## Package 'ROSeq'

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Type Package

Title Modeling expression ranks for noise-tolerant differential expression analysis of scRNA-Seq data

Version 1.21.0

**Description** ROSeq - A rank based approach to modeling gene expression with filtered and normalized read count matrix. ROSeq takes filtered and normalized read matrix and cell-annotation/condition as input and determines the differentially expressed genes between the contrasting groups of single cells. One of the input parameters is the number of cores to be used.

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## Contents

computeDEG	2
findParams	3
getd	3
getDataStatistics	4
getdu1da	4
getdu1db	5
getdu2da	5
getdu2db	6
getdvda	6
getdvdb	7
getI	7
getu1	8
getu2	8
getv	9
initiateAnalysis	9
L_Tung_single	0
minimizeNLL	0
ROSeq	1
TMMnormalization	.2
1	3

## Index

computeDEG	Computes differential expression for the gene in question, by compar-
	ing the optimal parameters for sub-populations one and two

## Description

Uses the (asymptotically) optimum two-sample Wald test based on the MLE of the parameters and its asymptotic variances given by the inverse of the Fisher information matrix

## Usage

```
computeDEG(results_1, results_2)
```

## Arguments

results_1	A vector corresponding to sub-population one and containing 5 values (a, b, A, number of bins, R2)
results_2	A vector corresponding to sub-population two and containing 5 values (a, b, A, number of bins, R2)

## Value

T The Wald test statistic for testing the null hypothesis

## See Also

getI, findParams

Finds the optimal values of parameters a and b that model the probability distribution of ranks, by Maximising the Log-Likelihood

#### Description

findParams

Takes in as input the read count data corresponding to one sub-population and the typical gene statistics. Then it splits the entire range into equally sized bins of size  $k * \sigma$ , where k is a scalar with a default value of 0.05, and  $\sigma$  is the standard deviation of the pulled expression estimates across the cell-groups. Each of these bins corresponds to a rank. Therefore, for each group, cell frequency for each bin maps to a rank. These frequencies are normalized group-wise by dividing by the total cell count within a concerned group.

#### Usage

```
findParams(ds, geneStats)
```

#### Arguments

ds	The (normalized and filtered) read count data corresponding to a sub-population
geneStats	A vector containing 7 values corresponding to the gene data (maximum, mini- mum, mean, standard deviation, upper multiple of the standard deviation, lower multiple of standard deviation and log_2(fold change))

#### Value

results A vector containing 5 values (a, b, A, number of bins, R2)

getd

Finds the double derivative of A

#### Description

Finds the double derivative of A with with respect to a, (a, b), b, (a, b) in respective templates from right to left. This first derivative is evaluated at the optimal  $(a_hat, b_hat)$ . u1, v and u2 constitute the equations required for evaluating the first and second order derivatives of A with respect to parameters a and b

## Usage

getd(u1, v, du1da, dvda)

#### Arguments

u1	u1
V	V
du1da	First derivative of u1 with respect to parameter a
dvda	First derivative of v with respect to parameter a

## Value

d2logAda2

getDataStatistics Evaluates statistics of the read counts corresponding to the gene

#### Description

Takes in the complete read count vector corresponding to the gene (sp) and also the data corresponding to the two sub-populations (sp1 and sp2)

#### Usage

getDataStatistics(sp, spOne, spTwo)

#### Arguments

sp	The complete (normalized and filtered) read count data corresponding to the gene in question
sp0ne	The (normalized and filtered) read count data corresponding to the first sub- population
spTwo	The (normalized and filtered) read count data corresponding to the second sub- population

#### Value

geneStats A vector containing 6 values corresponding to the gene data(maximum, minimum, mean, standard deviation, upper multiple of standard deviation and lower multiple of standard deviation)

getdu1da	Finds the first derivative of u1 with respect to a. This first derivative is
	evaluated at the optimal (a_hat, b_hat).

