Package ‘scGPS’

March 14, 2024

Type Package

Title A complete analysis of single cell subpopulations, from identifying subpopulations to analysing their relationship (scGPS = single cell Global Predictions of Subpopulation)

Version 1.16.0

Description The package implements two main algorithms to answer two key questions: a SCORE (Stable Clustering at Optimal REsolution) to find subpopulations, followed by scGPS to investigate the relationships between subpopulations.

Encoding UTF-8

LazyData true

License GPL-3

BugReports https://github.com/IMB-Computational-Genomics-Lab/scGPS/issues

url https://github.com/IMB-Computational-Genomics-Lab/scGPS/

RoxygenNote 7.1.1

Depends R (>= 3.6), SummarizedExperiment, dynamicTreeCut, SingleCellExperiment

biocViews SingleCell, Clustering, DataImport, Sequencing, Coverage

Imports glmnet (> 2.0), caret (>= 6.0), ggplot2 (>= 2.2.1), fastcluster, dplyr, Rcpp, RcppArmadillo, RcppParallel, grDevices, graphics, stats, utils, DESeq2, locfit

Suggests Matrix (>= 1.2), testthat, knitr, parallel, rmarkdown, RColorBrewer, ReactomePA, clusterProfiler, cowplot, org.Hs.eg.db, reshape2, xlsx, dendextend, networkD3, Rtsne, BiocParallel, e1071, WGCNA, devtools, DOSE

VignetteBuilder knitr

LinkingTo Rcpp, RcppArmadillo, RcppParallel

SystemRequirements GNU make

git_url https://git.bioconductor.org/packages/scGPS

git_branch RELEASE_3_18
R topics documented:

```
add_import .......................................................... 3
annotate_clusters .................................................... 3
bootstrap_parallel ................................................... 4
bootstrap_prediction ................................................ 5
calcDist ............................................................... 7
calcDistArma ........................................................ 7
clustering .............................................................. 8
clustering_bagging ................................................... 9
CORE_bagging ........................................................ 10
CORE_clustering ..................................................... 11
CORE_subcluster .................................................... 13
day_2_cardio_cell_sample ......................................... 14
day_5_cardio_cell_sample ......................................... 14
distvec ................................................................. 15
find_markers .......................................................... 16
find_optimal_stability ............................................. 17
find_stability ......................................................... 18
mean_cpp ............................................................... 19
new_scGPS_object .................................................. 19
new_summarized_scGPS_object ................................... 20
PCA ................................................................... 22
plot_CORE ............................................................ 22
plot_optimal_CORE .................................................. 23
plot_reduced ........................................................ 24
predicting ............................................................. 25
PrinComp_cpp ........................................................ 27
rand_index ........................................................... 27
rcpp_Eucl_distance_NotPar ....................................... 28
rcpp_parallel_distance ............................................ 29
reformat_LASSO ..................................................... 29
subset_cpp ........................................................... 30
sub_clustering ....................................................... 31
summary_accuracy .................................................. 32
summary_deviance .................................................. 33
summary_prediction_lasso ......................................... 34
```
Description
import packages to namespace

annotate_clusters
annotate_clusters functionally annotates the identified clusters

Description
often we need to label clusters with unique biological characters. One of the common approach to annotate a cluster is to perform functional enrichment analysis. The annotate implements ReactomePA and clusterProfiler for this analysis type in R. The function require installation of several databases as described below.

Usage
annotate_clusters(
  DEgeneList,
  pvalueCutoff = 0.05,
  gene_symbol = TRUE,
  species = "human"
)

Arguments
DEgeneList is a vector of gene symbols, convertable to ENTREZID
pvalueCutoff is a numeric of the cutoff p value
gene_symbol logical of whether the geneList is a gene symbol
species is the selection of 'human' or 'mouse', default to 'human' genes

Value
write enrichment test output to a file and an enrichment test object for plotting
Examples

```r
genes <- training_gene_sample
gen <- genes$Merged_unique[seq_len(50)]
enrichment_test <- annotate_clusters(genes, pvalueCutoff=0.05,
gene_symbol=TRUE, species = 'human')
clusterProfiler::dotplot(enrichment_test, showCategory=15)
```

