab.size=0.6)
plot(resDLBCL2,dim=c(1,3),label.tol=0.03,col.group=CDLBCL,lab.size=0.6)
plot(resDLBCL2,dim=c(1,4),label.tol=0.03,col.group=CDLBCL,lab.size=0.6)

```

```

plot(resDLBCL2,dim=c(1,5),label.tol=0.03,col.group=CDLBCL,lab.size=0.6)
plot(resDLBCL2,dim=c(2,3),label.tol=0.03,col.group=CDLBCL,lab.size=0.6)
plot(resDLBCL2,dim=c(2,4),label.tol=0.03,col.group=CDLBCL,lab.size=0.6)
plot(resDLBCL2,dim=c(2,5),label.tol=0.03,col.group=CDLBCL,lab.size=0.6)
plot(resDLBCL2,dim=c(3,4),label.tol=0.03,col.group=CDLBCL,lab.size=0.6)
plot(resDLBCL2,dim=c(3,5),label.tol=0.03,col.group=CDLBCL,lab.size=0.6)
plot(resDLBCL2,dim=c(4,5),label.tol=0.03,col.group=CDLBCL,lab.size=0.6)

}

## End(Not run)

```

---

|              |   |
|--------------|---|
| fabiaVersion | <i>Display version info for package and for FABIA</i> |
|--------------|---|

---

### Description

fabiaVersion displays version information about the package.

### Usage

```
fabiaVersion()
```

### Author(s)

Sepp Hochreiter

### See Also

[fabia](#), [fabias](#), [fabiap](#), [fabi](#), [fabiasp](#), [mfsc](#), [nmfdiv](#), [nmfeu](#), [nmfsc](#), [plot](#), [extractPlot](#), [extractBic](#), [plotBicluster](#), [Factorization](#), [projFuncPos](#), [projFunc](#), [estimateMode](#), [makeFabiaData](#), [makeFabiaDataBlocks](#), [makeFabiaDataPos](#), [makeFabiaDataBlocksPos](#), [matrixImagePlot](#), [summary](#), [show](#), [showSelected](#), [fabiaDemo](#), [fabiaVersion](#)

### Examples

```
fabiaVersion()
```

---

|       |  |
|-------|--|
| fabia | <i>Factor Analysis for Bicluster Acquisition: Laplace Prior (FABI)</i> |
|-------|--|

---

### Description

fabia: R implementation of [fabia](#), therefore it is **slow**.

## Usage

```
fabi(X, p=5, alpha=0.1, cyc=500, spl=0.5, spz=0.5, center=2, norm=1)
```

## Arguments

|        |  |
|--------|--|
| X      | the data matrix.   |
| p      | number of hidden factors = number of biclusters; default = 5.                |
| alpha  | sparseness loadings (0.1-1.0); default = 0.1.                                |
| cyc    | number of iterations; default = 500.   |
| spl    | sparseness prior loadings (0.5 - 2.0); default = 0.5 (Laplace).              |
| spz    | sparseness factors (0.5-2.0); default = 0.5 (Laplace).                       |
| center | data centering: 1 (mean), 2 (median), > 2 (mode), 0 (no); default = 2.       |
| norm   | data normalization: 1 (0.75-0.25 quantile), >1 (var=1), 0 (no); default = 1. |

## Details

Biclusters are found by sparse factor analysis where *both* the factors and the loadings are sparse. Essentially the model is the sum of outer products of vectors:

$$X = \sum_{i=1}^p \lambda_i z_i^T + U$$

where the number of summands  $p$  is the number of biclusters. The matrix factorization is

$$X = LZ + U$$

Here  $\lambda_i$  are from  $R^n$ ,  $z_i$  from  $R^l$ ,  $L$  from  $R^{n \times p}$ ,  $Z$  from  $R^{p \times l}$ , and  $X, U$  from  $R^{n \times l}$ .

If the nonzero components of the sparse vectors are grouped together then the outer product results in a matrix with a nonzero block and zeros elsewhere.

We recommend to *normalize the components to variance one* in order to make the signal and noise comparable across components.

The model selection is performed by a variational approach according to Girolami 2001 and Palmer et al. 2006.

We included a prior on the parameters and minimize a lower bound on the posterior of the parameters given the data. The update of the loadings includes an additive term which pushes the loadings toward zero (Gaussian prior leads to a multiplicative factor).

The code is implemented in R, therefore it is **slow**.

## Value

object of the class `Factorization`. Containing `LZ` (estimated noise free data  $LZ$ ), `L` (loadings  $L$ ), `Z` (factors  $Z$ ), `U` (noise  $X - LZ$ ), `center` (centering vector), `scaleData` (scaling vector), `X` (centered and scaled data  $X$ ), `Psi` (noise variance  $\sigma$ ), `lapla` (variational parameter), `avini` (the information which the factor  $z_{ij}$  contains about  $x_j$  averaged over  $j$ ) `xavini` (the information which the factor  $z_j$  contains about  $x_j$ ) `ini` (for each  $j$  the information which the factor  $z_{ij}$  contains about  $x_j$ ).



**Author(s)**

Sepp Hochreiter

**References**

S. Hochreiter et al., 'FABIA: Factor Analysis for Biclust Acquisition', *Bioinformatics* 26(12):1520-1527, 2010. <http://bioinformatics.oxfordjournals.org/cgi/content/abstract/btq227>

Mark Girolami, 'A Variational Method for Learning Sparse and Overcomplete Representations', *Neural Computation* 13(11): 2517-2532, 2001.

J. Palmer, D. Wipf, K. Kreutz-Delgado, B. Rao, 'Variational EM algorithms for non-Gaussian latent variable models', *Advances in Neural Information Processing Systems* 18, pp. 1059-1066, 2006.

**See Also**

[fabi](#), [fabias](#), [fabiap](#), [fabi](#), [fabiasp](#), [mfsc](#), [nmfdiv](#), [nmfeu](#), [nmfsc](#), [plot](#), [extractPlot](#), [extractBic](#), [plotBicluster](#), [Factorization](#), [projFuncPos](#), [projFunc](#), [estimateMode](#), [makeFabiData](#), [makeFabiDataBlocks](#), [makeFabiDataPos](#), [makeFabiDataBlocksPos](#), [matrixImagePlot](#), [summary](#), [show](#), [showSelected](#), [fabiDemo](#), [fabiVersion](#)

**Examples**

```
#-----
# TEST
#-----

dat <- makeFabiDataBlocks(n = 100,l= 50,p = 3,f1 = 5,f2 = 5,
  of1 = 5,of2 = 10,sd_noise = 3.0,sd_z_noise = 0.2,mean_z = 2.0,
  sd_z = 1.0,sd_l_noise = 0.2,mean_l = 3.0,sd_l = 1.0)

X <- dat[[1]]
Y <- dat[[2]]

resEx <- fabi(X,3,0.1,20)

## Not run:
#-----
# DEMO1
#-----

dat <- makeFabiDataBlocks(n = 1000,l= 100,p = 10,f1 = 5,f2 = 5,
  of1 = 5,of2 = 10,sd_noise = 3.0,sd_z_noise = 0.2,mean_z = 2.0,
  sd_z = 1.0,sd_l_noise = 0.2,mean_l = 3.0,sd_l = 1.0)

X <- dat[[1]]
Y <- dat[[2]]

resToy <- fabi(X,13,0.1,200)

rToy <- extractPlot(resToy,ti="FABI",Y=Y)

#-----
# DEMO2
```

```

#-----
avail <- require(fabiaData)

if (!avail) {
  message("")
  message("")
  message("#####")
  message("Package 'fabiaData' is not available: please install.")
  message("#####")
} else {

data(Breast_A)

X <- as.matrix(XBreast)

resBreast <- fabia(X,5,0.1,200)

rBreast <- extractPlot(resBreast,ti="FABI Breast cancer(Veer)")

#sorting of predefined labels
CBreast
}

#-----
# DEMO3
#-----

avail <- require(fabiaData)

if (!avail) {
  message("")
  message("")
  message("#####")
  message("Package 'fabiaData' is not available: please install.")
  message("#####")
} else {

data(Multi_A)

X <- as.matrix(XMulti)

resMulti <- fabia(X,5,0.1,200)

rMulti <- extractPlot(resMulti,ti="FABI Multiple tissues(Su)")

#sorting of predefined labels
CMulti
}

#-----
# DEMO4
#-----

```

```

avail <- require(fabiaData)

if (!avail) {
  message("")
  message("")
  message("#####")
  message("Package 'fabiaData' is not available: please install.")
  message("#####")
} else {

data(DLBCL_B)

X <- as.matrix(XDLBCL)

resDLBCL <- fabi(X,5,0.1,200)

rDLBCL <- extractPlot(resDLBCL,ti="FABI Lymphoma (Rosenwald) ")

