

# Package ‘fabMix’

September 29, 2017

**Type** Package

**Title** Overfitting Bayesian Mixtures of Factor Analyzers with an Unknown Number of Components

**Version** 2.0

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## Description

Model-based clustering of multivariate continuous data with or without missing values. The underlying model is a Bayesian mixture of factor analyzers with a large number of components (overfitting mixture). Suitable prior assumptions ensure that asymptotically the extra components will have zero posterior weight (empty), therefore, the inference on the number of clusters is based on the “alive” components. The number of factors is considered fixed, and the optimal one can be estimated using information criteria. Identifiability issues related to label switching are dealt by post-processing the simulated output with the ECR algorithm.

**Imports** MASS, doParallel, foreach, label.switching, mvtnorm

**License** GPL-2

**NeedsCompilation** no

## R topics documented:

fabMix-package . . . . .	2
complete.log.likelihood . . . . .	4
complete.log.likelihood_Sj . . . . .	4
compute_A_B_G_D_and_simulate_mu_Lambda . . . . .	5
compute_A_B_G_D_and_simulate_mu_Lambda_Sj . . . . .	6
compute_sufficient_statistics . . . . .	7
dealWithLabelSwitching . . . . .	7
fabMix . . . . .	8
fabMix_missing_values . . . . .	10
getStuffForDIC . . . . .	12
log_dirichlet_pdf . . . . .	14
myDirichlet . . . . .	14

observed.log.likelihood0 . . . . .	15
observed.log.likelihood0_Sj . . . . .	15
overfittingMFA . . . . .	16
overfittingMFA_missing_values . . . . .	17
overfittingMFA_Sj . . . . .	18
overfittingMFA_Sj_missing_values . . . . .	19
simData . . . . .	20
update_all_y . . . . .	21
update_all_y_Sj . . . . .	22
update_OmegaINV . . . . .	22
update_SigmaINV_faster . . . . .	23
update_SigmaINV_faster_Sj . . . . .	24
update_z2 . . . . .	24
update_z2_Sj . . . . .	25
update_z4 . . . . .	26
update_z4_Sj . . . . .	26
update_z_b . . . . .	27
update_z_b_Sj . . . . .	28
waveDataset1500 . . . . .	28

## Index 30

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fabMix-package	<i>Overfitting Bayesian Mixtures of Factor Analyzers with an Unknown Number of Components</i>
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## Description

Model-based clustering of multivariate continuous data with or without missing values. The underlying model is a Bayesian mixture of factor analyzers with a large number of components (overfitting mixture). Suitable prior assumptions ensure that asymptotically the extra components will have zero posterior weight (empty), therefore, the inference on the number of clusters is based on the “alive” components. The number of factors is considered fixed, and the optimal one can be estimated using information criteria. Identifiability issues related to label switching are dealt by post-processing the simulated output with the ECR algorithm.

## Author(s)

Panagiotis Papastamoulis

Maintainer: Panagiotis Papastamoulis <papapast@yahoo.gr>

## References

- Fokoue, E. and Titterington, D.M. (2003). Mixtures of Factor Analysers: Bayesian Estimation and Inference by Stochastic Simulation. *Machine Learning*, 50(1): 73-94.
- Papastamoulis P. and Iliopoulos G. (2010). An artificial allocations based solution to the label switching problem in Bayesian analysis of mixtures of distributions. *Journal of Computational and Graphical Statistics*, 19: 313-331.

van Havre, Z., White, N., Rousseau, J. and Mengersen, K. (2015). Overfitting Bayesian Mixture Models with an Unknown Number of Components. PLOS ONE, 10(7): 1-27.

Papastamoulis, P. (2016). label.switching: An R Package for Dealing with the Label Switching Problem in MCMC Outputs. Journal of Statistical Software, 69(1), 1-24.

Papastamoulis, P. (2017). Overfitting Bayesian mixtures of factor analyzers with an unknown number of components. arXiv:1701.04605 [stat.ME]

## See Also

[fabMix](#), [dealWithLabelSwitching](#), [getStuffForDIC](#)

## Examples

```
# simulate a synthetic dataset along the lines of the paper:
n = 1000                # sample size
p = 40                  # number of variables
q = 4                   # number of factors
K = 10                  # number of clusters
sINV_diag = 1/((1:p)) # diagonal of inverse variance of errors
set.seed(10)
syntheticDataset <- simData(K.true = K, n = n, q = q, p = p, sINV_values = sINV_diag )

## Not run:

# define parameters
Kmax <- 20    # number of overfitted mixture components
nChains <- 8  # number of parallel chains
dN <- 1
# Dirichlet prior of mixture weights per chain.
# The target chain corresponds to the first entry.
dirPriorAlphas <- c(1, 1 + dN * (2:nChains - 1))/Kmax
outputFolder <- "fabMixExample"
# Run algorithm
fabMix( dirPriorAlphas = dirPriorAlphas,
        rawData = syntheticDataset$data,
        outDir = outputFolder, Kmax = Kmax, mCycles = 1200,
        burnCycles = 200, q = q)

# Compute information criteria:
getStuffForDIC(x_data = syntheticDataset$data, outputFolder = outputFolder, q = q)

# Deal with label switching:
dealWithLabelSwitching(x_data = syntheticDataset$data,
                      outputFolder = outputFolder, q = q,
                      compute_regularized_expression = TRUE, Km = Kmax)

## End(Not run)
```

