

# Package ‘scCAN’

June 13, 2024

**Type** Package

**Title** Single-Cell Clustering using Autoencoder and Network Fusion

**Version** 1.0.5

**Maintainer** Bang Tran <s.tran@csus.edu>

**Description** A single-cell Clustering method using 'Autoencoder' and Network fusion ('scCAN') Bang Tran (2022) <[doi:10.1038/s41598-022-14218-6](https://doi.org/10.1038/s41598-022-14218-6)> for segregating the cells from the high-dimensional 'scRNA-Seq' data. The software automatically determines the optimal number of clusters and then partitions the cells in a way such that the results are robust to noise and dropouts. 'scCAN' is fast and it supports Windows, Linux, and Mac OS.

**License** LGPL

**Encoding** UTF-8

**LazyData** true

**LazyDataCompression** xz

**Depends** R (>= 4.2.0), scDHA, FNN, purrr

**Imports** stats

**RoxygenNote** 7.2.3

**Suggests** knitr, rmarkdown

**VignetteBuilder** knitr

**NeedsCompilation** no

**Author** Bang Tran [aut, cre],  
Duc Tran [aut],  
Hung Nguyen [aut],  
Tin Nguyen [fnd]

**Repository** CRAN

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## Contents

adjustedRandIndex . . . . .	2
calculate_celltype_prob . . . . .	2
curate_markers . . . . .	3
find_markers . . . . .	4
find_specific_marker . . . . .	4
get_cluster_markers . . . . .	5
scCAN . . . . .	5
SCE . . . . .	7

<b>Index</b>	<b>8</b>
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adjustedRandIndex	<i>adjustedRandIndex</i>
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### Description

The function to calculate adjusted Rand index value with the inputs of true clusters and predicted clusters

### Usage

```
adjustedRandIndex(x, y)
```

### Arguments

x	A vector that contain predicted cluster assignment.
y	A vector that contain true cluster assignment.

### Value

An value number ranging from 0 to 1 where 1 indicates a perfect clustering result and 0 means random partition.

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calculate_celltype_prob	<i>calculate_celltype_prob</i>
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### Description

Calculate clusters and cell types similarity based on the markers.

### Usage

```
calculate_celltype_prob(clt_marker_list, marker_database_list, type = "jacc")
```

**Arguments**

<code>clt_marker_list</code>	A list of markers for all cluster.
<code>marker_database_list</code>	A list of markers of all reference cell types.
<code>type</code>	A parameter to select the method to measure cluster and cell type similarity <ul style="list-style-type: none"> <li>• jacc - Jaccard index.</li> <li>• ac - Accuracy.</li> <li>• f1 - F1 score.</li> </ul>

**Value**

A confusion matrix between clusters and cell types. Each cell represents a probability of a cluster belongs to a cell type.

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<code>curate_markers</code>	<i>curate_markers</i>
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**Description**

Filter genes that have low p-value and fold-change.

**Usage**

```
curate_markers(
  whole_list,
  gene_names,
  wilcox_threshold = 0.001,
  logfc_threshold = 1.5
)
```

**Arguments**

<code>whole_list</code>	A list of markers for all clusters.
<code>gene_names</code>	All the gene names of the expression matrix.
<code>wilcox_threshold</code>	A threshold for p-value <code>wilcox_threshold = 0.001</code> by default.
<code>logfc_threshold</code>	A threshold for fold-change <code>logfc_threshold = 1.5</code> by default.

**Value**

A list of markers that are strong expressed for discovered clusters.

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find_markers	<i>find_markers</i>
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**Description**

Perform cluster-wise Wilcox test and fold-change for each gene.

**Usage**

```
find_markers(input_data_matrix, cluster_labels, identity = 1, threads = 8)
```

**Arguments**

input_data_matrix	An expression matrix in which rows are genes and columns are cells.
cluster_labels	A vector of cluster labels obtained from clustering methods.
identity	A parameter to select specific cluster identity = 1 by default.
threads	A parameter to control number of cores used for analysis threads = 1 by default.

**Value**

A list that contains p-value and fold-change ratio for all genes of each cluster.

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find_specific_marker	<i>find_specific_marker</i>
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**Description**

Calculate cluster and cell type similarity based on the markers.