#sorting of predefined labels
CDLBCL
}

## End(Not run)

```

---

Factorization-class

*The Factorization Class*

---

### Description

Factorization is the class structure for results of matrix factorization. Especially it is designed for factor analysis used for biclustering.

The `summary` method shows information about biclusters. The `show` method plots information about biclusters. The `plot` method produces biplots of biclusters.

### Objects from the Class

Objects can be created by `fabia`, `fabias`, `fabiap`, `fabiasp`, `mfsc`, `nmfsc`, `nmfdiv`, and `nmfeu`.

### Slots

Objects of class `Factorization` have the following slots:

`parameters`: Saves parameters of the factorization method in a list: ("method", "number of cycles", "sparseness weight", "sparseness prior for loadings", "sparseness prior for factors", "number biclusters", "projection sparseness loadings", "projection sparseness factors", "initialization range", "are loadings rescaled after each iterations", "normalization = scaling of rows", "centering method of rows", "parameter for method").

**n:** number of rows, left dimension.  
**p1:** right dimension of left matrix.  
**p2:** left dimension of right matrix.  
**l:** number of columns, right dimension.  
**center:** vector of the centers.  
**scaleData:** vector of the scaling factors.  
**X:** centered and scaled data matrix  $n \times l$ .  
**L:** left matrix  $n \times p1$ .  
**Z:** right matrix  $p2 \times l$ .  
**M:** middle matrix  $p1 \times p2$ .  
**LZ:** matrix  $L \times M \times Z$ .  
**U:** noise matrix.  
**avini:** information of each bicluster, vector of length  $p2$ .  
**xavini:** information extracted from each sample, vector of length  $l$ .  
**ini:** information of each bicluster in each sample, matrix  $p2 \times l$ .  
**Psi:** noise variance per row, vector of length  $n$ .  
**lapla:** prior information for each sample, vector of length  $l$ .

### Details

This class contains the result of different matrix factorization methods. The methods may be generative or not.

Methods may be "singular value decomposition" (M contains singular values as well as avini, L and Z are orthonormal matrices), "independent component analysis" (Z contains the projection/sources, L is the mixing matrix, M is unity), "factor analysis" (Z contains factors, L the loadings, M is unity, U the noise, Psi the noise covariance, lapla is a variational parameter for non-Gaussian factors, avini and ini are the information the factors convey about the observations).

### Author(s)

Sepp Hochreiter

### See Also

[fabia](#), [fabias](#), [fabiap](#), [fabi](#), [fabiasp](#), [mfsc](#), [nmfdi](#), [nmfeu](#), [nmfsc](#), [plot](#), [extractPlot](#), [extractBic](#), [plotBicluster](#), [Factorization](#), [projFuncPos](#), [projFunc](#), [estimateMode](#), [makeFabiaData](#), [makeFabiaDataBlocks](#), [makeFabiaDataPos](#), [makeFabiaDataBlocksPos](#), [matrixImagePlot](#), [summary](#), [show](#), [showSelected](#), [fabiaDemo](#), [fabiaVersion](#)

---

 makeFabiaDataBlocksPos

*Generation of Bicluster Data with Bicluster Blocks*


---

## Description

makeFabiaDataBlocksPos: **R** implementation of makeFabiaDataBlocksPos.

## Usage

```
makeFabiaDataBlocksPos(n, l, p, f1, f2, of1, of2, sd_noise, sd_z_noise,
                        mean_z, sd_z, sd_l_noise, mean_l, sd_l)
```

## Arguments

|            |   |
|------------|---|
| n          | number of observations.   |
| l          | number of samples.  |
| p          | number of biclusters.   |
| f1         | nn/f1 max. additional samples are active in a bicluster.              |
| f2         | n/f2 max. additional observations that form a pattern in a bicluster. |
| of1        | minimal active samples in a bicluster.                                |
| of2        | minimal observations that form a pattern in a bicluster.              |
| sd_noise   | Gaussian zero mean noise std on data matrix.                          |
| sd_z_noise | Gaussian zero mean noise std for deactivated hidden factors.          |
| mean_z     | Gaussian mean for activated factors.                                  |
| sd_z       | Gaussian std for activated factors.                                   |
| sd_l_noise | Gaussian zero mean noise std if no observation patterns are present.  |
| mean_l     | Gaussian mean for observation patterns.                               |
| sd_l       | Gaussian std for observation patterns.                                |

## Details

Bicluster data is generated for visualization because the biclusters are now in block format. That means observations and samples that belong to a bicluster are consecutive. This allows visual inspection because the user can identify blocks and whether they have been found or reconstructed.

Essentially the data generation model is the sum of outer products of sparse vectors:

$$X = \sum_{i=1}^p \lambda_i z_i^T + U$$

where the number of summands  $p$  is the number of biclusters. The matrix factorization is

$$X = LZ + U$$

and noise free

$$Y = LZ$$

Here  $\lambda_i$  are from  $R^n$ ,  $z_i$  from  $R^l$ ,  $L$  from  $R^{n \times p}$ ,  $Z$  from  $R^{p \times l}$ , and  $X, U, Y$  from  $R^{n \times l}$ .

Sequentially  $L_i$  are generated using `n`, `f2`, `of2`, `sd_l_noise`, `mean_l`, `sd_l`. `of2` gives the minimal observations participating in a bicluster to which between 0 and  $n/f2$  observations are added, where the number is uniformly chosen. `sd_l_noise` gives the noise of observations not participating in the bicluster. `mean_l` and `sd_l` determines the Gaussian from which the values are drawn for the observations that participate in the bicluster. "POS": The sign of the mean is fixed.

Sequentially  $Z_i$  are generated using `l`, `f1`, `of1`, `sd_z_noise`, `mean_z`, `sd_z`. `of1` gives the minimal samples participating in a bicluster to which between 0 and  $l/f1$  samples are added, where the number is uniformly chosen. `sd_z_noise` gives the noise of samples not participating in the bicluster. `mean_z` and `sd_z` determines the Gaussian from which the values are drawn for the samples that participate in the bicluster.

$U$  is the overall Gaussian zero mean noise generated by `sd_noise`.

Implementation in R.

### Value

|    |   |
|----|---|
| Y  | the noise data from $R^{n \times l}$ .                                  |
| X  | the noise free data from $R^{n \times l}$ .                             |
| ZC | list where i-th element gives samples belonging to i-th bicluster.      |
| LC | list where i-th element gives observations belonging to i-th bicluster. |

### Author(s)

Sepp Hochreiter

### See Also

[fabia](#), [fabias](#), [fabiap](#), [fabi](#), [fabiasp](#), [mfsc](#), [nmfdiiv](#), [nmfeu](#), [nmfsc](#), [plot](#), [extractPlot](#), [extractBic](#), [plotBicluster](#), [Factorization](#), [projFuncPos](#), [projFunc](#), [estimateMode](#), [makeFabiaData](#), [makeFabiaDataBlocks](#), [makeFabiaDataPos](#), [makeFabiaDataBlocksPos](#), [matrixImagePlot](#), [summary](#), [show](#), [showSelected](#), [fabiaDemo](#), [fabiaVersion](#)

### Examples

```
#-----
# TEST
#-----

dat <- makeFabiaDataBlocksPos(n = 100, l = 50, p = 3, f1 = 5, f2 = 5,
  of1 = 5, of2 = 10, sd_noise = 3.0, sd_z_noise = 0.2, mean_z = 2.0,
  sd_z = 1.0, sd_l_noise = 0.2, mean_l = 3.0, sd_l = 1.0)

X <- dat[[1]]
Y <- dat[[2]]

matrixImagePlot(Y)
x11()
matrixImagePlot(X)
```

```

## Not run:
#-----
# DEMO
#-----

dat <- makeFabiaDataBlocksPos(n = 1000,l= 100,p = 10,f1 = 5,f2 = 5,
  of1 = 5,of2 = 10,sd_noise = 3.0,sd_z_noise = 0.2,mean_z = 2.0,
  sd_z = 1.0,sd_l_noise = 0.2,mean_l = 3.0,sd_l = 1.0)

Y <- dat[[1]]
X <- dat[[2]]

matrixImagePlot(Y)
x11()
matrixImagePlot(X)

## End(Not run)

```

---

```
makeFabiaDataBlocks
```

*Generation of Bicluster Data with Bicluster Blocks*

---

## Description

makeFabiaDataBlocks: **R** implementation of makeFabiaDataBlocks.

## Usage

```
makeFabiaDataBlocks(n, l, p, f1, f2, of1, of2, sd_noise, sd_z_noise,
  mean_z, sd_z, sd_l_noise, mean_l, sd_l)
```

## Arguments

|            |   |
|------------|---|
| n          | number of observations.   |
| l          | number of samples.  |
| p          | number of biclusters.   |
| f1         | nn/f1 max. additional samples are active in a bicluster.              |
| f2         | n/f2 max. additional observations that form a pattern in a bicluster. |
| of1        | minimal active samples in a bicluster.                                |
| of2        | minimal observations that form a pattern in a bicluster.              |
| sd_noise   | Gaussian zero mean noise std on data matrix.                          |
| sd_z_noise | Gaussian zero mean noise std for deactivated hidden factors.          |
| mean_z     | Gaussian mean for activated factors.                                  |
| sd_z       | Gaussian std for activated factors.                                   |

|            |  |
|------------|--|
| sd_l_noise | Gaussian zero mean noise std if no observation patterns are present. |
| mean_l     | Gaussian mean for observation patterns.                              |
| sd_l       | Gaussian std for observation patterns.                               |

### Details

Bicluster data is generated for visualization because the biclusters are now in block format. That means observations and samples that belong to a bicluster are consecutive. This allows visual inspection because the user can identify blocks and whether they have been found or reconstructed. Essentially the data generation model is the sum of outer products of sparse vectors:

$$X = \sum_{i=1}^p \lambda_i z_i^T + U$$

where the number of summands  $p$  is the number of biclusters. The matrix factorization is

$$X = LZ + U$$

and noise free

$$Y = LZ$$

Here  $\lambda_i$  are from  $R^n$ ,  $z_i$  from  $R^l$ ,  $L$  from  $R^{n \times p}$ ,  $Z$  from  $R^{p \times l}$ , and  $X, U, Y$  from  $R^{n \times l}$ .

Sequentially  $L_i$  are generated using `n`, `f2`, `of2`, `sd_l_noise`, `mean_l`, `sd_l`. `of2` gives the minimal observations participating in a bicluster to which between 0 and  $n/f2$  observations are added, where the number is uniformly chosen. `sd_l_noise` gives the noise of observations not participating in the bicluster. `mean_l` and `sd_l` determines the Gaussian from which the values are drawn for the observations that participate in the bicluster. The sign of the mean is randomly chosen for each component.

Sequentially  $Z_i$  are generated using `l`, `f1`, `of1`, `sd_z_noise`, `mean_z`, `sd_z`. `of1` gives the minimal samples participating in a bicluster to which between 0 and  $l/f1$  samples are added, where the number is uniformly chosen. `sd_z_noise` gives the noise of samples not participating in the bicluster. `mean_z` and `sd_z` determines the Gaussian from which the values are drawn for the samples that participate in the bicluster.

$U$  is the overall Gaussian zero mean noise generated by `sd_noise`.

Implementation in R.

### Value

|    |   |
|----|---|
| Y  | the noise data from $R^{n \times l}$ .                                  |
| X  | the noise free data from $R^{n \times l}$ .                             |
| ZC | list where i-th element gives samples belonging to i-th bicluster.      |
| LC | list where i-th element gives observations belonging to i-th bicluster. |

### Author(s)

Sepp Hochreiter

### See Also

[fabia](#), [fabias](#), [fabiap](#), [fabi](#), [fabiasp](#), [mfsc](#), [nmfdiv](#), [nmfeu](#), [nmfsc](#), [plot](#), [extractPlot](#), [extractBic](#), [plotBicluster](#), [Factorization](#), [projFuncPos](#), [projFunc](#), [estimateMode](#), [makeFabiaData](#), [makeFabiaDataBlocks](#), [makeFabiaDataPos](#), [makeFabiaDataBlocksPos](#), [matrixImagePlot](#), [summary](#), [show](#), [showSelected](#), [fabiaDemo](#), [fabiaVersion](#)



**Examples**