---

`complete.log.likelihood`*Complete log-likelihood function*

---

**Description**

Complete log-likelihood function

**Usage**

```
complete.log.likelihood(x_data, w, mu, Lambda, SigmaINV, z)
```

**Arguments**

x_data	Data
w	Mixture weights
mu	Marginal means
Lambda	Factor loadings
SigmaINV	Precision matrix (inverse covariance)
z	Allocation vector of the data to the mixture components

**Value**

complete log-likelihood value

**Author(s)**

Panagiotis Papastamoulis

---

`complete.log.likelihood_Sj`*Complete log-likelihood function*

---

**Description**

Complete log-likelihood function

**Usage**

```
complete.log.likelihood_Sj(x_data, w, mu, Lambda, SigmaINV, z)
```

**Arguments**

x_data	Data
w	Mixture weights
mu	Marginal means
Lambda	Factor loadings
SigmaINV	Precision matrix (inverse covariance) per component
z	Allocation vector of the data to the mixture components

**Value**

complete log-likelihood value

**Author(s)**

Panagiotis Papastamoulis

---

compute\_A\_B\_G\_D\_and\_simulate\_mu\_Lambda  
*Computation and simulations*

---

**Description**

This function simulates  $\mu$  and  $\Lambda$ .

**Usage**

```
compute_A_B_G_D_and_simulate_mu_Lambda(SigmaINV,
suff_statistics, OmegaINV, K, priorConst1, T_INV, v_r)
```

**Arguments**

SigmaINV	Precision matrix $\Sigma^{-1}$
suff_statistics	Sufficient statistics
OmegaINV	Prior parameter: $\Omega^{-1}$
K	Number of overfitting mixture components
priorConst1	Prior constant: $T^{-1}\xi$
T_INV	Prior parameter: $T^{-1}\xi$
v_r	This vector is used to set to zero the upper right $(q-1) \times (q-1)$ diagonal block of factor loadings for identifiability purposes.

**Value**

A list containing  $A$ ,  $B$ ,  $\Gamma$ ,  $\Delta$  and a draw from the conditional distributions of  $\mu$  and  $\Lambda$ .

**Author(s)**

Panagiotis Papastamoulis

---

compute\_A\_B\_G\_D\_and\_simulate\_mu\_Lambda\_Sj  
*Computation and simulations*

---

**Description**

This function simulates  $\mu$  and  $\Lambda$ .

**Usage**

```
compute_A_B_G_D_and_simulate_mu_Lambda_Sj(SigmaINV,
suff_statistics, OmegaINV, K, priorConst1, T_INV, v_r)
```

**Arguments**

SigmaINV	Precision matrix $\Sigma^{-1}$ per component
suff_statistics	Sufficient statistics
OmegaINV	Prior parameter: $\Omega^{-1}$
K	Number of overfitting mixture components
priorConst1	Prior constant: $T^{-1}\xi$
T_INV	Prior parameter: $T^{-1}\xi$
v_r	This vector is used to set to zero the upper right $(q-1) \times (q-1)$ diagonal block of factor loadings for identifiability purposes.

**Value**

A list containing  $A$ ,  $B$ ,  $\Gamma$ ,  $\Delta$  and a draw from the conditional distributions of  $\mu$  and  $\Lambda$ .

**Author(s)**

Panagiotis Papastamoulis

---

compute\_sufficient\_statistics  
*Compute sufficient statistics*

---

### Description

Compute sufficient statistics given  $y$  and  $z$ .

### Usage

```
compute_sufficient_statistics(y, z, K, x_data)
```

### Arguments

$y$	Matrix of factors
$z$	Allocation vector
$K$	Number of components
$x\_data$	Data

### Value

A list with six entries of sufficient statistics.

### Author(s)

Panagiotis Papastamoulis

---

dealWithLabelSwitching  
*Apply label switching algorithms*

---

### Description

This functions is a wrapper for the `label.switching` package and applies the ECR and ECR.ITERATIVE.1 algorithms. The model may have the same variance of error terms per cluster or not.