---

**bootstrap_parallel**  
*BootStrap runs for both scGPS training and prediction with parallel option*

---

**Description**

same as bootstrap_prediction, but with an multicore option

**Usage**

```r
bootstrap_parallel(
  ncores = 4,
  nboots = 1,
  genes = genes,
  mixedpop1 = mixedpop1,
  mixedpop2 = mixedpop2,
  c_selectID,
  listData = list(),
  cluster_mixedpop1 = NULL,
  cluster_mixedpop2 = NULL
)
```

**Arguments**

- **ncores**  
a number specifying how many cpus to be used for running  
- **nboots**  
a number specifying how many bootstraps to be run  
- **genes**  
a gene list to build the model  
- **mixedpop1**  
a `SingleCellExperiment` object from a mixed population for training  
- **mixedpop2**  
a `SingleCellExperiment` object from a target mixed population for prediction  
- **c_selectID**  
the root cluster in mixedpop1 to be compared to clusters in mixedpop2  
- **listData**  
a list object, which contains trained results for the first mixed population  
- **cluster_mixedpop1**  
a vector of cluster assignment for mixedpop1  
- **cluster_mixedpop2**  
a vector of cluster assignment for mixedpop2
Value

A list with prediction results written in to the index `out_idx`.

Author(s)

Quan Nguyen, 2017-11-25

Examples

```r
day2 <- day_2_cardio_cell_sample
mixedpop1 <- new_scGPS_object(ExpressionMatrix = day2$dat2_counts,
     GeneMetadata = day2$dat2geneInfo, CellMetadata = day2$dat2_clusters)

day5 <- day_5_cardio_cell_sample
mixedpop2 <- new_scGPS_object(ExpressionMatrix = day5$dat5_counts,
     GeneMetadata = day5$dat5geneInfo, CellMetadata = day5$dat5_clusters)
genes <- training_gene_sample

genes <- genes$Merged_unique

# prl_boots <- bootstrap_parallel(ncores = 4, nboots = 1, genes = genes,
#     mixedpop1 = mixedpop2, mixedpop2 = mixedpop2, c_selectID = 1,
#     listData = list())

# prl_boots[[1]]$ElasticNetPredict
# prl_boots[[1]]$LDAPredict
```

Description

ElasticNet and LDA prediction for each of all the subpopulations in the new mixed population after training the model for a subpopulation in the first mixed population. The number of bootstraps to be run can be specified.

Usage

```r
bootstrap_prediction(nboots = 1,
     genes = genes,
     mixedpop1 = mixedpop1,
     mixedpop2 = mixedpop2,
     c_selectID = NULL,
     listData = list(),
     cluster_mixedpop1 = NULL,
     cluster_mixedpop2 = NULL,
     trainset_ratio = 0.5,
     LDA_run = TRUE,
     verbose = FALSE,
     log_transform = FALSE)
```
### Arguments

- **nboots**: A number specifying how many bootstraps to be run.
- **genes**: A gene list to build the model.
- **mixedpop1**: A `SingleCellExperiment` object from a mixed population for training.
- **mixedpop2**: A `SingleCellExperiment` object from a target mixed population for prediction.
- **c_selectID**: The root cluster in `mixedpop1` to be compared to clusters in `mixedpop2`.
- **listData**: A list object, which contains trained results for the first mixed population.
- **cluster_mixedpop1**: A vector of cluster assignment for `mixedpop1`.
- **cluster_mixedpop2**: A vector of cluster assignment for `mixedpop2`.
- **trainset_ratio**: A number specifying the proportion of cells to be part of the training subpopulation.
- **LDA_run**: Logical, if the LDA prediction is added to compare to ElasticNet.
- **verbose**: A logical whether to display additional messages.
- **log_transform**: Boolean whether log transform should be computed.

### Value

A list with prediction results written in to the index `out_idx`.