```

#-----
# TEST
#-----

dat <- makeFabiaDataBlocks(n = 100,l= 50,p = 3,f1 = 5,f2 = 5,
  of1 = 5,of2 = 10,sd_noise = 3.0,sd_z_noise = 0.2,mean_z = 2.0,
  sd_z = 1.0,sd_l_noise = 0.2,mean_l = 3.0,sd_l = 1.0)

X <- dat[[1]]
Y <- dat[[2]]

matrixImagePlot(Y)
x11()
matrixImagePlot(X)

## Not run:
#-----
# DEMO
#-----

dat <- makeFabiaDataBlocks(n = 1000,l= 100,p = 10,f1 = 5,f2 = 5,
  of1 = 5,of2 = 10,sd_noise = 3.0,sd_z_noise = 0.2,mean_z = 2.0,
  sd_z = 1.0,sd_l_noise = 0.2,mean_l = 3.0,sd_l = 1.0)

Y <- dat[[1]]
X <- dat[[2]]

matrixImagePlot(Y)
x11()
matrixImagePlot(X)

## End(Not run)

```

---

makeFabiaDataPos     *Generation of Bicluster Data*

---

**Description**

makeFabiaDataPos: **R** implementation of makeFabiaDataPos.

**Usage**

```

makeFabiaDataPos(n,l,p,f1,f2,of1,of2,sd_noise,sd_z_noise,
  mean_z,sd_z,sd_l_noise,mean_l,sd_l)

```

**Arguments**

|            |   |
|------------|---|
| n          | number of observations.   |
| l          | number of samples.  |
| p          | number of biclusters.   |
| f1         | nn/f1 max. additional samples are active in a bicluster.              |
| f2         | n/f2 max. additional observations that form a pattern in a bicluster. |
| of1        | minimal active samples in a bicluster.                                |
| of2        | minimal observations that form a pattern in a bicluster.              |
| sd_noise   | Gaussian zero mean noise std on data matrix.                          |
| sd_z_noise | Gaussian zero mean noise std for deactivated hidden factors.          |
| mean_z     | Gaussian mean for activated factors.                                  |
| sd_z       | Gaussian std for activated factors.                                   |
| sd_l_noise | Gaussian zero mean noise std if no observation patterns are present.  |
| mean_l     | Gaussian mean for observation patterns.                               |
| sd_l       | Gaussian std for observation patterns.                                |

**Details**

Essentially the data generation model is the sum of outer products of sparse vectors:

$$X = \sum_{i=1}^p \lambda_i z_i^T + U$$

where the number of summands  $p$  is the number of biclusters. The matrix factorization is

$$X = LZ + U$$

and noise free

$$Y = LZ$$

Here  $\lambda_i$  are from  $R^n$ ,  $z_i$  from  $R^l$ ,  $L$  from  $R^{n \times p}$ ,  $Z$  from  $R^{p \times l}$ , and  $X, U, Y$  from  $R^{n \times l}$ .

Sequentially  $L_i$  are generated using n, f2, of2, sd\_l\_noise, mean\_l, sd\_l. of2 gives the minimal observations participating in a bicluster to which between 0 and  $n/f2$  observations are added, where the number is uniformly chosen. sd\_l\_noise gives the noise of observations not participating in the bicluster. mean\_l and sd\_l determines the Gaussian from which the values are drawn for the observations that participate in the bicluster. "POS": The sign of the mean is fixed.

Sequentially  $Z_i$  are generated using l, f1, of1, sd\_z\_noise, mean\_z, sd\_z. of1 gives the minimal samples participating in a bicluster to which between 0 and  $l/f1$  samples are added, where the number is uniformly chosen. sd\_z\_noise gives the noise of samples not participating in the bicluster. mean\_z and sd\_z determines the Gaussian from which the values are drawn for the samples that participate in the bicluster.

$U$  is the overall Gaussian zero mean noise generated by sd\_noise.

Implementation in R.

**Value**

|    |   |
|----|---|
| X  | the noise data from $R^{n \times l}$ .                                  |
| Y  | the noise free data from $R^{n \times l}$ .                             |
| ZC | list where i-th element gives samples belonging to i-th bicluster.      |
| LC | list where i-th element gives observations belonging to i-th bicluster. |

**Author(s)**

Sepp Hochreiter

**See Also**

fabia, fabias, fabiap, fabi, fabiasp, mfsc, nmfdi, nmfeu, nmfsc, plot, extractPlot, extractBic, plotBicluster, Factorization, projFuncPos, projFunc, estimateMode, makeFabiaData, makeFabiaDataBlocks, makeFabiaDataPos, makeFabiaDataBlocksPos, matrixImagePlot, summary, show, showSelected, fabiaDemo, fabiaVersion

**Examples**

```
#-----
# TEST
#-----

dat <- makeFabiaDataPos(n = 100, l = 50, p = 3, f1 = 5, f2 = 5,
  of1 = 5, of2 = 10, sd_noise = 3.0, sd_z_noise = 0.2, mean_z = 2.0,
  sd_z = 1.0, sd_l_noise = 0.2, mean_l = 3.0, sd_l = 1.0)

X <- dat[[1]]
Y <- dat[[2]]

matrixImagePlot(Y)
x11()
matrixImagePlot(X)

## Not run:
#-----
# DEMO
#-----

dat <- makeFabiaDataPos(n = 1000, l = 100, p = 10, f1 = 5, f2 = 5,
  of1 = 5, of2 = 10, sd_noise = 3.0, sd_z_noise = 0.2, mean_z = 2.0,
  sd_z = 1.0, sd_l_noise = 0.2, mean_l = 3.0, sd_l = 1.0)

X <- dat[[1]]
Y <- dat[[2]]

matrixImagePlot(Y)
x11()
matrixImagePlot(X)

## End(Not run)
```

**Description**

makeFabiaData: R implementation of makeFabiaData.

**Usage**

```
makeFabiaData(n, l, p, f1, f2, of1, of2, sd_noise, sd_z_noise,
              mean_z, sd_z, sd_l_noise, mean_l, sd_l)
```

**Arguments**

|            |   |
|------------|---|
| n          | number of observations.   |
| l          | number of samples.  |
| p          | number of biclusters.   |
| f1         | nn/f1 max. additional samples are active in a bicluster.              |
| f2         | n/f2 max. additional observations that form a pattern in a bicluster. |
| of1        | minimal active samples in a bicluster.                                |
| of2        | minimal observations that form a pattern in a bicluster.              |
| sd_noise   | Gaussian zero mean noise std on data matrix.                          |
| sd_z_noise | Gaussian zero mean noise std for deactivated hidden factors.          |
| mean_z     | Gaussian mean for activated factors.                                  |
| sd_z       | Gaussian std for activated factors.                                   |
| sd_l_noise | Gaussian zero mean noise std if no observation patterns are present.  |
| mean_l     | Gaussian mean for observation patterns.                               |
| sd_l       | Gaussian std for observation patterns.                                |

**Details**

Essentially the data generation model is the sum of outer products of sparse vectors:

$$X = \sum_{i=1}^p \lambda_i z_i^T + U$$

where the number of summands  $p$  is the number of biclusters. The matrix factorization is

$$X = LZ + U$$

and noise free

$$Y = LZ$$

Here  $\lambda_i$  are from  $R^n$ ,  $z_i$  from  $R^l$ ,  $L$  from  $R^{n \times p}$ ,  $Z$  from  $R^{p \times l}$ , and  $X, U, Y$  from  $R^{n \times l}$ .

Sequentially  $L_i$  are generated using n, f2, of2, sd\_l\_noise, mean\_l, sd\_l. of2 gives the minimal observations participating in a bicluster to which between 0 and n/f2 observations are added, where the number is uniformly chosen. sd\_l\_noise gives the noise of observations not participating in the bicluster. mean\_l and sd\_l determines the Gaussian from which the values are drawn for the observations that participate in the bicluster. The sign of the mean is randomly chosen for each component.

Sequentially  $Z_i$  are generated using  $l, f1, of1, sd\_z\_noise, mean\_z, sd\_z$ .  $of1$  gives the minimal samples participating in a bicluster to which between 0 and  $l/f1$  samples are added, where the number is uniformly chosen.  $sd\_z\_noise$  gives the noise of samples not participating in the bicluster.  $mean\_z$  and  $sd\_z$  determines the Gaussian from which the values are drawn for the samples that participate in the bicluster.

$U$  is the overall Gaussian zero mean noise generated by  $sd\_noise$ .

Implementation in R.

### Value

|    |   |
|----|---|
| X  | the noise data from $R^{n \times l}$ .                                  |
| Y  | the noise free data from $R^{n \times l}$ .                             |
| ZC | list where i-th element gives samples belonging to i-th bicluster.      |
| LC | list where i-th element gives observations belonging to i-th bicluster. |

### Author(s)

Sepp Hochreiter

### See Also

[fabia](#), [fabias](#), [fabiap](#), [fabi](#), [fabiasp](#), [mfsc](#), [nmfdiv](#), [nmfeu](#), [nmfsc](#), [plot](#), [extractPlot](#), [extractBic](#), [plotBicluster](#), [Factorization](#), [projFuncPos](#), [projFunc](#), [estimateMode](#), [makeFabiaData](#), [makeFabiaDataBlocks](#), [makeFabiaDataPos](#), [makeFabiaDataBlocksPos](#), [matrixImagePlot](#), [summary](#), [show](#), [showSelected](#), [fabiaDemo](#), [fabiaVersion](#)

### Examples