### Usage

```
dealWithLabelSwitching(sameSigma, x_data, outputFolder, q, burn,  
z.true, compute_regularized_expression, Km)
```

**Arguments**

sameSigma	Logical value indicating whether the parameterization with the same error variance per cluster is used.
x_data	Data
outputFolder	Name of the folder where the fabMix function has saved its output
q	Number of factors
burn	Discard observations as burn-in period (optional).
z.true	An (optional) vector of cluster assignments which is considered as the ground-truth clustering of the data. Useful for direct comparisons against the real parameter values in simulated data.
compute_regularized_expression	Logical. Should regularized expression be computed?
Km	Number of components in the overfitted mixture model.

**Value**

The following files are produced in the output folder:

**Author(s)**

Panagiotis Papastamoulis

**References**

Papastamoulis, P. (2016). `label.switching`: An R Package for Dealing with the Label Switching Problem in MCMC Outputs. *Journal of Statistical Software*, 69(1), 1-24.

---

fabMix	<i>Main function of the package</i>
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---

**Description**

This function runs parallel chains under a prior tempering scheme of the Dirichlet prior distribution of mixture weights.

**Usage**

```
fabMix(sameSigma, dirPriorAlphas, rawData, outDir, Kmax, mCycles,
burnCycles, g, h, alpha_sigma, beta_sigma, q, normalize,
thinning, zStart, nIterPerCycle, gibbs_z)
```



**Arguments**

sameSigma	Logical value denoting the parameterization of the error variance per component. If TRUE, the parameterization $\Sigma_1 = \dots = \Sigma_K$ is fitted.
dirPriorAlphas	The prior Dirichlet parameters for each chain.
rawData	The observed data as an $n \times p$ matrix. Clustering is performed on the rows of the matrix.
outDir	Name of the output folder.
Kmax	Number of components in the overfitted mixture. Default: 20.
mCycles	Number of MCMC cycles. Each cycle consists of nIterPerCycle MCMC iterations. At the end of each cycle a swap of the state of two randomly chosen adjacent chains is attempted.
burnCycles	Number of cycles that will be discarded as burn-in period.
g	Prior parameter $g$ . Default value: $g = 2$ .
h	Prior parameter $h$ . Default value: $h = 1$ .
alpha_sigma	Prior parameter $\alpha$ . Default value: $\alpha = 2$ .
beta_sigma	Prior parameter $\beta$ . Default value: $\beta = 1$ .
q	Number of factors $q$ , where $1 \leq q \leq L$ . An error is thrown if the Ledermann bound ( $L$ ) is exceeded.
normalize	Should the observed data be normalized? Default value: TRUE.
thinning	Optional integer denoting the thinning of the kept MCMC cycles.
zStart	Optional starting value for the allocation vector.
nIterPerCycle	Number of iteration per MCMC cycle. Default value: 10.
gibbs_z	Select the gibbs sampling scheme for updating latent allocations of mixture model. Default value: 1.

**Value**

List of files written to outDir

**Note**

It is recommended to always use: `normalize = TRUE` (default). Tuning of `dirPriorAlphas` may be necessary to achieve reasonable acceptance rates of chain swaps. Also note that the output is not identifiable due to label switching and the user has to subsequently call the `dealWithLabelSwitching` function.

**Author(s)**

Panagiotis Papastamoulis

**References**

Papastamoulis, P. (2017). Overfitting Bayesian mixtures of factor analyzers with an unknown number of components. [arXiv:1701.04605](https://arxiv.org/abs/1701.04605) [stat.ME]

**See Also**

[dealWithLabelSwitching](#)

**Examples**

```
## Not run:
# simulate a synthetic dataset along the lines of the paper:
n = 1000          # sample size
p = 40            # number of variables
q = 4             # number of factors
K = 10            # number of clusters
sINV_diag = 1/((1:p)) # diagonal of inverse variance of errors
set.seed(10)
syntheticDataset <- simData(K.true = K, n = n, q = q, p = p, sINV_values = sINV_diag )

# define parameters
Kmax <- 20        # number of overfitted mixture components
nChains <- 8      # number of parallel chains
dN <- 1
# Dirichlet prior of mixture weights per chain.
# The target chain corresponds to the first entry.
dirPriorAlphas <- c(1, 1 + dN * (2:nChains - 1))/Kmax
outputFolder <- "fabMixExample"
# Run algorithm
fabMix( dirPriorAlphas = dirPriorAlphas,
        rawData = syntheticDataset$data,
        outDir = outputFolder, Kmax = Kmax, mCycles = 1200,
        burnCycles = 200, q = q)

# Compute information criteria:
getStuffForDIC(x_data = syntheticDataset$data, outputFolder = outputFolder, q = q)

# Deal with label switching:
dealWithLabelSwitching(x_data = syntheticDataset$data,
                       outputFolder = outputFolder, q = q,
                       compute_regularized_expression = TRUE, Km = Kmax)

## End(Not run)
```

---

fabMix\_missing\_values    *Main function for the case of missing values*

---

**Description**

This function runs parallel chains under a prior tempering scheme of the Dirichlet prior distribution of mixture weights. Missing values are simulated from their full conditional posterior distribution.

