

# Package ‘FEAST’

November 9, 2024

**Type** Package

**Title** FEAture SelcTion (FEAST) for Single-cell clustering

**Version** 1.14.0

**Description** Cell clustering is one of the most important and commonly performed tasks in single-cell RNA sequencing (scRNA-seq) data analysis.

An important step in cell clustering is to select a subset of genes (referred to as “features”), whose expression patterns will then be used for downstream clustering. A good set of features should include the ones that distinguish different cell types,

and the quality of such set could have significant impact on the clustering accuracy.

FEAST is an R library for selecting most representative features before performing the core of scRNA-seq clustering. It can be used

as a plug-

in for the established clustering algorithms such as SC3, TSCAN, SHARP, SIMLR, and Seurat.

The core of FEAST algorithm includes three steps:

1. consensus clustering;
2. gene-level significance inference;
3. validation of an optimized feature set.

**License** GPL-2

**Encoding** UTF-8

**LazyData** true

**Depends** R (>= 4.1), mclust, BiocParallel, SummarizedExperiment

**biocViews** Sequencing, SingleCell, Clustering, FeatureExtraction

**BugReports** <https://github.com/suke18/FEAST/issues>

**Imports** SingleCellExperiment, methods, stats, utils, irlba, TSCAN, SC3, matrixStats

**Suggests** rmarkdown, Seurat, ggpubr, knitr, testthat (>= 3.0.0), BiocStyle

**VignetteBuilder** knitr

**RoxygenNote** 7.1.1

**NeedsCompilation** yes

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align_CellType	<i>Align the cell types from the prediction with the truth.</i>
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---

### Description

Align the cell types from the prediction with the truth.

### Usage

```
align_CellType(tt0)
```

### Arguments

tt0            a N\*N table.

**Value**

the matched (re-ordered) table

**Examples**

```
vec1 = rep(1:4, each=100)
vec2 = sample(vec1)
tb = table(vec1, vec2)
#tb_arg = align_CellType(tb)
```

---

cal_F2	<i>Calculate the gene-level F score and corresponding significance level.</i>
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---

**Description**

Calculate the gene-level F score and corresponding significance level.

**Usage**

```
cal_F2(Y, classes)
```

**Arguments**

Y	A gene expression matrix
classes	The initial cluster labels NA values are allowed. This can directly from the Consensus function.

**Value**

The score vector

**Examples**

```
data(Yan)
cal_F2(Y, classes = trueclass)
```

---

cal_Fisher2	<i>Calculate the gene-level fisher score.</i>
-------------	---

---

**Description**

Calculate the gene-level fisher score.

**Usage**

```
cal_Fisher2(Y, classes)
```

**Arguments**

Y	A gene expression matrix
classes	The initial cluster labels NA values are allowed. This can directly from the Consensus function.

**Value**

The score vector This is from the paper <https://arxiv.org/pdf/1202.3725.pdf> Vector based calculation

---

cal_metrics	<i>Calculate 3 metrics and these methods are exported in C codes. flag = 1 — Rand index, flag = 2 — Fowlkes and Mallows's index, flag = 3 — Jaccard index</i>
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---

**Description**

Calculate 3 metrics and these methods are exported in C codes. flag = 1 — Rand index, flag = 2 — Fowlkes and Mallows's index, flag = 3 — Jaccard index

**Usage**

```
cal_metrics(cl1, cl2, randMethod = c("Rand", "FM", "Jaccard"))
```

**Arguments**

cl1	a vector
cl2	a vector
randMethod	a string chosen from "Rand", "FM", or "Jaccard"

**Value**

a numeric vector including three values

---

cal_MSE	<i>Standard way to preprocess the count matrix. It is the QC step for the genes.</i>
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---

**Description**

Standard way to preprocess the count matrix. It is the QC step for the genes.

**Usage**

```
cal_MSE(Ynorm, cluster, return_mses = FALSE)
```

**Arguments**

Ynorm	A normalized gene expression matrix. If not, we will normalize it for you.
cluster	The clustering outcomes. Specifically, they are cluster labels.
return_mses	True or False indicating whether returning the MSE.