```
#-----
# TEST
#-----

dat <- makeFabiaData(n = 100, l = 50, p = 3, f1 = 5, f2 = 5,
  of1 = 5, of2 = 10, sd_noise = 3.0, sd_z_noise = 0.2, mean_z = 2.0,
  sd_z = 1.0, sd_l_noise = 0.2, mean_l = 3.0, sd_l = 1.0)

X <- dat[[1]]
Y <- dat[[2]]

matrixImagePlot(Y)
x11()
matrixImagePlot(X)

## Not run:
#-----
# DEMO
#-----

dat <- makeFabiaData(n = 1000, l = 100, p = 10, f1 = 5, f2 = 5,
  of1 = 5, of2 = 10, sd_noise = 3.0, sd_z_noise = 0.2, mean_z = 2.0,
  sd_z = 1.0, sd_l_noise = 0.2, mean_l = 3.0, sd_l = 1.0)
```

```

X <- dat[[1]]
Y <- dat[[2]]

matrixImagePlot(Y)
x11()
matrixImagePlot(X)

## End(Not run)

```

---

matrixImagePlot      *Plotting of a Matrix*

---

### Description

matrixImagePlot: R implementation of myImagePlot.

### Usage

```
matrixImagePlot(x, xLabels=NULL, yLabels=NULL, zlim=NULL, title=NULL)
```

### Arguments

|         |  |
|---------|--|
| x       | the matrix.  |
| xLabels | vector of strings to label the columns (default "colnames(x)").    |
| yLabels | vector of strings to label the rows (default "rownames(x)").       |
| zlim    | vector containing a low and high value to use for the color scale. |
| title   | title of the plot.   |

### Details

Plotting a table of numbers as an image using R.

The color scale is based on the highest and lowest values in the matrix.

The original R code has been obtained by <http://www.phaget4.org/R/myImagePlot.R> and then has been modified.

### References

<http://www.phaget4.org/R/myImagePlot.R>

### See Also

[fabia](#), [fabias](#), [fabiap](#), [fabi](#), [fabiasp](#), [mfsc](#), [nmfdiv](#), [nmfeu](#), [nmfsc](#), [plot](#), [extractPlot](#), [extractBic](#), [plotBiclust](#), [Factorization](#), [projFuncPos](#), [projFunc](#), [estimateMode](#), [makeFabiaData](#), [makeFabiaDataBlocks](#), [makeFabiaDataPos](#), [makeFabiaDataBlocksPos](#), [matrixImagePlot](#), [summary](#), [show](#), [showSelected](#), [fabiaDemo](#), [fabiaVersion](#)

**Examples**

```

#-----
# TEST
#-----

dat <- makeFabiaDataBlocks(n = 100,l= 50,p = 3,f1 = 5,f2 = 5,
  of1 = 5,of2 = 10,sd_noise = 3.0,sd_z_noise = 0.2,mean_z = 2.0,
  sd_z = 1.0,sd_l_noise = 0.2,mean_l = 3.0,sd_l = 1.0)

X <- dat[[1]]
Y <- dat[[2]]

matrixImagePlot(Y)
x11()
matrixImagePlot(X)

## Not run:
#-----
# DEMO
#-----

dat <- makeFabiaDataBlocks(n = 1000,l= 100,p = 10,f1 = 5,f2 = 5,
  of1 = 5,of2 = 10,sd_noise = 3.0,sd_z_noise = 0.2,mean_z = 2.0,
  sd_z = 1.0,sd_l_noise = 0.2,mean_l = 3.0,sd_l = 1.0)

X <- dat[[1]]
Y <- dat[[2]]
X <- X- rowMeans(X)
XX <- (1/ncol(X))*tcrossprod(X)
dXX <- 1/sqrt(diag(XX)+0.001*as.vector(rep(1,nrow(X))))
X <- dXX*X

matrixImagePlot(X)

## End(Not run)

```

mfsc

*Sparse Matrix Factorization for Bicluster Analysis (MFSC)***Description**

mfsc: R implementation of mfsc.

**Usage**

mfsc(X,p=5,cyc=100,sL=0.6,sZ=0.6,center=2,norm=1)

**Arguments**

|        |  |
|--------|--|
| X      | the data matrix.   |
| p      | number of hidden factors = number of biclusters; default = 5.                |
| cyc    | maximal number of iterations; default = 100.                                 |
| sL     | final sparseness loadings; default = 0.6.                                    |
| sZ     | final sparseness factors; default = 0.6.                                     |
| center | data centering: 1 (mean), 2 (median), > 2 (mode), 0 (no); default = 2.       |
| norm   | data normalization: 1 (0.75-0.25 quantile), >1 (var=1), 0 (no); default = 1. |

**Details**

Biclusters are found by sparse matrix factorization where *both* factors are sparse.

Essentially the model is the sum of outer products of vectors:

$$X = \sum_{i=1}^p \lambda_i z_i^T$$

where the number of summands  $p$  is the number of biclusters. The matrix factorization is

$$X = LZ$$

Here  $\lambda_i$  are from  $R^n$ ,  $z_i$  from  $R^l$ ,  $L$  from  $R^{n \times p}$ ,  $Z$  from  $R^{p \times l}$ , and  $X$  from  $R^{n \times l}$ .

**No noise assumption:** In contrast to factor analysis there is no noise assumption.

If the nonzero components of the sparse vectors are grouped together then the outer product results in a matrix with a nonzero block and zeros elsewhere.

The model selection is performed by a constraint optimization according to Hoyer, 2004. The Euclidean distance (the Frobenius norm) is minimized subject to sparseness constraints.

Model selection is done by gradient descent on the Euclidean objective and thereafter projection of single vectors of  $L$  and single vectors of  $Z$  to fulfill the sparseness constraints.

The projection minimize the Euclidean distance to the original vector given an  $l_1$ -norm and an  $l_2$ -norm.

The projection is a convex quadratic problem which is solved iteratively where at each iteration at least one component is set to zero. Instead of the  $l_1$ -norm a sparseness measurement is used which relates the  $l_1$ -norm to the  $l_2$ -norm.

The code is implemented in R.

**Value**

object of the class `Factorization`. Containing LZ (estimated noise free data LZ), L (loadings L), Z (factors Z), U (noise  $X - LZ$ ), center (centering vector), scaleData (scaling vector), X (centered and scaled data X)

**Author(s)**

Sepp Hochreiter



## References

S. Hochreiter et al., 'FABIA: Factor Analysis for Bicluster Acquisition', *Bioinformatics* 26(12):1520-1527, 2010. <http://bioinformatics.oxfordjournals.org/cgi/content/abstract/btq227>

Patrik O. Hoyer, 'Non-negative Matrix Factorization with Sparseness Constraints', *Journal of Machine Learning Research* 5:1457-1469, 2004.

## See Also

[fabia](#), [fabias](#), [fabiap](#), [fabi](#), [fabiasp](#), [mfsc](#), [nmfdiv](#), [nmfeu](#), [nmfsc](#), [plot](#), [extractPlot](#), [extractBic](#), [plotBicluster](#), [Factorization](#), [projFuncPos](#), [projFunc](#), [estimateMode](#), [makeFabiaData](#), [makeFabiaDataBlocks](#), [makeFabiaDataPos](#), [makeFabiaDataBlocksPos](#), [matrixImagePlot](#), [summary](#), [show](#), [showSelected](#), [fabiaDemo](#), [fabiaVersion](#)

## Examples

```
#-----
# TEST
#-----

dat <- makeFabiaDataBlocks(n = 100,l= 50,p = 3,f1 = 5,f2 = 5,
  of1 = 5,of2 = 10,sd_noise = 3.0,sd_z_noise = 0.2,mean_z = 2.0,
  sd_z = 1.0,sd_l_noise = 0.2,mean_l = 3.0,sd_l = 1.0)

X <- dat[[1]]
Y <- dat[[2]]

resEx <- mfsc(X,3,30,0.6,0.6)

## Not run:

#-----
# DEMO1: Toy Data
#-----

n = 1000
l= 100
p = 10

dat <- makeFabiaDataBlocks(n = n,l= l,p = p,f1 = 5,f2 = 5,
  of1 = 5,of2 = 10,sd_noise = 3.0,sd_z_noise = 0.2,mean_z = 2.0,
  sd_z = 1.0,sd_l_noise = 0.2,mean_l = 3.0,sd_l = 1.0)

X <- dat[[1]]
Y <- dat[[2]]
ZC <- dat[[3]]
LC <- dat[[4]]

gclab <- rep.int(0,l)
gllab <- rep.int(0,n)
clab <- as.character(1:l)
llab <- as.character(1:n)
for (i in 1:p){
  for (j in ZC[i]){
```

```

      clab[j] <- paste(as.character(i), "_", clab[j], sep="")
    }
    for (j in LC[i]){
      llab[j] <- paste(as.character(i), "_", llab[j], sep="")
    }
    gclab[unlist(ZC[i])] <- gclab[unlist(ZC[i])] + p^i
    gllab[unlist(LC[i])] <- gllab[unlist(LC[i])] + p^i
  }

groups <- gclab

#### MFSC

resToy4 <- mfsc(X,13,100,0.6,0.6)

rToy4 <- extractPlot(resToy4,ti="MFSC",Y=Y)

raToy4 <- extractBic(resToy4,thresZ=0.01,thresL=0.05)

if ((raToy4$bic[[1]][1]>1) && (raToy4$bic[[1]][2]>1) {
  plotBicluster(raToy4,1)
}
if ((raToy4$bic[[2]][1]>1) && (raToy4$bic[[2]][2]>1) {
  plotBicluster(raToy4,2)
}
if ((raToy4$bic[[3]][1]>1) && (raToy4$bic[[3]][2]>1) {
  plotBicluster(raToy4,3)
}
if ((raToy4$bic[[4]][1]>1) && (raToy4$bic[[4]][2]>1) {
  plotBicluster(raToy4,4)
}

colnames(resToy4@X) <- clab

rownames(resToy4@X) <- llab

plot(resToy4,dim=c(1,2),label.tol=0.1,col.group = groups,lab.size=0.6)
plot(resToy4,dim=c(1,3),label.tol=0.1,col.group = groups,lab.size=0.6)
plot(resToy4,dim=c(2,3),label.tol=0.1,col.group = groups,lab.size=0.6)