**Usage**

```
fabMix_missing_values(sameSigma, dirPriorAlphas, rawData, outDir, Kmax, mCycles,
burnCycles, g, h, alpha_sigma, beta_sigma, q, normalize,
thinning, zStart, nIterPerCycle, gibbs_z)
```

**Arguments**

sameSigma	Logical value denoting the parameterization of the error variance per component. If TRUE, the parameterization $\Sigma_1 = \dots = \Sigma_K$ is fitted.
dirPriorAlphas	The prior Dirichlet parameters for each chain.
rawData	The observed data as an $n \times p$ matrix. Clustering is performed on the rows of the matrix.
outDir	Name of the output folder.
Kmax	Number of components in the overfitted mixture. Default: 20.
mCycles	Number of MCMC cycles. Each cycle consists of nIterPerCycle MCMC iterations. At the end of each cycle a swap of the state of two randomly chosen adjacent chains is attempted.
burnCycles	Number of cycles that will be discarded as burn-in period.
g	Prior parameter $g$ . Default value: $g = 2$ .
h	Prior parameter $h$ . Default value: $h = 1$ .
alpha_sigma	Prior parameter $\alpha$ . Default value: $\alpha = 2$ .
beta_sigma	Prior parameter $\beta$ . Default value: $\beta = 1$ .
q	Number of factors $q$ , where $1 \leq q \leq L$ . An error is thrown if the Ledermann bound ( $L$ ) is exceeded.
normalize	Should the observed data be normalized? Default value: TRUE.
thinning	Optional integer denoting the thinning of the kept MCMC cycles.
zStart	Optional starting value for the allocation vector.
nIterPerCycle	Number of iteration per MCMC cycle. Default value: 10.
gibbs_z	Select the gibbs sampling scheme for updating latent allocations of mixture model. Default value: 1.

**Value**

List of files written to outDir

**Note**

It is recommended to always use: `normalize = TRUE` (default). Tuning of `dirPriorAlphas` may be necessary to achieve reasonable acceptance rates of chain swaps. Also note that the output is not identifiable due to label switching and the user has to subsequently call the `dealWithLabelSwitching` function.

**Author(s)**

Panagiotis Papastamoulis

## References

Papastamoulis, P. (2017). Overfitting Bayesian mixtures of factor analyzers with an unknown number of components. arXiv:1701.04605 [stat.ME]

## See Also

[dealWithLabelSwitching](#)

## Examples

```
## Not run:
# simulate a synthetic dataset along the lines of the paper:
n = 1000          # sample size
p = 40            # number of variables
q = 4             # number of factors
K = 10            # number of clusters
sINV_diag = 1/((1:p)) # diagonal of inverse variance of errors
set.seed(10)
syntheticDataset <- simData(K.true = K, n = n, q = q, p = p, sINV_values = sINV_diag )

# define parameters
Kmax <- 20        # number of overfitted mixture components
nChains <- 8      # number of parallel chains
dN <- 1
# Dirichlet prior of mixture weights per chain.
# The target chain corresponds to the first entry.
dirPriorAlphas <- c(1, 1 + dN * (2:nChains - 1))/Kmax
outputFolder <- "fabMixExample"
# Run algorithm
fabMix( dirPriorAlphas = dirPriorAlphas,
        rawData = syntheticDataset$data,
        outDir = outputFolder, Kmax = Kmax, mCycles = 1200,
        burnCycles = 200, q = q)

# Compute information criteria:
getStuffForDIC(x_data = syntheticDataset$data, outputFolder = outputFolder, q = q)

# Deal with label switching:
dealWithLabelSwitching(x_data = syntheticDataset$data,
                      outputFolder = outputFolder, q = q,
                      compute_regularized_expression = TRUE, Km = Kmax)

## End(Not run)
```

**Description**

This function computes four information criteria for a given run of the fabMix algorithm, namely: AIC, BIC, DIC and DIC<sub>2</sub>. Given various runs with different number of factors, the selected model corresponds to the one with the smallest value of the selected criterion.