### Author(s)

Quan Nguyen, 2017-11-25

### See Also

- `bootstrap_parallel` for parallel options

### Examples

```r
day2 <- day_2_cardio_cell_sample
mixedpop1 <- new_scGPS_object(ExpressionMatrix = day2$dat2_counts,
                              GeneMetadata = day2$dat2geneInfo, CellMetadata = day2$dat2_clusters)
day5 <- day_5_cardio_cell_sample
mixedpop2 <- new_scGPS_object(ExpressionMatrix = day5$dat5_counts,
                              GeneMetadata = day5$dat5geneInfo, CellMetadata = day5$dat5_clusters)
genes <- training_gene_sample
genes <- genes$Merged_unique
cluster_mixedpop1 <- colData(mixedpop1)[,1]
cluster_mixedpop2 <- colData(mixedpop2)[,1]
c_selectID <- 2
test <- bootstrap_prediction(nboots = 1, mixedpop1 = mixedpop1,
                           mixedpop2 = mixedpop2, genes = genes, listData = list(),
                           cluster_mixedpop1 = cluster_mixedpop1,
                           cluster_mixedpop2 = cluster_mixedpop2, c_selectID = c_selectID)
names(test)
```
**calcDist**

*Compute Euclidean distance matrix by rows*

**Description**

Compute Euclidean distance matrix by rows

**Usage**

```r
calcDist(x)
```

**Arguments**

- `x` A numeric matrix

**Value**

a distance matrix

**Examples**

```r
mat_test <- matrix(rnbinom(1000, mu=0.01, size=10), nrow=1000)
calcDist(mat_test)
```

**calcDistArma**

*Compute Euclidean distance matrix by rows*

**Description**

Compute Euclidean distance matrix by rows

**Usage**

```r
calcDistArma(x)
```

**Arguments**

- `x` A numeric matrix

**Value**

a distance matrix
### Examples

```r
mat_test <- matrix(rnbinom(1000, mu = 0.01, size = 10), nrow = 1000)
#library(microbenchmark)
#microbenchmark(calcDistArma(mat_test), dist(mat_test), times=3)
```

### clustering

**HC clustering for a number of resolutions**

### Description

performs 40 clustering runs or more depending on windows

### Usage

```r
clustering(
  object = NULL,
  ngenes = 1500,
  windows = seq(from = 0.025, to = 1, by = 0.025),
  remove_outlier = c(0),
  nRounds = 1,
  PCA = FALSE,
  nPCs = 20,
  verbose = FALSE,
  log_transform = FALSE
)
```

### Arguments

- **object**
  - is a `SingleCellExperiment` object from the train mixed population
- **ngenes**
  - number of top variable genes to be used
- **windows**
  - a numeric specifying the number of windows to test
- **remove_outlier**
  - a vector containing IDs for clusters to be removed the default vector contains 0, as 0 is the cluster with singletons
- **nRounds**
  - number of iterations to remove a selected clusters
- **PCA**
  - logical specifying if PCA is used before calculating distance matrix
- **nPCs**
  - number of principal components from PCA dimensional reduction to be used
- **verbose**
  - a logical whether to display additional messages
- **log_transform**
  - boolean whether log transform should be computed

### Value

- clustering results
clustering_bagging

Author(s)
Quan Nguyen, 2017-11-25

Examples

day5 <- day_5_cardio_cell_sample
mixedpop2 <- new_summarized_scGPS_object(ExpressionMatrix = day5$dat5_counts,
   GeneMetadata = day5$dat5geneInfo, CellMetadata = day5$dat5_clusters)

test <- clustering(mixedpop2, remove_outlier = c(0))

classification_bagging  

HC clustering for a number of resolutions

Description

subsamples cells for each bagging run and performs 40 clustering runs or more depending on windows.

Usage

clustering_bagging(
  object = NULL,
  ngenes = 1500,
  bagging_run = 20,
  subsample_proportion = 0.8,
  windows = seq(from = 0.025, to = 1, by = 0.025),
  remove_outlier = c(0),
  nRounds = 1,
  PCA = FALSE,
  nPCs = 20,
  log_transform = FALSE
)

Arguments

object is a SingleCellExperiment object from the train mixed population.
ngenes number of genes used for clustering calculations.
bagging_run an integer specifying the number of bagging runs to be computed.
subsample_proportion a numeric specifying the proportion of the tree to be chosen in subsampling.
windows a numeric specifying the ranges of each window.
remove_outlier a vector containing IDs for clusters to be removed the default vector contains 0,
as 0 is the cluster with singletons.
nRounds a integer specifying the number rounds to attempt to remove outliers.
PCA logical specifying if PCA is used before calculating distance matrix.
nPCs an integer specifying the number of principal components to use.
log_transform boolean whether log transform should be computed
CORE_bagging

Value

a list of clustering results containing each bagging run as well as the clustering of the original tree and the tree itself.