#-----
# DEMO2: Laura van't Veer's gene expression
#       data set for breast cancer
#-----

avail <- require(fabiaData)

if (!avail) {
  message("")
  message("")
  message("#####")
  message("Package 'fabiaData' is not available: please install.")
  message("#####")
} else {

```

```

data(Breast_A)

X <- as.matrix(XBreast)

resBreast4 <- mfsc(X,5,100,0.6,0.6)

rBreast4 <- extractPlot(resBreast4,ti="MFSC Breast cancer(Veer)")

raBreast4 <- extractBic(resBreast4,thresZ=0.01,thresL=0.05)

if ((raBreast4$bic[[1]][1]>1) && (raBreast4$bic[[1]][2]>1) {
  plotBicluster(raBreast4,1)
}
if ((raBreast4$bic[[2]][1]>1) && (raBreast4$bic[[2]][2]>1) {
  plotBicluster(raBreast4,2)
}
if ((raBreast4$bic[[3]][1]>1) && (raBreast4$bic[[3]][2]>1) {
  plotBicluster(raBreast4,3)
}
if ((raBreast4$bic[[4]][1]>1) && (raBreast4$bic[[4]][2]>1) {
  plotBicluster(raBreast4,4)
}

plot(resBreast4,dim=c(1,2),label.tol=0.03,col.group=CBreast,lab.size=0.6)
plot(resBreast4,dim=c(1,3),label.tol=0.03,col.group=CBreast,lab.size=0.6)
plot(resBreast4,dim=c(1,4),label.tol=0.03,col.group=CBreast,lab.size=0.6)
plot(resBreast4,dim=c(1,5),label.tol=0.03,col.group=CBreast,lab.size=0.6)
plot(resBreast4,dim=c(2,3),label.tol=0.03,col.group=CBreast,lab.size=0.6)
plot(resBreast4,dim=c(2,4),label.tol=0.03,col.group=CBreast,lab.size=0.6)
plot(resBreast4,dim=c(2,5),label.tol=0.03,col.group=CBreast,lab.size=0.6)
plot(resBreast4,dim=c(3,4),label.tol=0.03,col.group=CBreast,lab.size=0.6)
plot(resBreast4,dim=c(3,5),label.tol=0.03,col.group=CBreast,lab.size=0.6)
plot(resBreast4,dim=c(4,5),label.tol=0.03,col.group=CBreast,lab.size=0.6)

}

#-----
# DEMO3: Su's multiple tissue types
#       gene expression data set
#-----

avail <- require(fabiaData)

if (!avail) {
  message("")
  message("")
  message("#####")
  message("Package 'fabiaData' is not available: please install.")
  message("#####")
} else {

data(Multi_A)

```

```

X <- as.matrix(XMulti)

resMulti4 <- mfsc(X,5,100,0.6,0.6)

rMulti4 <- extractPlot(resMulti4,ti="MFSC Multiple tissues (Su)")

raMulti4 <- extractBic(resMulti4,thresZ=0.01,thresL=0.05)

if ((raMulti4$bic[[1]][1]>1) && (raMulti4$bic[[1]][2]>1) {
  plotBicluster(raMulti4,1)
}
if ((raMulti4$bic[[2]][1]>1) && (raMulti4$bic[[2]][2]>1) {
  plotBicluster(raMulti4,2)
}
if ((raMulti4$bic[[3]][1]>1) && (raMulti4$bic[[3]][2]>1) {
  plotBicluster(raMulti4,3)
}
if ((raMulti4$bic[[4]][1]>1) && (raMulti4$bic[[4]][2]>1) {
  plotBicluster(raMulti4,4)
}

plot(resMulti4,dim=c(1,2),label.tol=0.01,col.group=CMulti,lab.size=0.6)
plot(resMulti4,dim=c(1,3),label.tol=0.01,col.group=CMulti,lab.size=0.6)
plot(resMulti4,dim=c(1,4),label.tol=0.01,col.group=CMulti,lab.size=0.6)
plot(resMulti4,dim=c(1,5),label.tol=0.01,col.group=CMulti,lab.size=0.6)
plot(resMulti4,dim=c(2,3),label.tol=0.01,col.group=CMulti,lab.size=0.6)
plot(resMulti4,dim=c(2,4),label.tol=0.01,col.group=CMulti,lab.size=0.6)
plot(resMulti4,dim=c(2,5),label.tol=0.01,col.group=CMulti,lab.size=0.6)
plot(resMulti4,dim=c(3,4),label.tol=0.01,col.group=CMulti,lab.size=0.6)
plot(resMulti4,dim=c(3,5),label.tol=0.01,col.group=CMulti,lab.size=0.6)
plot(resMulti4,dim=c(4,5),label.tol=0.01,col.group=CMulti,lab.size=0.6)

}

#-----
# DEMO4: Rosenwald's diffuse large-B-cell
#       lymphoma gene expression data set
#-----

avail <- require(fabiaData)

if (!avail) {
  message("")
  message("")
  message("#####")
  message("Package 'fabiaData' is not available: please install.")
  message("#####")
} else {

data(DLBCL_B)

X <- as.matrix(XDLBCL)

```

```

resDLBCL4 <- mfsc(X,5,100,0.6,0.6)

rDLBCL4 <- extractPlot(resDLBCL4,ti="MFSC Lymphoma (Rosenwald)")

raDLBCL4 <- extractBic(resDLBCL4,thresZ=0.01,thresL=0.05)

if ((raDLBCL4$bic[[1]][1]>1) && (raDLBCL4$bic[[1]][2]>1) {
  plotBicluster(raDLBCL4,1)
}
if ((raDLBCL4$bic[[2]][1]>1) && (raDLBCL4$bic[[2]][2]>1) {
  plotBicluster(raDLBCL4,2)
}
if ((raDLBCL4$bic[[3]][1]>1) && (raDLBCL4$bic[[3]][2]>1) {
  plotBicluster(raDLBCL4,3)
}
if ((raDLBCL4$bic[[4]][1]>1) && (raDLBCL4$bic[[4]][2]>1) {
  plotBicluster(raDLBCL4,4)
}

plot(resDLBCL4,dim=c(1,2),label.tol=0.03,col.group=CDLBCL,lab.size=0.6)
plot(resDLBCL4,dim=c(1,3),label.tol=0.03,col.group=CDLBCL,lab.size=0.6)
plot(resDLBCL4,dim=c(1,4),label.tol=0.03,col.group=CDLBCL,lab.size=0.6)
plot(resDLBCL4,dim=c(1,5),label.tol=0.03,col.group=CDLBCL,lab.size=0.6)
plot(resDLBCL4,dim=c(2,3),label.tol=0.03,col.group=CDLBCL,lab.size=0.6)
plot(resDLBCL4,dim=c(2,4),label.tol=0.03,col.group=CDLBCL,lab.size=0.6)
plot(resDLBCL4,dim=c(2,5),label.tol=0.03,col.group=CDLBCL,lab.size=0.6)
plot(resDLBCL4,dim=c(3,4),label.tol=0.03,col.group=CDLBCL,lab.size=0.6)
plot(resDLBCL4,dim=c(3,5),label.tol=0.03,col.group=CDLBCL,lab.size=0.6)
plot(resDLBCL4,dim=c(4,5),label.tol=0.03,col.group=CDLBCL,lab.size=0.6)

}

## End(Not run)

```

---

nmfdiv

*Non-negative Matrix Factorization: Kullback-Leibler Divergence*


---

## Description

nmfdiv: R implementation of nmfdiv.

## Usage

```
nmfdiv(X,p=5,cyc=100)
```

**Arguments**

|                  |   |
|------------------|---|
| <code>X</code>   | the data matrix.  |
| <code>p</code>   | number of hidden factors = number of biclusters; default = 5. |
| <code>cyc</code> | maximal number of iterations; default = 100.                  |

**Details**

Non-negative Matrix Factorization represents positive matrix  $X$  by positive matrices  $L$  and  $Z$ .

Objective for reconstruction is Kullback-Leibler divergence.

Essentially the model is the sum of outer products of vectors:

$$X = \sum_{i=1}^p \lambda_i z_i^T$$

where the number of summands  $p$  is the number of biclusters. The matrix factorization is

$$X = LZ$$

Here  $\lambda_i$  are from  $R^n$ ,  $z_i$  from  $R^l$ ,  $L$  from  $R^{n \times p}$ ,  $Z$  from  $R^{p \times l}$ , and  $X$  from  $R^{n \times l}$ .

The model selection is performed according to D. D. Lee and H. S. Seung, 1999, 2001.

The code is implemented in R.

**Value**

object of the class `Factorization`. Containing `LZ` (estimated noise free data  $LZ$ ), `L` (loading  $L$ ), `Z` (factors  $Z$ ), `U` (noise  $X - LZ$ ), `X` (scaled data  $X$ ).

**Author(s)**

Sepp Hochreiter

**References**

D. D. Lee and H. S. Seung, 'Algorithms for non-negative matrix factorization', In Advances in Neural Information Processing Systems 13, 556-562, 2001.

D. D. Lee and H. S. Seung, 'Learning the parts of objects by non-negative matrix factorization', Nature, 401(6755):788-791, 1999.

**See Also**

[fabia](#), [fabias](#), [fabiap](#), [fabi](#), [fabiasp](#), [mfsc](#), [nmfdiv](#), [nmfeu](#), [nmfsc](#), [plot](#), [extractPlot](#), [extractBic](#), [plotBiccluster](#), [Factorization](#), [projFuncPos](#), [projFunc](#), [estimateMode](#), [makeFabiaData](#), [makeFabiaDataBlocks](#), [makeFabiaDataPos](#), [makeFabiaDataBlocksPos](#), [matrixImagePlot](#), [summary](#), [show](#), [showSelected](#), [fabiaDemo](#), [fabiaVersion](#)

**Examples**