**Usage**

```
getStuffForDIC(sameSigma, x_data, outputFolder, q, burn, Km, normalize, discardLower)
```

**Arguments**

sameSigma	Logical value indicating whether the parameterization with the same variance of errors per component is used. Default: TRUE.
x_data	Observed data.
outputFolder	Name of the folder where the fabMix function has saved its output.
q	Number of factors. Note that this should coincide with the number of factors in the fabMix run.
burn	Discard observations as burn-in period (optional).
Km	Number of components in the overfitted mixture model. Note that this should coincide with the same entry in the fabMix run.
normalize	Should the observed data be normalized? Note that this should coincide with the same entry in the fabMix run. Default value: TRUE.
discardLower	Discard draws with log-likelihood values lower than the specific quantile. This applied only for the DIC computation.

**Details**

If necessary, more details than the description above

**Value**

The information criteria are saved to the informationCriteria\_map\_model.txt file in the code-outputFolder.

**Note**

It is well known that DIC tends to overfit, so it is advised to compare models with different number of factors using AIC or BIC.

**Author(s)**

Panagiotis Papastamoulis

---

log_dirichlet_pdf	<i>Log-density function of the Dirichlet distribution</i>
-------------------	-----------------------------------------------------------

---

**Description**

Log-density function of the Dirichlet distribution

**Usage**

```
log_dirichlet_pdf(alpha, weights)
```

**Arguments**

alpha	Parameter vector
weights	Vector of weights

**Value**

Log-density of the  $D(\alpha_1, \dots, \alpha_k)$  evaluated at  $w_1, \dots, w_k$ .

**Author(s)**

Panagiotis Papastamoulis

---

myDirichlet	<i>Simulate from the Dirichlet distribution</i>
-------------	-------------------------------------------------

---

**Description**

Generate a random draw from the Dirichlet distribution  $D(\alpha_1, \dots, \alpha_k)$ .

**Usage**

```
myDirichlet(alpha)
```

**Arguments**

alpha	Parameter vector
-------	------------------

**Value**

Simulated vector

**Author(s)**

Panagiotis Papastamoulis

---

`observed.log.likelihood0`*Log-likelihood of the mixture model*

---

**Description**

Log-likelihood of the mixture model evaluated only at the alive components.

**Usage**

```
observed.log.likelihood0(x_data, w, mu, Lambda, Sigma, z)
```

**Arguments**

x_data	The observed data
w	Vector of mixture weights
mu	Vector of marginal means
Lambda	Factor loadings
Sigma	Common covariance matrix of the errors per cluster
z	Allocation vector

**Value**

Log-likelihood value

**Author(s)**

Panagiotis Papastamoulis

---

`observed.log.likelihood0_Sj`*Log-likelihood of the mixture model*

---

**Description**

Log-likelihood of the mixture model evaluated only at the alive components.

**Usage**

```
observed.log.likelihood0_Sj(x_data, w, mu, Lambda, Sigma, z)
```

**Arguments**

x_data	The observed data
w	Vector of mixture weights
mu	Vector of marginal means
Lambda	Factor loadings
Sigma	Covariance matrix of the errors per cluster
z	Allocation vector

**Value**

Log-likelihood value

**Author(s)**

Panagiotis Papastamoulis

---

overfittingMFA

*Basic MCMC sampler*


---

**Description**

Gibbs sampling for fitting a mixture model of factor analyzers.

**Usage**

```
overfittingMFA(x_data, originalX, outputDirectory, Kmax, m, thinning, burn,
g, h, alpha_prior, alpha_sigma, beta_sigma, start_values, q, zStart, gibbs_z)
```

**Arguments**

x_data	normalized data
originalX	observed raw data (only for plotting purpose)
outputDirectory	Name of the output folder
Kmax	Number of mixture components
m	Number of iterations
thinning	Thinning of chain
burn	Burn-in period
g	Prior parameter $g$ . Default value: $g = 2$ .
h	Prior parameter $h$ . Default value: $h = 1$ .
alpha_prior	Parameters of the Dirichlet prior distribution of mixture weights.
alpha_sigma	Prior parameter $\alpha$ . Default value: $\alpha = 2$ .



beta_sigma	Prior parameter $\beta$ . Default value: $\beta = 1$ .
start_values	Optional (not used)
q	Number of factors.
zStart	Optional (not used)
gibbs_z	Optional

**Value**

List of files

**Author(s)**

Panagiotis Papastamoulis

---

overfittingMFA\_missing\_values

*Basic MCMC sampler for the case of missing data*

---

**Description**

Gibbs sampling for fitting a mixture model of factor analyzers.