#### Description

u1, v and u2 constitute the equations required for evaluating the first and second order derivatives of A with respect to parameters a and b

## Usage

```
getdu1da(coefficients, r)
```

## Arguments

coefficients	the optimal values of a and b
r	the rank vector

## Value

du1da

getdu1db Finds the first derivative of u1 with respect to b. This first derivative is evaluated at the optimal (a\_hat, b\_hat).

## Description

u1, v and u2 constitute the equations required for evaluating the first and second order derivatives of A with respect to parameters a and b

## Usage

getdu1db(coefficients, r)

## Arguments

coefficients	the optimal values of a and b
r	the rank vector

## Value

du1db

getdu2da	Finds the first derivative of u2 with respect to a. This first derivative is
	evaluated at the optimal (a_hat, b_hat).

#### Description

u1, v and u2 constitute the equations required for evaluating the first and second order derivatives of A with respect to parameters a and b

## Usage

```
getdu2da(coefficients, r)
```

## Arguments

coefficients	the optimal values of a and b
r	the rank vector

## Value

du2da

getdu2db

## Description

u1, v and u2 constitute the equations required for evaluating the first and second order derivatives of A with respect to parameters a and b

## Usage

getdu2db(coefficients, r)

## Arguments

coefficients	the optimal values of a and b
r	the rank vector

## Value

du2db

getdvda	Finds the first derivative of v with respect to a.	This first derivative is
	evaluated at the optimal (a_hat, b_hat).	

#### Description

u1, v and u2 constitute the equations required for evaluating the first and second order derivatives of A with respect to parameters a and b

## Usage

```
getdvda(coefficients, r)
```

## Arguments

coefficients the optimal values of a and b r the rank vector

## Value

dvda

getdvdb

Finds the first derivative of v with respect to b. This first derivative is evaluated at the optimal (a\_hat, b\_hat).

## Description

u1, v and u2 constitute the equations required for evaluating the first and second order derivatives of A with respect to parameters a and b

## Usage

```
getdvdb(coefficients, r)
```

## Arguments

coefficients	the optimal values of a and b
r	the rank vector

## Value

dvdb

getI	Computes the Fisher Information Matrix
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## Description

The Fisher Information Matrix and its derivatives are essential to evulate the minima of log likelihood

## Usage

```
getI(results)
```

#### Arguments

results A vector containing 5 values (a, b, A, number of bins, R2)

## Value

I The Fisher Information Matrix

getu1

## Description

u1, v and u2 constitute the equations required for evaluating the first and second order derivatives of A with respect to parameters a and b

## Usage

getu1(coefficients, r)

#### Arguments

coefficients	the optimal values of a and b
r	the rank vector

#### Value

u1

getu2

#### Computes u2

## Description

u1, v and u2 constitute the equations required for evaluating the first and second order derivatives of A with respect to parameters a and b

#### Usage

getu2(coefficients, r)

#### Arguments

coefficients	the optimal values of a and b
r	the rank vector

## Value

u2

getv

#### Description

u1, v and u2 constitute the equations required for evaluating the first and second order derivatives of A with respect to parameters a and b

## Usage

getv(coefficients, r)

#### Arguments

coefficients	the optimal values of a and b
r	the rank vector

## Value

v

initiateAnalysis Computes differential analysis for a given gene

#### Description

Takes in the row index which corresponds to a gene and evaluates for differential expression across two cell types.

## Usage

initiateAnalysis(gene, scdata, scgroups, classOne, classTwo)

### Arguments

gene	The row index of the normalised and filtered, read count matrix
scdata	The normalised and filtered, read count matrix
scgroups	The location of the two sub-populations
classOne	The location of the first sub-population, for example, sample names as given as columns names
classTwo	The location of thesecond sub-population, for example, sample names as given as columns names

## Value

combinedResults A vector containing 12 values (gr1: a, g1: b, gr1: A, gr1: number of bins, gr1: R2, gr2: a, gr2: b, gr2: A, gr2: number of bins, gr2: R2, T, p)

L\_Tung\_single

#### Description

Three replicates from three human induced pluripotent stem cell (iPSC) lines were considered. 96 single cells were considered in each of the three replicates corresponding to one of the three individuals (these shall be referred to by their labels NA19098,NA19101 and NA19239)

#### Usage

```
data("L_Tung_single")
```

#### Format

The format is: list of cells corresponding NA19098 versus NA19101 and groups labels.