```

#-----
# TEST
#-----

dat <- makeFabiaDataBlocks(n = 100,l= 50,p = 3,f1 = 5,f2 = 5,
  of1 = 5,of2 = 10,sd_noise = 3.0,sd_z_noise = 0.2,mean_z = 2.0,
  sd_z = 1.0,sd_l_noise = 0.2,mean_l = 3.0,sd_l = 1.0)

X <- dat[[1]]
Y <- dat[[2]]
X <- abs(X)

resEx <- nmfddiv(X,3)

## Not run:
#-----
# DEMO
#-----

dat <- makeFabiaDataBlocks(n = 1000,l= 100,p = 10,f1 = 5,f2 = 5,
  of1 = 5,of2 = 10,sd_noise = 3.0,sd_z_noise = 0.2,mean_z = 2.0,
  sd_z = 1.0,sd_l_noise = 0.2,mean_l = 3.0,sd_l = 1.0)

X <- dat[[1]]
Y <- dat[[2]]
X <- abs(X)

resToy <- nmfddiv(X,13)

rToy <- extractPlot(resToy,ti="NMFDIV",Y=Y)

## End(Not run)

```

---

nmfeu

*Non-negative Matrix Factorization: Euclidean Distance*


---

**Description**

nmfeu: R implementation of nmfeu.

**Usage**

```
nmfeu(X, p=5, cyc=100)
```

**Arguments**

|                  |   |
|------------------|---|
| <code>X</code>   | the data matrix.  |
| <code>p</code>   | number of hidden factors = number of biclusters; default = 5. |
| <code>cyc</code> | maximal number of iterations; default = 100.                  |

**Details**

Non-negative Matrix Factorization represents positive matrix  $X$  by positive matrices  $L$  and  $Z$ .

Objective for reconstruction is Euclidean distance.

Essentially the model is the sum of outer products of vectors:

$$X = \sum_{i=1}^p \lambda_i z_i^T$$

where the number of summands  $p$  is the number of biclusters. The matrix factorization is

$$X = LZ$$

Here  $\lambda_i$  are from  $R^n$ ,  $z_i$  from  $R^l$ ,  $L$  from  $R^{n \times p}$ ,  $Z$  from  $R^{p \times l}$ , and  $X$  from  $R^{n \times l}$ .

The model selection is performed according to D. D. Lee and H. S. Seung, 2001.

The code is implemented in R.

**Value**

object of the class `Factorization`. Containing `LZ` (estimated noise free data  $LZ$ ), `L` (loadings  $L$ ), `Z` (factors  $Z$ ), `U` (noise  $X - LZ$ ), `X` (scaled data  $X$ ).

**Author(s)**

Sepp Hochreiter

**References**

Paatero, P and Tapper, U, 'Least squares formulation of robust non-negative factor analysis', *Chemometr. Intell. Lab. 37*: 23-35, 1997.

D. D. Lee and H. S. Seung, 'Algorithms for non-negative matrix factorization', In *Advances in Neural Information Processing Systems 13*, 556-562, 2001.

**See Also**

[fabia](#), [fabias](#), [fabiap](#), [fabi](#), [fabiasp](#), [mfsc](#), [nmfdiv](#), [nmfeu](#), [nmfsc](#), [plot](#), [extractPlot](#), [extractBic](#), [plotBiccluster](#), [Factorization](#), [projFuncPos](#), [projFunc](#), [estimateMode](#), [makeFabiaData](#), [makeFabiaDataBlocks](#), [makeFabiaDataPos](#), [makeFabiaDataBlocksPos](#), [matrixImagePlot](#), [summary](#), [show](#), [showSelected](#), [fabiaDemo](#), [fabiaVersion](#)



**Examples**

```

#-----
# TEST
#-----

dat <- makeFabiaDataBlocks(n = 100,l= 50,p = 3,f1 = 5,f2 = 5,
  of1 = 5,of2 = 10,sd_noise = 3.0,sd_z_noise = 0.2,mean_z = 2.0,
  sd_z = 1.0,sd_l_noise = 0.2,mean_l = 3.0,sd_l = 1.0)

X <- dat[[1]]
Y <- dat[[2]]
X <- abs(X)

resEx <- nmfeu(X,3)

## Not run:
#-----
# DEMO
#-----

dat <- makeFabiaDataBlocks(n = 1000,l= 100,p = 10,f1 = 5,f2 = 5,
  of1 = 5,of2 = 10,sd_noise = 3.0,sd_z_noise = 0.2,mean_z = 2.0,
  sd_z = 1.0,sd_l_noise = 0.2,mean_l = 3.0,sd_l = 1.0)

X <- dat[[1]]
Y <- dat[[2]]
X <- abs(X)

resToy <- nmfeu(X,13)

rToy <- extractPlot(resToy,ti="NMFEU",Y=Y)

## End(Not run)

```

nmfsc

*Non-negative Sparse Matrix Factorization***Description**

nmfsc: R implementation of nmfsc.

**Usage**

```
nmfsc(X, p=5, cyc=100, sL=0.6, sZ=0.6)
```

**Arguments**

|                  |   |
|------------------|---|
| <code>X</code>   | the data matrix.  |
| <code>p</code>   | number of hidden factors = number of biclusters; default = 5. |
| <code>cyc</code> | maximal number of iterations; default = 100.                  |
| <code>sL</code>  | sparseness loadings; default = 0.6.                           |
| <code>sZ</code>  | sparseness factors; default = 0.6.                            |

**Details**

Non-negative Matrix Factorization represents positive matrix  $X$  by positive matrices  $L$  and  $Z$  that are sparse.

Objective for reconstruction is Euclidean distance and sparseness constraints.

Essentially the model is the sum of outer products of vectors:

$$X = \sum_{i=1}^p \lambda_i z_i^T$$

where the number of summands  $p$  is the number of biclusters. The matrix factorization is

$$X = LZ$$

Here  $\lambda_i$  are from  $R^n$ ,  $z_i$  from  $R^l$ ,  $L$  from  $R^{n \times p}$ ,  $Z$  from  $R^{p \times l}$ , and  $X$  from  $R^{n \times l}$ .

If the nonzero components of the sparse vectors are grouped together then the outer product results in a matrix with a nonzero block and zeros elsewhere.

The model selection is performed by a constraint optimization according to Hoyer, 2004. The Euclidean distance (the Frobenius norm) is minimized subject to sparseness and non-negativity constraints.

Model selection is done by gradient descent on the Euclidean objective and thereafter projection of single vectors of  $L$  and single vectors of  $Z$  to fulfill the sparseness and non-negativity constraints.

The projection minimize the Euclidean distance to the original vector given an  $l_1$ -norm and an  $l_2$ -norm and enforcing non-negativity.

The projection is a convex quadratic problem which is solved iteratively where at each iteration at least one component is set to zero. Instead of the  $l_1$ -norm a sparseness measurement is used which relates the  $l_1$ -norm to the  $l_2$ -norm.

The code is implemented in R.

**Value**

object of the class `Factorization`. Containing `LZ` (estimated noise free data  $LZ$ ), `L` (loadings  $L$ ), `Z` (factors  $Z$ ), `U` (noise  $X - LZ$ ), `X` (data  $X$ ).

**Author(s)**

Sepp Hochreiter

**References**

Patrik O. Hoyer, 'Non-negative Matrix Factorization with Sparseness Constraints', *Journal of Machine Learning Research* 5:1457-1469, 2004.

D. D. Lee and H. S. Seung, 'Algorithms for non-negative matrix factorization', In *Advances in Neural Information Processing Systems* 13, 556-562, 2001.

**See Also**

[fabia](#), [fabias](#), [fabiap](#), [fabi](#), [fabiasp](#), [mfsc](#), [nmfdiv](#), [nmfeu](#), [nmfsc](#), [plot](#), [extractPlot](#), [extractBic](#), [plotBicluster](#), [Factorization](#), [projFuncPos](#), [projFunc](#), [estimateMode](#), [makeFabiaData](#), [makeFabiaDataBlocks](#), [makeFabiaDataPos](#), [makeFabiaDataBlocksPos](#), [matrixImagePlot](#), [summary](#), [show](#), [showSelected](#), [fabiaDemo](#), [fabiaVersion](#)

**Examples**

```
#-----
# TEST
#-----

dat <- makeFabiaDataBlocks(n = 100,l= 50,p = 3,f1 = 5,f2 = 5,
  of1 = 5,of2 = 10,sd_noise = 3.0,sd_z_noise = 0.2,mean_z = 2.0,
  sd_z = 1.0,sd_l_noise = 0.2,mean_l = 3.0,sd_l = 1.0)

X <- dat[[1]]
Y <- dat[[2]]
X <- abs(X)

resEx <- nmfsc(X,3,30,0.6,0.6)

## Not run:
#-----
# DEMO
#-----

dat <- makeFabiaDataBlocks(n = 1000,l= 100,p = 10,f1 = 5,f2 = 5,
  of1 = 5,of2 = 10,sd_noise = 3.0,sd_z_noise = 0.2,mean_z = 2.0,
  sd_z = 1.0,sd_l_noise = 0.2,mean_l = 3.0,sd_l = 1.0)

X <- dat[[1]]
Y <- dat[[2]]
X <- abs(X)

resToy <- nmfsc(X,13,100,0.6,0.6)

rToy <- extractPlot(resToy,ti="NMFSC",Y=Y)

## End(Not run)
```

---

plotBicluster

*Plotting of a bicluster*


---

**Description**

plotBicluster: R implementation of plotBicluster.

**Usage**

