# Package 'mixSPE'

June 19, 2019

Туре	Package
Title	Mixtures of Power Exponential and Skew Power Exponential Distributions for Use in Model-Based Clustering and Classification
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Auth	or Utkarsh J. Dang[aut, cre], Michael P. B. Gallaugher[ctb], Ryan P. Browne[aut, cre], and Paul D. McNicholas[aut]
Main	ntainer Utkarsh J. Dang <udang@binghamton.edu></udang@binghamton.edu>
Desci	<b>ription</b> Mixtures of skewed and elliptical distributions are implemented using mixtures of multivariate skew power exponential and power exponential distributions, respectively. A generalized expectation-
	maximization framework is used for parameter estimation. Methodology for mixtures of power exponential distributions is from Dang et al. (2015) <doi: 10.1111="" biom.12351="">.</doi:>
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 mixSPE-package
 Mixtures of skew power exponential or power exponential distributions

#### **Description**

An implementation of skewed and elliptical mixture distributions for use in model-based clustering.

#### **Details**

Package: mixSPE
Type: Package
Version: 0.1.1
Date: 2019-06-18
License: GPL (>= 2)

mpe Function for model-based clustering with the multivariate power exponential (PE) distribution.

## Description

For fitting of a family of 16 mixture models based on mixtures of multivariate skew power exponential distributions with eigen-decomposed covariance structures.

#### Usage

```
mpe(verbose = FALSE, dat = NULL, seedno = 1, G = 1:4, start = "kmeans", kmeansinit = 10,
eps = 0.005, maxit = 5000, label = NULL, modelnames = c("EIIE", "VIIE", "EEIE", "VVIE",
"EEEE", "EEVE", "VVEE", "VVVE", "EIIV", "VIIV", "EEIV", "VVIV", "EEEV", "EEVV", "VVEV",
"VVVV"))
```

#### **Arguments**

verbose A short progress indicator.

dat A matrix such that rows correspond to observations and columns correspond to

variables.

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seedno Seed number for initialization of k-means or random starts.

G A sequence of integers corresponding to the number of components to be fitted.

start Inputting "kmeans" initializes the component labels for each observation from a

k-means classification. Option "random" results in a random hard initialization

for the component label for each observation.

kmeansinit Number of random starts to the k-means initialization function.

eps Threshold for convergence for the GEM algorithm used in the Aitken's stopping

criterion.

maxit Maximum number of GEM iterations allowed.

label Used for model-based classification aka semi-supervised classification.

modelnames A total of 16 models are provided: "EIIE", "VIIE", "EEIE", "VVIE", "EEEE",

"EEVE", "VVEE", "VVVE", "EIIV", "VIIV", "EEIV", "VVIV", "EEEV", "EEVV",

"VVEV", "VVVV".

#### **Details**

The component scale matrix is decomposed using an eigen-decomposition:

$$\Sigma_g = \lambda_g \; \Gamma_g \; \Delta_g \; \Gamma_g'$$

The nomenclature is as follows: a EEVE model denotes a model with equal constants associated with the eigenvalues ( $\lambda$ ) for each group, equal orthogonal matrix of eigenvectors ( $\Gamma$ ), variable diagonal matrices with values proportional to the eigenvalues of each component scale matrix ( $\Delta_g$ ), and equal shape parameter ( $\beta$ ).

#### Value

call Function call.
time Time taken.
modelnames Models fitted.

msc Matrix of results with BIC, ICL, and log-likelihood values achieved for each

model.

bicclassification

Maximum a posteriori component label indicators of each observation from the

model selected by the BIC.

iclclassification

Maximum a posteriori component label indicators of each observation from the

model selected by the ICL.

bicselection Model selected by the BIC including estimates.

iclselection Model selected by the ICL including estimates.

zlist List of initial labels for each observation from the initialization function for each

number of components.

#### Author(s)

Utkarsh J. Dang, Ryan P. Browne, and Paul D. McNicholas

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#### See Also

See Also mspe.

#### **Examples**

mspe

Function for model-based clustering with the multivariate skew power exponential (SPE) distribution.

## Description

For fitting of a family of 16 mixture models based on mixtures of multivariate skew power exponential distributions with eigen-decomposed covariance structures.

#### Usage

```
mspe(verbose = FALSE, dat = NULL, seedno = 1, G = 1:4, start = "kmeans", kmeansinit = 10,
eps = 0.005, maxit = 2000, anneal = NULL, label = NULL, psistart = "zero", modelnames =
c("EIIE", "VIIE", "EEIE", "VVIE", "EEEE", "EEVE", "VVEE", "VVVE", "EIIV", "VIIV", "EEIV",
"VVIV", "EEEV", "EEVV", "VVEV", "VVVV"))
```

#### **Arguments**

verbose	A short progress indicator.
dat	A matrix such that rows correspond to observations and columns correspond to variables.
seedno	Seed number for initialization of k-means or random starts.
G	A sequence of integers corresponding to the number of components to be fitted.
start	Inputting "kmeans" initializes the component labels for each observation from a k-means classification. Option "random" results in a random hard initialization for the component label for each observation.
kmeansinit	Number of random starts to the k-means initialization function.

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eps Threshold for convergence for the GEM algorithm used in the Aitken's stopping

criterion.

maxit Maximum number of GEM iterations allowed

anneal For deterministic annealing based initilization. Provide a non-decreasing vec-

tor of numbers rising from a small number to 1. Example: rep(seq(.05, 1,

length.out=6),each=2). Takes experimentation.

label Used for model-based classification aka semi-supervised classification.

psistart Default is a vector of zeros for each group. If "est" is used, a non-parameteric

estimate using the mean and median of the inferred cluster based on initialized

labels is used.

modelnames A total of 16 models are provided: "EIIE", "VIIE", "EEIE", "VVIE", "EEEE",

"EEVE", "VVEE", "VVVE", "EIIV", "VIIV", "EEIV", "VVIV", "EEEV", "EEVV",

"VVEV", "VVVV".

