# Package 'RRmix'

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Type Packag	ge				
Title RRmix	Fitle RRmix: Model-Based Classification with Simultaneous Adjustment for Unwanted Variation				
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Description	NEED				
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R topics	documented:				
ope RRi	ctors	4			
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nfactors	Number of factors to be estimated in the RRmix model				
		_			

# Description

The number of factors to be used in the RRmix model such that var.exp of the variance in the data is explained.

# Usage

```
nfactors(expr, var.exp = 0.8, plot = TRUE)
```

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### **Arguments**

expr	An n by G matrix of G gene expression variables, or compound abundances (standardized), on n samples.
var.exp	The minimum cumulative proportion of the variance required to be explained by the determined number of factors $(q.in)$ . Float on $(0,1)$ (default = $0.8$ )
plot	boolean. Produce a scree plot of the variance explained by each factor (default = TRUE).

#### **Details**

This function performs Principal Component Analysis (PCA) on the covariance matrix for the raw data (expr). var.exp sets the criteria for the minimum variance explained by the determined number of factors (q.in) for the RRmix model. plot = TRUE produces a scree plot of the variance explained by each factor.

#### Value

The number of factors that cumulatively explain >= var.exp

#### References

Gao, C., Tignor, N. L., Salit, J., Strulovici-Barel, Y., Hackett, N. R., Crystal, R. G., and Mezey, J. G. (2014). HEFT: eQTL analysis of many thousands of expressed genes while simultaneously controlling for hidden factors. Bioinformatics, 30(3):369-376.

## **Examples**

```
expr <- log(operators[, 1:12])  # Log-Transformed, First Two Operators
expr <- t(expr)  # Transpose Matrix for n x G
q <- nfactors(expr); q  # Number of Factors for 80% Variance</pre>
```

operators

Operator Batch Effect Data Frame

## **Description**

This dataset contains the relative abundances of 265 metabolites across a total of 24 samples. The samples were collected by four different operators, namely A, X, D, and Z. Each operator performed a metabolomics experiment on 6 samples: three untreated (control) replicates, and three treated replicates. Both operators A and X were given samples treated with the drug 2-deoxy-glucose (2DG). Metabolites are in rows (265 metabolites), and samples are in columns (24 samples).

### Usage

operators

## Format

A data frame with abundances of 265 filtered metabolites on 24 samples

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#### Source

The Locasale Research Group - Department of Pharmacology & Cancer Biology, Duke University - Durham, North Carolina

#### References

**NEED** 

#### **Examples**

```
dim(operators) # [1] 265 24
summary(operators) # Quantiles for each metabolite
```

RRmix

RRmix: Model-Based Classification with Simultaneous Adjustment for Unwanted Variation

# Description

**NEED** 

## **Details**

**NEED** 

The number of hidden factors q is determined using the function nfactors, which is based on the method described in Gao et al. (2014). Principal Component Analysis (PCA) is performed on the correlation matrix of the raw data, and the number of factors is chosen based on how many principal components explain var.exp of the total variation, or through visual examination of the scree plot (plot = TRUE). Within a reasonable range of values, RRmix is robust to the value of q (Wan 2015).

## Author(s)

Muting Wan, Martin Wells, James Booth, Stephen Salerno

## References

Gao, C., Tignor, N. L., Salit, J., Strulovici-Barel, Y., Hackett, N. R., Crystal, R. G., and Mezey, J. G. (2014). HEFT: eQTL analysis of many thousands of expressed genes while simultaneously controlling for hidden factors. Bioinformatics, 30(3):369-376.

M. Wan, "Model-based classification with applications to high-dimensional data in bioinformatics," Ph.D. dissertation, Cornell University, 2015.

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runRRmix	Emperical Bayes ECM Implementation of RRmix Algorithm	

# Description

This function provides a variant on the Expectation-Maximization (EM) Algorithm for the estimation of the RRmix hierarchical mixture model parameters. Empirical Bayes inference is implemented via an EM algorithm with classification based on the posterior expectation of the latent indicator variables. This model-based classification method with simultaneous adjustment for unwanted variation is adapted to solve association detection problems for high-dimensional data in the presence of unwanted variation.

# Usage

```
runRRmix(Y.in, SNP.in, Xc.in = matrix(nrow = 0, ncol = 0),
betac.0 = matrix(nrow = 0, ncol = 0), sig20.0 = 1, sig21.0 = 0.1,
p.0 = 0.05, er_tol.in = 10^(-3), q.in = 1)
```

## **Arguments**

Y.in	An n by G matrix of G gene expression variables, or compound abundances (standardized), on n samples.
SNP.in	A G by 1 indicator vector for treatment condition or minor allele presence in a single SNP (standardized).
Xc.in	$n \ by \ r \ matrix \ of \ r \ known \ covariates \ (standardized, default = \texttt{matrix}(\texttt{nrow=0}, \texttt{ncol=0})).$
betac.0	n by r matrix of initial values for EM estimated covariate term coefficients (default = matrix(nrow=0, ncol=0)).
sig20.0	Initial value for EM estimated first variance component for $\beta_g b_g$ (default = 1.0).
sig21.0	Initial value for EM estimated second variance component for $\beta_g b_g$ (default = 0.1).
p.0	Initial value for EM estimated proportion of differentially abundant compounds (default = $0.05$ ).
er_tol.in	Convergence criterion for EM algorithm (default = 0.001).
q.in	The number of factors to be estimated (default $= 1$ ).

# Value

A list object containing the following named attributes:

er.all	Vector of error/tolerances at each iteration of the EM algorithm until convergence.
lc	Vector of likelihood values at each iteration of the EM algorithm until convergence.
mu	Vector of EM estimated sample-level means over genes
sig20	EM estimated first variance component for $\beta_g b_g$ .
sig21	EM estimated second variance component for $\beta_g b_g$ .
Lam	Estimated $n \times q$ loading matrix $(\Lambda)$ for the factor analysis component of the model.

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sig2_g	Estimated compound-specific error variance.
b_g	Vector of the posterior probabilities of differential abundance for each of the G compounds.
р	EM estimated proportion of differentially abundant compounds.
psi	EM estimated main effect of differential abundance.
beta_g.1	Estimated $2 \times G$ coefficient matrix for the primary effect of treatment condition.
beta_g.0	Initial $2 \times G$ coefficient matrix for the primary effect of treatment condition.
F_g.1	Estimated $q \times G$ factor matrix for the factor analysis component of the model.
F_g.0	Initial $q \times G$ factor matrix for the factor analysis component of the model.
assoc.coefs	Vector of G associated coefficients for each of the G compounds.
sig20.0	Initial value for EM estimated first variance component for $\beta_g b_g$ .
sig21.0	Initial value for EM estimated second variance component for $\beta_g b_g$ .
p.0	Initial value for EM estimated proportion of differentially abundant compounds.
psi.0	Initial value for EM estimated main effect of differential abundance.

#### References

M. Wan, "Model-based classification with applications to high-dimensional data in bioinformatics," Ph.D. dissertation, Cornell University, 2015.

# **Examples**

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