**Usage**

```
overfittingMFA_missing_values(missing_entries, x_data, originalX, outputDirectory, Kmax,
m, thinning, burn, g, h, alpha_prior, alpha_sigma,
beta_sigma, start_values, q, zStart, gibbs_z)
```

**Arguments**

missing_entries	list which contains the row number (1st entry) and column indexes (subsequent entries) for every row containing missing values.
x_data	normalized data
originalX	observed raw data (only for plotting purpose)
outputDirectory	Name of the output folder
Kmax	Number of mixture components
m	Number of iterations
thinning	Thinning of chain
burn	Burn-in period
g	Prior parameter $g$ . Default value: $g = 2$ .
h	Prior parameter $h$ . Default value: $h = 1$ .

alpha_prior	Parameters of the Dirichlet prior distribution of mixture weights.
alpha_sigma	Prior parameter $\alpha$ . Default value: $\alpha = 2$ .
beta_sigma	Prior parameter $\beta$ . Default value: $\beta = 1$ .
start_values	Optional (not used)
q	Number of factors.
zStart	Optional (not used)
gibbs_z	Optional

**Value**

List of files

**Author(s)**

Panagiotis Papastamoulis

---

overfittingMFA_Sj	<i>Basic MCMC sampler using different error variance per component</i>
-------------------	------------------------------------------------------------------------

---

**Description**

Gibbs sampling for fitting a mixture model of factor analyzers.

**Usage**

```
overfittingMFA_Sj(x_data, originalX, outputDirectory, Kmax, m, thinning, burn,
g, h, alpha_prior, alpha_sigma, beta_sigma, start_values, q, zStart, gibbs_z)
```

**Arguments**

x_data	normalized data
originalX	observed raw data (only for plotting purpose)
outputDirectory	Name of the output folder
Kmax	Number of mixture components
m	Number of iterations
thinning	Thinning of chain
burn	Burn-in period
g	Prior parameter $g$ . Default value: $g = 2$ .
h	Prior parameter $h$ . Default value: $h = 1$ .
alpha_prior	Parameters of the Dirichlet prior distribution of mixture weights.
alpha_sigma	Prior parameter $\alpha$ . Default value: $\alpha = 2$ .

beta_sigma	Prior parameter $\beta$ . Default value: $\beta = 1$ .
start_values	Optional (not used)
q	Number of factors.
zStart	Optional (not used)
gibbs_z	Optional

**Value**

List of files

**Author(s)**

Panagiotis Papastamoulis

---

overfittingMFA\_Sj\_missing\_values

*Basic MCMC sampler for the case of missing data and different error variance*

---

**Description**

Gibbs sampling for fitting a mixture model of factor analyzers.

**Usage**

```
overfittingMFA_Sj_missing_values(missing_entries, x_data, originalX,
outputDirectory, Kmax,
m, thinning, burn, g, h, alpha_prior, alpha_sigma,
beta_sigma, start_values, q, zStart, gibbs_z)
```

**Arguments**

missing_entries	list which contains the row number (1st entry) and column indexes (subsequent entries) for every row containing missing values.
x_data	normalized data
originalX	observed raw data (only for plotting purpose)
outputDirectory	Name of the output folder
Kmax	Number of mixture components
m	Number of iterations
thinning	Thinning of chain
burn	Burn-in period
g	Prior parameter $g$ . Default value: $g = 2$ .

<code>h</code>	Prior parameter $h$ . Default value: $h = 1$ .
<code>alpha_prior</code>	Parameters of the Dirichlet prior distribution of mixture weights.
<code>alpha_sigma</code>	Prior parameter $\alpha$ . Default value: $\alpha = 2$ .
<code>beta_sigma</code>	Prior parameter $\beta$ . Default value: $\beta = 1$ .
<code>start_values</code>	Optional (not used)
<code>q</code>	Number of factors.
<code>zStart</code>	Optional (not used)
<code>gibbs_z</code>	Optional

**Value**

List of files

**Author(s)**

Panagiotis Papastamoulis

---

<code>simData</code>	<i>Synthetic data generator</i>
----------------------	---------------------------------

---

**Description**

Simulate data from a multivariate normal mixture using a mixture of factor analyzers mechanism.

**Usage**

```
simData(sameSigma, p, q, K.true, n, loading_means, loading_sd, sINV_values)
```

**Arguments**

<code>sameSigma</code>	Logical.
<code>p</code>	The dimension of the multivariate normal distribution ( $p > 1$ ).
<code>q</code>	Number of factors. It should be strictly smaller than <code>p</code> .
<code>K.true</code>	The number of mixture components (clusters).
<code>n</code>	Sample size.
<code>loading_means</code>	A vector which contains the means of blocks of factor loadings. Default: <code>loading_means = c(-30, -20, -10, 10, 20, 30)</code> .
<code>loading_sd</code>	A vector which contains the standard deviations of blocks of factor loadings. Default: <code>loading_sd &lt;- rep(2, length(loading_means))</code> .
<code>sINV_values</code>	A vector which contains the values of the diagonal of the (common) inverse covariance matrix, if <code>sigmaTrue = TRUE</code> . An $K \times p$ matrix which contains the values of the diagonal of the inverse covariance matrix per component, if <code>sigmaTrue = FALSE</code> . Default: <code>sINV_values = rgamma(p, shape = 1, rate = 1)</code> .