```
plotBicluster(r, p, opp=FALSE, zlim=NULL, title=NULL, which=c(1, 2))
```

**Arguments**

|       |  |
|-------|--|
| r     | the result of extract_bic.   |
| p     | the bicluster to plot.   |
| opp   | plot opposite bicluster, default = FALSE.  |
| zlim  | vector containing a low and high value to use for the color scale.   |
| title | title of the plot.   |
| which | which plots are shown: 1=data matrix with bicluster on upper left, 2=plot of the bicluster; default c(1, 2). |

**Details**

One bicluster is visualized by two plots. The variable "which" indicates which plots should be shown.

Plot1 (which=1): The data matrix is sorted such that the bicluster appear at the upper left corner. The bicluster is marked by a rectangle.

Plot2 (which=2): Only the bicluster is plotted.

Implementation in R.

**Author(s)**

Sepp Hochreiter

**See Also**

[fabia](#), [fabias](#), [fabiap](#), [fabi](#), [fabiasp](#), [mfsc](#), [nmfdi](#), [nmfeu](#), [nmfsc](#), [plot](#), [extractPlot](#), [extractBic](#), [plotBicluster](#), [Factorization](#), [projFuncPos](#), [projFunc](#), [estimateMode](#), [makeFabiaData](#), [makeFabiaDataBlocks](#), [makeFabiaDataPos](#), [makeFabiaDataBlocksPos](#), [matrixImagePlot](#), [summary](#), [show](#), [showSelected](#), [fabiaDemo](#), [fabiaVersion](#)

**Examples**

```
#-----
# TEST
#-----

dat <- makeFabiaDataBlocks(n = 100, l = 50, p = 3, f1 = 5, f2 = 5,
  of1 = 5, of2 = 10, sd_noise = 3.0, sd_z_noise = 0.2, mean_z = 2.0,
  sd_z = 1.0, sd_l_noise = 0.2, mean_l = 3.0, sd_l = 1.0)

X <- dat[[1]]
Y <- dat[[2]]
```

```

resEx <- fabia(X,3,0.1,20)

rEx <- extractBic(resEx)

plotBicluster(rEx,p=1)

## Not run:
#-----
# DEMO1
#-----

dat <- makeFabiaDataBlocks(n = 1000,l= 100,p = 10,f1 = 5,f2 = 5,
  of1 = 5,of2 = 10,sd_noise = 3.0,sd_z_noise = 0.2,mean_z = 2.0,
  sd_z = 1.0,sd_l_noise = 0.2,mean_l = 3.0,sd_l = 1.0)

X <- dat[[1]]
Y <- dat[[2]]

resToy <- fabia(X,13,0.1,200)

rToy <- extractBic(resToy)

plotBicluster(rToy,p=1)

#-----
# DEMO2
#-----

avail <- require(fabiaData)

if (!avail) {
  message("")
  message("")
  message("#####")
  message("Package 'fabiaData' is not available: please install.")
  message("#####")
} else {

data(Breast_A)

X <- as.matrix(XBreast)

resBreast <- fabia(X,5,0.1,200)

rBreast <- extractBic(resBreast)

plotBicluster(rBreast,p=1)

}

## End(Not run)

```

**Description**

Produces a (biplot) of a Matrix Factorization result

**Usage**

```
## S4 method for signature 'Factorization,missing':
plot(x, Rm=NULL, Cm=NULL, dim = c(1, 2),
     zoom = rep(1, 2), col.group = NULL,
     colors = c("orange1", "red", rainbow(length(unique(col.group))),
               start=2/6, end=4/6)),
     col.areas = TRUE, col.symbols = c(1, rep(2, length(unique(col.group)))),
     sampleNames = TRUE, rot = rep(-1, length(dim)),
     labels = NULL, label.tol = 0.1, lab.size = 0.725, col.size = 10,
     row.size = 10, do.smoothScatter = FALSE,
     do.plot = TRUE, ... )
```

**Arguments**

|                          |   |
|--------------------------|---|
| <code>x</code>           | object of the class <code>Factorization</code> .  |
| <code>Rm</code>          | row weighting vector. If <code>NULL</code> , it defaults to <code>rep(1, nrow(x@L))</code> .  |
| <code>Cm</code>          | column weighting vector. If <code>NULL</code> , it defaults to <code>rep(1, ncol(x@Z))</code> .   |
| <code>dim</code>         | optional principal factors that are plotted along the horizontal and vertical axis. Defaults to <code>c(1, 2)</code> .  |
| <code>zoom</code>        | optional zoom factor for row and column items. Defaults to <code>c(1, 1)</code> .   |
| <code>col.group</code>   | optional vector (character or numeric) indicating the different groupings of the columns. Defaults to 1.  |
| <code>colors</code>      | vector specifying the colors for the annotation of the plot; the first two elements concern the rows; the third till the last element concern the columns; the first element will be used to color the unlabeled rows; the second element for the labeled rows and the remaining elements to give different colors to different groups of columns. Defaults to <code>c("orange1", "red", rainbow(length(unique(col.group))), start=2/6, end=4/6)</code> . |
| <code>col.areas</code>   | logical value indicating whether columns should be plotted as squares with areas proportional to their marginal mean and colors representing the different groups ( <code>TRUE</code> ), or with symbols representing the groupings and identical size ( <code>FALSE</code> ). Defaults to <code>TRUE</code> .  |
| <code>col.symbols</code> | vector of symbols when <code>col.areas=FALSE</code> corresponds to the <code>pch</code> argument of the function <code>plot</code> . Defaults to <code>c(1, rep(2, length(unique(col.group))))</code> .   |
| <code>sampleNames</code> | either a logical vector of length one or a character vector of length equal to the number of samples in the dataset. If a logical is provided, sample names will be displayed on the plot ( <code>TRUE</code> ; default) or not ( <code>FALSE</code> ); if a character vector is provided, the names provided will be used to label the samples instead of the default column names.  |
| <code>rot</code>         | rotation of plot. Defaults to <code>c(-1, -1)</code> .  |

|                  |   |
|------------------|---|
| labels           | character vector to be used for labeling points on the graph; if NULL (default), the row names of <code>x</code> are used instead.  |
| label.tol        | numerical value specifying either the percentile ( <code>label.tol &lt;= 1</code> ) of rows or the number of rows ( <code>label.tol &gt; 1</code> ) most distant from the plot-center (0,0) that are labeled and are plotted as circles with area proportional to the marginal means of the original data. Defaults to 1. |
| lab.size         | size of identifying labels for row- and column-items as <code>cex</code> parameter of the <code>text</code> function. Defaults to 0.725.  |
| col.size         | size of the column symbols in mm. Defaults to 10.   |
| row.size         | size of the row symbols in mm. Defaults to 10.  |
| do.smoothScatter | use <code>smoothScatter</code> or not instead of plotting individual points. Defaults to FALSE.   |
| do.plot          | produce a plot or not. Defaults to TRUE.  |
| ...              | further arguments are passed on to <code>eqscaleplotLoc</code> which draws the canvas for the plot; useful for adding a <code>main</code> or a custom <code>sub</code> .  |

### Details

The function `plot` is based on the function `plot.mpm` in the R package `mpm` (Version: 1.0-16, Date: 2009-08-26, Title: Multivariate Projection Methods, Maintainer: Tobias Verbeke <tobias.verbeke@openanalytics.be>, Author: Luc Wouters <wouters\_luc@telenet.be>).

Biclusters are found by sparse factor analysis where *both* the factors and the loadings are sparse.

Essentially the model is the sum of outer products of vectors:

$$X = \sum_{i=1}^p \lambda_i z_i^T + U$$

where the number of summands  $p$  is the number of biclusters. The matrix factorization is

$$X = LZ + U$$

Here  $\lambda_i$  are from  $R^n$ ,  $z_i$  from  $R^l$ ,  $L$  from  $R^{n \times p}$ ,  $Z$  from  $R^{p \times l}$ , and  $X, U$  from  $R^{n \times l}$ .

For noise free projection like independent component analysis we set the noise term to zero:  $U = 0$ .

The argument `label.tol` can be used to select the most informative rows, i.e. rows that are most distant from the center of the plot (smaller 1: percentage of rows, larger 1: number of rows).

Only these row-items are then labeled and represented as circles with their areas proportional to the row weighting.

If the column-items are grouped these groups can be visualized by colors given by `col.group`.

### Value

|         |   |
|---------|---|
| Rows    | a list with the X and Y coordinates of the rows and an indication <code>Select</code> of whether the row was selected according to <code>label.tol</code> . |
| Columns | a list with the X and Y coordinates of the columns.   |

### Methods

`signature(x = "Factorization", y = "missing")` Plot of a Matrix Factorization

**Author(s)**

Sepp Hochreiter

**See Also**

[fabia](#), [fabias](#), [fabiap](#), [fabi](#), [fabiasp](#), [mfsc](#), [nmfdiv](#), [nmfeu](#), [nmfsc](#), [plot](#), [extractPlot](#), [extractBic](#), [plotBicluster](#), [Factorization](#), [projFuncPos](#), [projFunc](#), [estimateMode](#), [makeFabiaData](#), [makeFabiaDataBlocks](#), [makeFabiaDataPos](#), [makeFabiaDataBlocksPos](#), [matrixImagePlot](#), [summary](#), [show](#), [showSelected](#), [fabiaDemo](#), [fabiaVersion](#)

**Examples**

```
n=200
l=100
p=4

dat <- makeFabiaDataBlocks(n = n, l= l, p = p, f1 = 5, f2 = 5,
  of1 = 5, of2 = 10, sd_noise = 3.0, sd_z_noise = 0.2, mean_z = 2.0,
  sd_z = 1.0, sd_l_noise = 0.2, mean_l = 3.0, sd_l = 1.0)

X <- dat[[1]]
ZC <- dat[[3]]
LC <- dat[[4]]

resEx <- fabia(X, p, 0.1, 400)

gclab <- rep.int(0, l)
gllab <- rep.int(0, n)
clab <- as.character(1:l)
llab <- as.character(1:n)
for (i in 1:p){
  for (j in ZC[i]){
    clab[j] <- paste(as.character(i), "_", clab[j], sep="")
  }
  for (j in LC[i]){
    llab[j] <- paste(as.character(i), "_", llab[j], sep="")
  }
  gclab[unlist(ZC[i])] <- gclab[unlist(ZC[i])] + p^i
  gllab[unlist(LC[i])] <- gllab[unlist(LC[i])] + p^i
}

groups <- gclab

colnames(resEx@X) <- clab

rownames(resEx@X) <- llab

plot(resEx, dim=c(1, 2), label.tol=0.1, col.group = groups, lab.size=0.6)
plot(resEx, dim=c(1, 3), label.tol=0.1, col.group = groups, lab.size=0.6)
plot(resEx, dim=c(2, 3), label.tol=0.1, col.group = groups, lab.size=0.6)
```



---

`projFuncPos`*Projection of a Vector to a Non-negative Sparse Vector*

---

**Description**

`projFuncPos`: R implementation of `projFuncPos`.

**Usage**