**Value**

The MSE of the clustering centers with the predicted Y.

**Examples**

```
data(Yan)
Ynorm = Norm_Y(Y)
cluster = trueclass
MSE_res = cal_MSE(Ynorm, cluster)
```

---

Consensus

*Consensus Clustering*

---

**Description**

Consensus Clustering

**Usage**

```
Consensus(Y, num_pcs = 10, top_pctg = 0.33, k = 2, thred = 0.9, nProc = 1)
```

**Arguments**

Y	A expression matrix. It is recommended to use the raw count matrix. Users can input normalized matrix directly.
num_pcs	The number of top pcs that will be investigated on through consensus clustering.
top_pctg	Top percentage of features for dimension reduction
k	The number of input clusters (best guess).
thred	For the final GMM clustering, the probability of a cell belonging to a certain cluster.
nProc	number of cores for BiocParallel enviroment.

**Value**

the clustering labels and the featured genes.

**Examples**

```
data(Yan)
set.seed(123)
rixs = sample(nrow(Y), 500)
cixs = sample(ncol(Y), 40)
Y = Y[rixs, cixs]
con = Consensus(Y, k=5)
```

---

eval_Cluster	<i>Calculate the a series of the evaluation statistics.</i>
--------------	---

---

**Description**

Calculate the a series of the evaluation statistics.

**Usage**

```
eval_Cluster(vec1, vec2)
```

**Arguments**

vec1	a vector.
vec2	a vector. x and y are with the same length.

**Value**

a vector of evaluation metrics

**Examples**

```
vec2 = vec1 = rep(1:4, each = 100)
vec2[1:10] = 4
acc = eval_Cluster(vec1, vec2)
```

---

FEAST	<i>FEAST main function</i>
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**Description**

FEAST main function

**Usage**

```
FEAST(  
  Y,  
  k = 2,  
  num_pcs = 10,  
  dim_reduce = c("irlba", "svd", "pca"),  
  split = FALSE,  
  batch_size = 1000,  
  nProc = 1  
)
```

**Arguments**

<code>Y</code>	A expression matrix. Raw count matrix or normalized matrix.
<code>k</code>	The number of input clusters (best guess).
<code>num_pcs</code>	The number of top pcs that will be investigated through the consensus clustering.
<code>dim_reduce</code>	dimension reduction methods chosen from <code>pca</code> , <code>svd</code> , or <code>irlba</code> .
<code>split</code>	boolean. If T, using subsampling to calculate the gene-level significance.
<code>batch_size</code>	when <code>split</code> is true, need to claim the batch size for splitting the cells.
<code>nProc</code>	number of cores for BiocParallel enviroment.

**Value**

the rankings of the gene-significance.

**Examples**

```
data(Yan)
k = length(unique(trueclass))
set.seed(123)
rixs = sample(nrow(Y), 500)
cixs = sample(ncol(Y), 40)
Y = Y[rixs, cixs]
ixs = FEAST(Y, k=k)
```

---

FEAST\_fast

*FEAST main function (fast version)*


---

**Description**

FEAST main function (fast version)

**Usage**

```
FEAST_fast(Y, k = 2, num_pcs = 10, split = FALSE, batch_size = 1000, nProc = 1)
```

**Arguments**

<code>Y</code>	A expression matrix. Raw count matrix or normalized matrix.
<code>k</code>	The number of input clusters (best guess).
<code>num_pcs</code>	The number of top pcs that will be investigated through the consensus clustering.
<code>split</code>	boolean. If T, using subsampling to calculate the gene-level significance.
<code>batch_size</code>	when <code>split</code> is true, need to claim the batch size for splitting the cells.
<code>nProc</code>	number of cores for BiocParallel enviroment.

**Value**

the rankings of the gene-significance.