**Value**

A list with the following entries:

data	$n \times p$ array containing the simulated data.
class	$n$ -dimensional vector containing the class of each observation.
factorloadings	$K.true \times p \times q$ -array containing the factor loadings $\Lambda_{krj}$ per cluster $k$ , feature $r$ and factor $j$ , where $k = 1, \dots, K$ ; $r = 1, \dots, p$ ; $j = 1, \dots, q$ .
means	$K.true \times p$ matrix containing the marginal means $\mu_{kr}$ , $k = 1, \dots, K$ ; $r = 1, \dots, p$ .
variance	$p \times p$ diagonal matrix containing the variance of errors $\sigma_{rr}$ , $r = 1, \dots, p$ . Note that the same variance of errors is assumed for each cluster.
factors	$n \times q$ matrix containing the simulated factor values.
weights	$K.true$ -dimensional vector containing the weight of each cluster.

**Note**

The marginal variance for cluster  $k$  is equal to  $\Lambda_k \Lambda_k^T + \Sigma$ .

**Author(s)**

Panagiotis Papastamoulis

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update_all_y	<i>Gibbs sampling for y</i>
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---

**Description**

Gibbs sampling for  $y$

**Usage**

```
update_all_y(x_data, mu, SigmaINV, Lambda, z)
```

**Arguments**

x_data	Data
mu	Marginal means
SigmaINV	Precision matrix
Lambda	Factor loadings
z	Allocation vector

**Value**

A matrix with generated factors

**Author(s)**

Panagiotis Papastamoulis

---

update_all_y_Sj	<i>Gibbs sampling for <math>y</math></i>
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---

**Description**

Gibbs sampling for  $y$

**Usage**

update\_all\_y\_Sj(x\_data, mu, SigmaINV, Lambda, z)

**Arguments**

x_data	Data
mu	Marginal means
SigmaINV	Precision matrix per component
Lambda	Factor loadings
z	Allocation vector

**Value**

A matrix with generated factors

**Author(s)**

Panagiotis Papastamoulis

---

update_OmegaINV	<i>Gibbs sampling for <math>\Omega^{-1}</math></i>
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---

**Description**

Gibbs sampling for  $\Omega^{-1}$

**Usage**

update\_OmegaINV(Lambda, K, g, h)

**Arguments**

Lambda	Factor loadings
K	Number of components
g	Prior parameter
h	Prior parameter

**Value**
 $\Omega^{-1}$ 
**Author(s)**

Panagiotis Papastamoulis

---

 update\_SigmaINV\_faster

*Gibbs sampling for  $\Sigma^{-1}$* 


---

**Description**
 Gibbs sampling for  $\Sigma^{-1}$ 
**Usage**

update\_SigmaINV\_faster(x\_data, z, y, Lambda, mu, K, alpha\_sigma, beta\_sigma)

**Arguments**

x_data	Data
z	Allocation vector
y	Factors
Lambda	Factor loadings
mu	Marginal means
K	Number of components
alpha_sigma	Prior parameter
beta_sigma	Prior parameter

**Value**
 $\Sigma^{-1}$ 
**Author(s)**

Panagiotis Papastamoulis

---

update\_SigmaINV\_faster\_Sj

*Gibbs sampling for  $\Sigma^{-1}$  per component*


---

### Description

Gibbs sampling for  $\Sigma^{-1}$  per component

### Usage

```
update_SigmaINV_faster_Sj(x_data, z, y, Lambda, mu, K, alpha_sigma, beta_sigma)
```

### Arguments

x_data	Data
z	Allocation vector
y	Factors
Lambda	Factor loadings
mu	Marginal means
K	Number of components
alpha_sigma	Prior parameter
beta_sigma	Prior parameter

### Value

$\Sigma^{-1}$

### Author(s)

Panagiotis Papastamoulis

---

update\_z2

*Collapsed Gibbs for  $z$  using matrix inversion lemma*


---

### Description

Collapsed Gibbs for  $z$  using matrix inversion lemma

### Usage

```
update_z2(w, mu, Lambda, SigmaINV, K, x_data)
```



**Arguments**

w	Mixture weights
mu	Marginal means
Lambda	Factor loadings
SigmaINV	Precision matrix
K	Number of components
x_data	Data

**Value**

Allocation vector

**Author(s)**

Panagiotis Papastamoulis

---

update_z2_Sj	<i>Collapsed Gibbs for <math>z</math> using matrix inversion lemma</i>
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---

**Description**

Collapsed Gibbs for  $z$  using matrix inversion lemma

**Usage**

update\_z2\_Sj(w, mu, Lambda, SigmaINV, K, x\_data)