```
projFuncPos(s, k1, k2)
```

**Arguments**

|                 |                                    |
|-----------------|------------------------------------|
| <code>s</code>  | data vector.                       |
| <code>k1</code> | sparseness, $l_1$ norm constraint. |
| <code>k2</code> | $l_2$ norm constraint.             |

**Details**

The projection minimize the Euclidean distance to the original vector given an  $l_1$ -norm and an  $l_2$ -norm and enforcing non-negativity.

The projection is a convex quadratic problem which is solved iteratively where at each iteration at least one component is set to zero.

In the applications, instead of the  $l_1$ -norm a sparseness measurement is used which relates the  $l_1$ -norm to the  $l_2$ -norm:

Implementation in R.

**Value**

`v` non-negative sparse projected vector.

**Author(s)**

Sepp Hochreiter

**References**

Patrik O. Hoyer, 'Non-negative Matrix Factorization with Sparseness Constraints', Journal of Machine Learning Research 5:1457-1469, 2004.

**See Also**

[fabia](#), [fabias](#), [fabiap](#), [fabi](#), [fabiasp](#), [mfsc](#), [nmfdiv](#), [nmfeu](#), [nmfsc](#), [plot](#), [extractPlot](#), [extractBic](#), [plotBicluster](#), [Factorization](#), [projFuncPos](#), [projFunc](#), [estimateMode](#), [makeFabiaData](#), [makeFabiaDataBlocks](#), [makeFabiaDataPos](#), [makeFabiaDataBlocksPos](#), [matrixImagePlot](#), [summary](#), [show](#), [showSelected](#), [fabiaDemo](#), [fabiaVersion](#)

**Examples**

```

#-----
# DEMO
#-----

size <- 30
sparseness <- 0.7

s <- as.vector(rnorm(size))
sp <- sqrt(1.0*size)-(sqrt(1.0*size)-1.0)*sparseness

ss <- projFuncPos(s, k1=sp, k2=1)

s
ss

```

projFunc

*Projection of a Vector to a Sparse Vector***Description**

projFunc: R implementation of projFunc.

**Usage**

```
projFunc(s, k1, k2)
```

**Arguments**

|    |                                    |
|----|------------------------------------|
| s  | data vector.                       |
| k1 | sparseness, $l_1$ norm constraint. |
| k2 | $l_2$ norm constraint.             |

**Details**

The projection is done according to Hoyer, 2004: given an  $l_1$ -norm and an  $l_2$ -norm minimize the Euclidean distance to the original vector. The projection is a convex quadratic problem which is solved iteratively where at each iteration at least one component is set to zero.

In the applications, instead of the  $l_1$ -norm a sparseness measurement is used which relates the  $l_1$ -norm to the  $l_2$ -norm.

Implementation in R.

**Value**

|   |                          |
|---|--------------------------|
| v | sparse projected vector. |
|---|--------------------------|

**Author(s)**

Sepp Hochreiter

**References**

Patrik O. Hoyer, 'Non-negative Matrix Factorization with Sparseness Constraints', Journal of Machine Learning Research 5:1457-1469, 2004.

**See Also**

[fabia](#), [fabias](#), [fabiap](#), [fabi](#), [fabiasp](#), [mfsc](#), [nmfdi](#), [nmfeu](#), [nmfsc](#), [plot](#), [extractPlot](#), [extractBic](#), [plotBicluster](#), [Factorization](#), [projFuncPos](#), [projFunc](#), [estimateMode](#), [makeFabiaData](#), [makeFabiaDataBlocks](#), [makeFabiaDataPos](#), [makeFabiaDataBlocksPos](#), [matrixImagePlot](#), [summary](#), [show](#), [showSelected](#), [fabiaDemo](#), [fabiaVersion](#)

**Examples**

```
#-----
# DEMO
#-----

size <- 30
sparseness <- 0.7

s <- as.vector(rnorm(size))
sp <- sqrt(1.0*size)-(sqrt(1.0*size)-1.0)*sparseness

ss <- projFunc(s,k1=sp,k2=1)

s
ss
```

---

show-methods

*Plot Statistics of a Matrix Factorization*

---

**Description**

This function plots statistics on a matrix factorization which is stored as an instance of [Factorization-class](#).

**Usage**

```
## S4 method for signature 'Factorization':
show(object)
```

**Arguments**

`object` An instance of [Factorization-class](#).

## Details

The following is plotted:

1. the information content of biclusters.
2. the information content of samples.
3. the loadings per bicluster.
4. the factors per bicluster.

## Value

no value.

## Methods

`signature(object = "Factorization")` Display Statistics of a Matrix Factorization

## Author(s)

Sepp Hochreiter

## See Also

[fabia](#), [fabias](#), [fabiap](#), [fabi](#), [fabiasp](#), [mfsc](#), [nmfdiv](#), [nmfeu](#), [nmfsc](#), [plot](#), [extractPlot](#), [extractBic](#), [plotBicluster](#), [Factorization](#), [projFuncPos](#), [projFunc](#), [estimateMode](#), [makeFabiaData](#), [makeFabiaDataBlocks](#), [makeFabiaDataPos](#), [makeFabiaDataBlocksPos](#), [matrixImagePlot](#), [summary](#), [show](#), [showSelected](#), [fabiaDemo](#), [fabiaVersion](#)

## Examples

```
#-----  
# TEST  
#-----  
  
dat <- makeFabiaDataBlocks(n = 100, l = 50, p = 3, f1 = 5, f2 = 5,  
  of1 = 5, of2 = 10, sd_noise = 3.0, sd_z_noise = 0.2, mean_z = 2.0,  
  sd_z = 1.0, sd_l_noise = 0.2, mean_l = 3.0, sd_l = 1.0)  
  
X <- dat[[1]]  
  
resEx <- fabia(X, 3, 0.1, 100)  
  
show(resEx)
```

---

```
showSelected-methods
```

*Plot Selected Statistics of a Matrix Factorization*

---

### Description

This function plots selected statistics on a matrix factorization which is stored as an instance of `Factorization-class`.

### Usage

```
## S4 method for signature 'Factorization':
showSelected(object, which=c(1,2,3,4))
```

### Arguments

|                     |  |
|---------------------|--|
| <code>object</code> | An instance of <code>Factorization-class</code> .  |
| <code>which</code>  | used to provide a list of which plots should be generated: 1=the information content of biclusters, 2=the information content of samples, 3=the loadings per bicluster, 4=the factors per bicluster, default <code>c(1,2,3,4)</code> . |

### Details

The following is plotted depending on the display selection variable `which`:

1. the information content of biclusters.
2. the information content of samples.
3. the loadings per bicluster.
4. the factors per bicluster.

### Value

no value.

### Methods

```
signature(object="Factorization") Display Statistics of a Matrix Factorization
```

### Author(s)

Sepp Hochreiter

### See Also

`fabia`, `fabias`, `fabiap`, `fabi`, `fabiasp`, `mfsc`, `nmfdiv`, `nmfeu`, `nmfsc`, `plot`, `extractPlot`, `extractBic`, `plotBicluster`, `Factorization`, `projFuncPos`, `projFunc`, `estimateMode`, `makeFabiaData`, `makeFabiaDataBlocks`, `makeFabiaDataPos`, `makeFabiaDataBlocksPos`, `matrixImagePlot`, `summary`, `show`, `showSelected`, `fabiaDemo`, `fabiaVersion`

**Examples**

```

#-----
# TEST
#-----

dat <- makeFabiaDataBlocks(n = 100,l= 50,p = 3,f1 = 5,f2 = 5,
  of1 = 5,of2 = 10,sd_noise = 3.0,sd_z_noise = 0.2,mean_z = 2.0,
  sd_z = 1.0,sd_l_noise = 0.2,mean_l = 3.0,sd_l = 1.0)

X <- dat[[1]]

resEx <- fabia(X,3,0.1,100)

showSelected(resEx,which=1)
showSelected(resEx,which=2)

```

---

summary-methods      *Summary of Matrix Factorization*

---

**Description**

This function gives information on a matrix factorization which is stored as an instance of `Factorization-class`.

**Usage**

```
## S4 method for signature 'Factorization':
summary(object, ...)
```

**Arguments**

`object`            An instance of `Factorization-class` .  
`...`                further arguments.

**Details**

First, it gives the number of rows and columns of the original matrix.

Then the number of clusters for rows and columns is given.

Then for the row cluster the information content is given.

Then for each column its information is given.

Then for each column cluster a summary is given.

Then for each row cluster a summary is given.

**Value**

no value.

**Methods**

```
signature(object = "Factorization") Summary of Matrix Factorization
```

**Author(s)**

Sepp Hochreiter

**See Also**

[fabia](#), [fabias](#), [fabiap](#), [fabi](#), [fabiasp](#), [mfsc](#), [nmfdiv](#), [nmfeu](#), [nmfsc](#), [plot](#), [extractPlot](#), [extractBic](#), [plotBicluster](#), [Factorization](#), [projFuncPos](#), [projFunc](#), [estimateMode](#), [makeFabiaData](#), [makeFabiaDataBlocks](#), [makeFabiaDataPos](#), [makeFabiaDataBlocksPos](#), [matrixImagePlot](#), [summary](#), [show](#), [showSelected](#), [fabiaDemo](#), [fabiaVersion](#)

**Examples**

```
#-----  
# TEST  
#-----  
  
dat <- makeFabiaDataBlocks(n = 100, l = 50, p = 3, f1 = 5, f2 = 5,  
  of1 = 5, of2 = 10, sd_noise = 3.0, sd_z_noise = 0.2, mean_z = 2.0,  
  sd_z = 1.0, sd_l_noise = 0.2, mean_l = 3.0, sd_l = 1.0)  
  
X <- dat[[1]]  
  
resEx <- fabia(X, 3, 0.1, 100)  
  
summary(resEx)
```

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