**Examples**

```
data(Yan)
k = length(unique(trueclass))
res = FEAST_fast(Y, k=k)
```

---

Norm_Y	<i>Normalize the count expression matrix by the size factor and take the log transformation.</i>
--------	--

---

**Description**

Normalize the count expression matrix by the size factor and take the log transformation.

**Usage**

```
Norm_Y(Y)
```

**Arguments**

Y                    a count expression matrix

**Value**

a normalized matrix

**Examples**

```
data(Yan)
Ynorm = Norm_Y(Y)
```

---

process_Y	<i>Standard way to preprocess the count matrix. It is the QC step for the genes.</i>
-----------	--

---

**Description**

Standard way to preprocess the count matrix. It is the QC step for the genes.

**Usage**

```
process_Y(Y, thre = 2)
```

**Arguments**

Y                    A gene expression data (Raw count matrix)  
 thre                The threshold of minimum number of cells expressing a certain gene (default =2)

**Value**

A processed gene expression matrix. It is *not log transformed*

**Examples**

```
data(Yan)
YY = process_Y(Y, thre=2)
```



---

Purity	<i>Calculate the purity between two vectors.</i>
--------	--

---

**Description**

Calculate the purity between two vectors.

**Usage**

Purity(x, y)

**Arguments**

x	a vector.
y	a vector. x and y are with the same length.

**Value**

the purity score

---

SC3_Clust	<i>SC3 Clustering</i>
-----------	-----------------------

---

**Description**

SC3 Clustering

**Usage**

SC3\_Clust(Y, k = NULL, input\_markers = NULL)

**Arguments**

Y	A expression matrix. It is recommended to use the raw count matrix.
k	The number of clusters. If it is not provided, k is estimated by the default method in SC3.
input_markers	A character vector including the featured genes. If they are not presented, SC3 will take care of this.

**Value**

the clustering labels and the featured genes.

---

Select\_Model\_short\_SC3

*Using clustering results based on feature selection to perform model selection.*

---

### Description

Using clustering results based on feature selection to perform model selection.

### Usage

```
Select_Model_short_SC3(Y, cluster, tops = c(500, 1000, 2000))
```

### Arguments

Y	A gene expression matrix
cluster	The initial cluster labels NA values are allowed. This can directly from the Consensus function.
tops	A numeric vector containing a list of numbers corresponding to top genes; e.g., tops = c(500, 1000, 2000).

### Value

mse and the SC3 clustering result.

### Examples

```
data(Yan)
k = length(unique(trueclass))
Y = process_Y(Y, thre = 2) # preprocess the data
set.seed(123)
rixs = sample(nrow(Y), 500)
cixs = sample(ncol(Y), 40)
Y = Y[rixs, cixs]
con_res = Consensus(Y, k=k)
# not run
# mod_res = Select_Model_short_SC3(Y, cluster = con_res$cluster, top = c(100, 200))
```

---

Select\_Model\_short\_TSCAN

*Using clustering results (from TSCAN) based on feature selection to perform model selection.*

---

### Description

Using clustering results (from TSCAN) based on feature selection to perform model selection.

**Usage**

```
Select_Model_short_TSCAN(
  Y,
  cluster,
  minexpr_percent = 0.5,
  cvcutoff = 1,
  tops = c(500, 1000, 2000)
)
```

**Arguments**

Y	A gene expression matrix
cluster	The initial cluster labels NA values are allowed. This can directly from the Consensus function.
minexpr_percent	The threshold used for processing data in TSCAN. Using it by default.
cvcutoff	The threshold used for processing data in TSCAN. Using it by default.
tops	A numeric vector containing a list of numbers corresponding to top genes; e.g., tops = c(500, 1000, 2000).

**Value**

mse and the TSCAN clustering result.

**Examples**

```
data(Yan)
k = length(unique(trueclass))
Y = process_Y(Y, thre = 2) # preprocess the data
set.seed(123)
rixs = sample(nrow(Y), 500)
cixs = sample(ncol(Y), 40)
Y = Y[rixs, cixs]
con_res = Consensus(Y, k=k)
# not run
# mod_res = Select_Model_short_TSCAN(Y, cluster = con_res$cluster, top = c(100, 200))
```

---

setUp\_BPPARAM

*set up for the parallel computing for biocParallel.*

---

**Description**

This function sets up the environment for parallel computing.