**Arguments**

w	Mixture weights
mu	Marginal means
Lambda	Factor loadings
SigmaINV	Precision matrix per component
K	Number of components
x_data	Data

**Value**

Allocation vector

**Author(s)**

Panagiotis Papastamoulis

---

update\_z4

*Collapsed Gibbs for  $z$* 


---

**Description**

Collapsed Gibbs for  $z$

**Usage**

```
update_z4(w, mu, Lambda, SigmaINV, K, x_data)
```

**Arguments**

w	Mixture weights
mu	Marginal means
Lambda	Factor loadings
SigmaINV	Precision matrix
K	Number of components
x_data	Data

**Value**

Allocation vector

**Author(s)**

Panagiotis Papastamoulis

---

update\_z4\_Sj

*Collapsed Gibbs for  $z$* 


---

**Description**

Collapsed Gibbs for  $z$

**Usage**

```
update_z4_Sj(w, mu, Lambda, SigmaINV, K, x_data)
```

**Arguments**

w	Mixture weights
mu	Marginal means
Lambda	Factor loadings
SigmaINV	Precision matrix per component
K	Number of components
x_data	Data

**Value**

Allocation vector

**Author(s)**

Panagiotis Papastamoulis

---

update\_z\_b

*Gibbs sampling for  $z$*

---

**Description**

Gibbs sampling for  $z$

**Usage**

```
update_z_b(w, mu, Lambda, y, SigmaINV, K, x_data)
```

**Arguments**

w	Mixture weights
mu	Marginal means
Lambda	Factor loadings
y	Matrix of factors
SigmaINV	Precision matrix
K	Number of components
x_data	Data

**Value**

Allocation vector

**Author(s)**

Panagiotis Papastamoulis

---

update_z_b_Sj	<i>Gibbs sampling for <math>z</math></i>
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---

**Description**

Gibbs sampling for  $z$

**Usage**

update\_z\_b\_Sj(w, mu, Lambda, y, SigmaINV, K, x\_data)

**Arguments**

w	Mixture weights
mu	Marginal means
Lambda	Factor loadings
y	Matrix of factors
SigmaINV	Precision matrix per component
K	Number of components
x_data	Data

**Value**

Allocation vector

**Author(s)**

Panagiotis Papastamoulis

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waveDataset1500	<i>Wave dataset</i>
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**Description**

A subset of 1500 randomly sampled observations from the wave dataset (version 1), available from the UCI machine learning repository. It contains 3 classes of waves (variable class with values “1”, “2” and “3”) and 21 attributes. Each class is generated from a combination of 2 of 3 base waves with noise.

**Usage**

waveDataset1500

**Format**

A data frame with 1500 rows and 22 columns. The first column denotes the class of each observation.

**Source**

[https://archive.ics.uci.edu/ml/datasets/Waveform+Database+Generator+\(Version+1\)](https://archive.ics.uci.edu/ml/datasets/Waveform+Database+Generator+(Version+1))

**References**

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# Index

\*Topic **datasets**  
    waveDataset1500, [28](#)

\*Topic **package**  
    fabMix-package, [2](#)

complete.log.likelihood, [4](#)  
complete.log.likelihood\_Sj, [4](#)  
compute\_A\_B\_G\_D\_and\_simulate\_mu\_Lambda,  
    [5](#)  
compute\_A\_B\_G\_D\_and\_simulate\_mu\_Lambda\_Sj,  
    [6](#)  
compute\_sufficient\_statistics, [7](#)

dealWithLabelSwitching, [3](#), [7](#), [10](#), [12](#)

fabMix, [3](#), [8](#)  
fabMix-package, [2](#)  
fabMix\_missing\_values, [10](#)

getStuffForDIC, [3](#), [12](#)

log\_dirichlet\_pdf, [14](#)

myDirichlet, [14](#)

observed.log.likelihood0, [15](#)  
observed.log.likelihood0\_Sj, [15](#)  
overfittingMFA, [16](#)  
overfittingMFA\_missing\_values, [17](#)  
overfittingMFA\_Sj, [18](#)  
overfittingMFA\_Sj\_missing\_values, [19](#)

simData, [20](#)

update\_all\_y, [21](#)  
update\_all\_y\_Sj, [22](#)  
update\_OmegaINV, [22](#)  
update\_SigmaINV\_faster, [23](#)  
update\_SigmaINV\_faster\_Sj, [24](#)  
update\_z2, [24](#)  
update\_z2\_Sj, [25](#)  
update\_z4, [26](#)  
update\_z4\_Sj, [26](#)  
update\_z\_b, [27](#)  
update\_z\_b\_Sj, [28](#)  
waveDataset1500, [28](#)