#### **Details**

The component scale matrix is decomposed using an eigen-decomposition:

 $\Sigma_g = \lambda_g \; \Gamma_g \; \Delta_g \; \Gamma_g'$ 

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#### Value

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time Time taken.

modelnames Models fitted.

msc Matrix of results with BIC, ICL, and log-likelihood values achieved for each

model.

bicclassification

Maximum a posteriori component label indicators of each observation from the

model selected by the BIC.

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Maximum a posteriori component label indicators of each observation from the

model selected by the ICL.

bicselection Model selected by the BIC including estimates. iclselection Model selected by the ICL including estimates.

zlist List of initial labels for each observation from the initialization function for each

number of components.

#### Author(s)

Utkarsh J. Dang, Michael P. B. Gallaugher, Ryan P. Browne, and Paul D. McNicholas

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#### See Also

See Also mpe.

#### **Examples**

```
set.seed(1)
Nobs1 <- 200
Nobs2 <- 250
X1 <- rpe(n = Nobs1, mean = c(0,0), scale = diag(2), beta = 1)
X2 <- rpe(n = Nobs2, mean = c(3,0), scale = diag(2), beta = 2)
x <- as.matrix(rbind(X1, X2))
membership <- c(rep(1, Nobs1), rep(2, Nobs2))
msperun <- mspe(verbose = TRUE, dat = x, seedno = 1, G = 1:2, start="kmeans", modelnames = c("EIIV"))
print(msperun)
print(table(membership,msperun$bicclassification))</pre>
```

print.pemix

Print a summary of the model fit.

#### **Description**

Print a summary of the model fit including the number of components and the scale structure selected by the BIC and the ICL.

#### Usage

```
## S3 method for class 'pemix'
print(x, ...)
```

## **Arguments**

```
x An object of class "pemix".... Ignore this
```

#### Author(s)

Utkarsh J. Dang, Ryan P. Browne, and Paul D. McNicholas

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print.spemix

Print a summary of the model fit.

### Description

Print a summary of the model fit including the number of components and the scale structure selected by the BIC and the ICL.

## Usage

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## S3 method for class 'spemix'
print(x, ...)
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#### **Arguments**

x An object of class "spemix".

... Ignore this

#### Author(s)

Utkarsh J. Dang, Michael P. B. Gallaugher, Ryan P. Browne, and Paul D. McNicholas

rpe

Simulate data from the multivariate power exponential distribution.

#### **Description**

Simulate data from the multivariate power exponential distribution given the mean, scale matrix, and the shape parameter.

#### Usage

```
rpe(n = NULL, beta = NULL, mean = NULL, scale = NULL)
```

#### **Arguments**

n Number of observations to simulate.

beta A positive shape parameter  $\beta$  that determines the kurtosis of the distribution.

mean A p-dimensional vector.  $\mu$ .

scale A p-dimensional square scale matrix  $\Sigma$ .

#### Value

A matrix with rows representing the p-dimensional observations.

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#### Author(s)

Utkarsh J. Dang, Ryan P. Browne, and Paul D. McNicholas

#### References

For simulating from the MPE distribution, a modified version of the function rmvpowerexp from package MNM (Nordhausen and Oja, 2011) is used. The function was modified due to a typo in the rmvpowerexp code, as mentioned in the publication (Dang et al., 2015). This program utilizes the stochastic representation of the MPE distribution (Gómez et al., 1998) to generate data. Dang, Utkarsh J., Ryan P. Browne, and Paul D. McNicholas. "Mixtures of multivariate power exponential distributions." Biometrics 71, no. 4 (2015): 1081-1089. Gómez, E., M. A. Gomez-Viilegas, and J. M. Marin. "A multivariate generalization of the power exponential family of distributions." Communications in Statistics-Theory and Methods 27, no. 3 (1998): 589-600. Nordhausen, Klaus, and Hannu Oja. "Multivariate L1 methods: the package MNM." Journal of Statistical Software 43, no. 5 (2011): 1-28.

#### **Examples**

```
dat <- rpe(n = 1000, beta = 2, mean = rep(0,5), scale = diag(5)) dat <- rpe(n = 1000, beta = 0.8, mean = rep(0,5), scale = diag(5))
```

rspe

Simulate data from the multivariate skew power exponential distribution.

#### **Description**

Simulate data from the multivariate power exponential distribution given the location, scale matrix, shape, and skewness parameter.

#### Usage

```
rspe(n, location = rep(0, nrow(scale)), scale = diag(length(location)), beta = 1, psi = c(0, 0))
```

#### **Arguments**

n Number of observations to simulate.

location A p-dimensional vector.  $\mu$ .

scale A p-dimensional square scale matrix  $\Sigma$ .

beta A positive shape parameter  $\beta$  that determines the kurtosis of the distribution.

psi A p-dimensional vector determining skewness.  $\mu$ .

#### **Details**

Based on a Metropolis-Hastings rule.

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## Value

A matrix with rows representing the p-dimensional observations.

## Author(s)

Utkarsh J. Dang, Ryan P. Browne, and Paul D. McNicholas

## Examples

```
dat <- rspe(n = 1000, beta = 0.75, location = c(0,0), scale = matrix(c(1,0.7,0.7,1),2,2), psi = c(5,5))
```

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