#### Details

filtered and normalized data

#### Source

Tung, P.-Y.et al.Batch effects and the effective design of single-cell geneexpression studies. Scientific reports7, 39921 (2017).

## References

Tung, P.-Y.et al.Batch effects and the effective design of single-cell geneexpression studies. Scientific reports7, 39921 (2017).

#### Examples

```
data(L_Tung_single)
## summary(ROSeq::L_Tung_single)
```

minimizeNLL

Minimizes the Negative Log-Likelihood by iterating across values of parameters a and b

#### Description

Takes in as input a vector of values (coefficients), the number of bins and the normalized probability dsitribution of ranks

## Usage

```
minimizeNLL(coefficients, r, readCount)
```

#### ROSeq

#### Arguments

coefficients	A vector containing two values for a and b
r	The number of bins
readCount	A vector of (normalized) frequency of read counts that fall within each bin

## Value

NLL Negative-Log Likelihood for the input coefficients

#### See Also

findParams

ROSeq	Modeling expression ranks for noise-tolerant differential expression
	analysis of scRNA-Seq data

#### Description

Takes in the complete filtered and normalized read count matrix, the location of the two subpopulations and the number of cores to be used

## Usage

ROSeq(countData, condition, numCores = 1)

#### Arguments

countData	The normalised and filtered, read count matrix, with row names as genes name/ID
	and column names as sample id/name
condition	Labels for the two sub-populations
numCores	The number of cores to be used

#### Value

pValues and FDR adjusted p significance values

#### Examples

```
countData<-list()
countData$count<-ROSeq::L_Tung_single$NA19098_NA19101_count
countData$group<-ROSeq::L_Tung_single$NA19098_NA19101_group
head(countData$count)
gene_names<-rownames(countData$count)
countData$count<-apply(countData$count,2,function(x) as.numeric(x))
rownames(countData$count]<-gene_names
countData$count<-countData$count[,colSums(countData$count> 0) > 2000]
g_keep <- apply(countData$count[g_keep,]
countData$count<-limma::voom(ROSeq::TMMnormalization(countData$count))
output<-ROSeq(countData=countData$count$E, condition = countData$group)
output</pre>
```

TMMnormalization TMM Normalization.

#### Description

Trimmed Means of M values (TMM) normalization (on the basis of edgeR package)

## Usage

```
TMMnormalization(countTable)
```

#### Arguments

countTable The filtered, read count matrix, with row names as genes name/ID and column names as sample id/name

## Value

countTableTMM

#### Examples

```
countData<-list()
countData$count<-ROSeq::L_Tung_single$NA19098_NA19101_count
countData$group<-ROSeq::L_Tung_single$NA19098_NA19101_group
head(countData$count)
gene_names<-rownames(countData$count)
countData$count<-apply(countData$count,2,function(x) as.numeric(x))
rownames(countData$count)<-gene_names
countData$count<-countData$count[,colSums(countData$count> 0) > 2000]
g_keep <- apply(countData$count,1,function(x) sum(x>2)>=3)
countData$count<-countData$count[g_keep,]
countTableTMM<-ROSeq::TMMnormalization(countData$count)
countTableTMM</pre>
```

# Index

\* datasets L\_Tung\_single, 10 computeDEG, 2 findParams, 2, 3, 11 getd, 3 getDataStatistics, 4 getdu1da, 4 getdu1db, 5 getdu2da, 5 getdu2db, 6 getdvda, 6getdvdb, 7 getI, 2, 7 getu1,8 getu2,<mark>8</mark> getv, 9 initiateAnalysis,9 L\_Tung\_single, 10 minimizeNLL, 10 ROSeq, 11 TMMnormalization, 12