**Usage**

```
find_specific_marker(gene_name, f_list, type = "jacc")
```

**Arguments**

gene_name	A list of markers belong to the cluster.
f_list	A list of markers belongs to a reference cell type.
type	A parameter to select the method to measure cluster and cell type similarity <ul style="list-style-type: none"> <li>• jacc - Jaccard index.</li> <li>• ac - Accuracy.</li> <li>• f1 - F1 score.</li> </ul>

**Value**

A vector of probabilities of a cluster belongs to cell types.

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get\_cluster\_markers    *get\_cluster\_markers*

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**Description**

Find markers for each cluster

**Usage**

```
get_cluster_markers(input_data_matrix, labels_vector, threads = 1)
```

**Arguments**

`input_data_matrix`    An expression matrix in which rows are genes and columns are cells.

`labels_vector`    A vector of cluster labels obtained from clustering methods.

`threads`    A parameter to control number of cores used for analysis threads = 1 by default.

**Value**

A list that contains markers for each cluster.

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scCAN    *scCAN*

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**Description**

This is the main function to perform sc-RNA seq data clustering. scCAN is fully unsupervised scRNA-seq clustering framework that uses deep neural network and network fusion-based clustering algorithm. First, scCAN applies a non-negative autoencoder to filter scRNA-seq data. Second, the filtered data is passed to stacked Bayesian autoencoder to get multiple low-dimensional representations of input data. Subsequently, scCAN converts these compressed data into networks and unify those networks to a single graph. Then, scCAN uses a spectral clustering algorithm to obtain final clusters assignment.

**Usage**

```

scCAN(
  data,
  sparse = FALSE,
  n.neighbors = 30,
  alpha = 0.5,
  n.iters = 10,
  ncores = 10,
  r.seed = 1,
  subsamp = TRUE,
  k = 2:15,
  samp.size = 5000
)

```

**Arguments**

<code>data</code>	Gene expression matrix, with rows represent samples and columns represent genes.
<code>sparse</code>	Boolean variable indicating whether data is a sparse matrix. The input must be a non negative sparse matrix.
<code>n.neighbors</code>	Number of neighboring cells that are used to calculate the edge's weight. The number of neighbors are set <code>n.neighbors = 30</code> by default.
<code>alpha</code>	A hyper parameter that control the weight of graph. This values is set to <code>alpha = 0.5</code> by default.
<code>n.iters</code>	A hyper-parameter to set the number of network fusion iterations. It is set to <code>n.iters = 10</code> by default.
<code>ncores</code>	Number of processor cores to use.
<code>r.seed</code>	A parameter to set a seed for reproducibility. This values is set to <code>r.seed = 1</code> by default.
<code>subsamp</code>	Enable subsampling process for big data. This values is set to <code>subsamp = T</code> by default.
<code>k</code>	A vector to search for optimal number of cluster.
<code>samp.size</code>	A parameter to control number of sub-sampled cells.

**Value**

List with the following keys:

- `cluster` - A numeric vector containing cluster assignment for each sample.
- `k` - The optimal number of cluster.
- `latent` - The latent data generated from autoencoders.

**References**

1. Duc Tran, Hung Nguyen, Bang Tran, Carlo La Vecchia, Hung N. Luu, Tin Nguyen (2021). Fast and precise single-cell data analysis using a hierarchical autoencoder. *Nature Communications*, 12, 1029. doi: 10.1038/s41467-021-21312-2

**Examples**

```
## Not run:
# Not run if scDHA has not installed yet.
# Load the package and the example data (SCE dataset)
library(scCAN)
#Load example data
data("SCE")

#Get data matrix and label
data <- t(SCE$data); label <- as.character(SCE$cell_type1)

#Generate clustering result, the input matrix has rows as samples and columns as genes
result <- scCAN(data, r.seed = 1)

#Get the clustering result
cluster <- result$cluster

#Calculate adjusted Rand Index
ari <- round(scCAN::adjustedRandIndex(cluster,label), 2)
message(paste0("ARI = ", ari))

## End(Not run)
```

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SCE

*SCE*

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**Description**

SCE dataset includes scRNA-seq data and cell type information.

**Usage**

SCE

**Format**

An object of class `list` of length 2.

# Index

## \* datasets

SCE, [7](#)

adjustedRandIndex, [2](#)

calculate\_celltype\_prob, [2](#)

curate\_markers, [3](#)

find\_markers, [4](#)

find\_specific\_marker, [4](#)

get\_cluster\_markers, [5](#)

scCAN, [5](#)

SCE, [7](#)