**Usage**

```
setUp_BPPARAM(nProc = 0, BPPARAM = NULL)
```

**Arguments**

nProc	number of processors
BPPARAM	bpparameter from bpparam

**Value**

BAPPARAM settings

**Examples**

```
setUp_BPPARAM(nProc=1)
```

---

trueclass

*An example single cell dataset for the cell label information (Yan)*

---

**Description**

The true cell type labels for Yan dataset. It includes 8 different cell types.

**Usage**

```
data("Yan")
```

**Format**

A character vector contains the cell type label

**Source**

<https://www.ncbi.nlm.nih.gov/geo/query/acc.cgi?acc=GSE36552>

**References**

Yan, Liying, et al. "Single-cell RNA-Seq profiling of human preimplantation embryos and embryonic stem cells." *Nature structural & molecular biology* 20.9 (2013): 1131.

**Examples**

```
data("Yan")
table(trueclass)
```

---

TSCAN\_Clust

*TSCAN Clustering*

---

**Description**

TSCAN Clustering

**Usage**

```
TSCAN_Clust(Y, k, minexpr_percent = 0.5, cvcutoff = 1, input_markers = NULL)
```

**Arguments**

Y	A expression matrix. It is recommended to use the raw count matrix.
k	The number of clusters. If it is not provided, k is estimated by the default method in SC3.
minexpr_percent	minimum expression threshold (default = 0.5).
cvcutoff	the cv cutoff to filter the genes (default = 1).
input_markers	A character vector including the featured genes. If they are not presented, SC3 will take care of this.

**Value**

the clustering labels and the featured genes.

**Examples**

```
data(Yan)
k = length(unique(trueclass))
# TSCAN_res = TSCAN_Clust(Y, k=k)
```

---

vector2matrix                    *function for convert a vector to a binary matrix*

---

**Description**

function for convert a vector to a binary matrix

**Usage**

```
vector2matrix(vec)
```

**Arguments**

vec                    a vector.

**Value**

a n by n binary matrix indicating the adjacency.

---

Visual_Rslt	<i>Using clustering results based on feature selection to perform model selection.</i>
-------------	--

---

**Description**

Using clustering results based on feature selection to perform model selection.

**Usage**

```
Visual_Rslt(model_cv_res, trueclass)
```

**Arguments**

model_cv_res	model selection result from Select_Model_short_SC3.
trueclass	The real class labels

**Value**

a list of mse dataframe, clustering accuracy dataframe, and ggplot object.

**Examples**

```
data(Yan)
k = length(unique(trueclass))
Y = process_Y(Y, thre = 2) # preprocess the data
set.seed(123)
rixs = sample(nrow(Y), 500)
cixs = sample(ncol(Y), 40)
Y = Y[rixs, ]
con_res = Consensus(Y, k=k)
# Not run
# mod_res = Select_Model_short_SC3(Y, cluster = con_res$cluster, top = c(100, 200))
library(ggpubr)
# Visual_Rslt(model_cv_res = mod_res, trueclass = trueclass)
```

---

Y

*An example single cell count expression matrix (Yan)*

---

**Description**

Y is a count expression matrix which belongs to "matrix" class. The data includes 124 cells about human preimplantation embryos and embryonic stem cells. It contains 19304 genes after removing genes with extreme high dropout rate.

**Usage**

```
data("Yan")
```

**Format**

An object of "matrix" class contains the count expressions

**Source**

<https://www.ncbi.nlm.nih.gov/geo/query/acc.cgi?acc=GSE36552>

**References**

Yan, Liying, et al. "Single-cell RNA-Seq profiling of human preimplantation embryos and embryonic stem cells." *Nature structural & molecular biology* 20.9 (2013): 1131.

**Examples**

```
data("Yan")  
Y[1:10, 1:4]
```

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