Author(s)

Quan Nguyen, 2017-11-25

Examples

day5 <- day_5_cardio_cell_sample
mixedpop2 <- new_summarized_scGPS_object(ExpressionMatrix = day5$dat5_counts,
  GeneMetadata = day5$dat5geneInfo, CellMetadata = day5$dat5_clusters)
test <- clustering_bagging(mixedpop2, remove_outlier = c(0),
  bagging_run = 2, subsample_proportion = .7)

CORE_bagging

Main clustering SCORE (CORE V2.0) Stable Clustering at Optimal REsolution with bagging and bootstrapping

Description

CORE is an algorithm to generate reproducible clustering, CORE is first implemented in ascend R package. Here, CORE V2.0 uses bagging analysis to find a stable clustering result and detect rare clusters mixed population.

Usage

CORE_bagging(
  mixedpop = NULL,
  bagging_run = 20,
  subsample_proportion = 0.8,
  windows = seq(from = 0.025, to = 1, by = 0.025),
  remove_outlier = c(0),
  nRounds = 1,
  PCA = FALSE,
  nPCs = 20,
  ngenes = 1500,
  log_transform = FALSE
)

Arguments

mixedpop is a SingleCellExperiment object from the train mixed population.
bagging_run an integer specifying the number of bagging runs to be computed.
subsample_proportion a numeric specifying the proportion of the tree to be chosen in subsampling.
windows         a numeric vector specifying the ranges of each window.
remove_outlier  a vector containing IDs for clusters to be removed the default vector contains 0, as 0 is the cluster with singletons.
nRounds         an integer specifying the number rounds to attempt to remove outliers.
PCA             logical specifying if PCA is used before calculating distance matrix.
nPCs            an integer specifying the number of principal components to use.
genres           number of genes used for clustering calculations.
log_transform   boolean whether log transform should be computed

Value

a list with clustering results of all iterations, and a selected optimal resolution

Author(s)

Quan Nguyen, 2018-05-11

Examples

day5 <- day_5_cardio_cell_sample
cellnames<-colnames(day5$dat5_counts)
cluster <-day5$dat5_clusters
cellnames <- data.frame('cluster' = cluster, 'cellBarcodes' = cellnames)
#day5$dat5_counts needs to be in a matrix format
mixedpop2 <-new_summarized_scGPS_object(ExpressionMatrix = day5$dat5_counts,
                                      GeneMetadata = day5$dat5geneInfo, CellMetadata = day5$dat5_clusters)
test <- CORE_bagging(mixedpop2, remove_outlier = c(0), PCA=FALSE,
                      bagging_run = 2, subsample_proportion = .7)

CORE_clustering       Main clustering CORE V2.0 updated

Description

CORE is an algorithm to generate reproducible clustering, CORE is first implemented in ascend R package. Here, CORE V2.0 introduces several new functionalities, including three key features: fast (and more memory efficient) implementation with C++ and parallelisation options allowing clustering of hundreds of thousands of cells (ongoing development), outlier removal important if singletons exist (done), a number of dimensionality reduction methods including the imputation implementation (CIDR) for confirming clustering results (done), and an option to select the number of optimisation tree height windows for increasing resolution.
CORE_clustering

Usage

CORE_clustering(
  mixedpop = NULL,
  windows = seq(from = 0.025, to = 1, by = 0.025),
  remove_outlier = c(0),
  nRounds = 1,
  PCA = FALSE,
  nPCs = 20,
  ngenes = 1500,
  verbose = FALSE,
  log_transform = FALSE
)

Arguments

mixedpop is a SingleCellExperiment object from the train mixed population
windows a numeric specifying the number of windows to test
remove_outlier a vector containing IDs for clusters to be removed the default vector contains 0, as 0 is the cluster with singletons.
nRounds an integer specifying the number rounds to attempt to remove outliers.
PCA logical specifying if PCA is used before calculating distance matrix
nPCs an integer specifying the number of principal components to use.
ngenes number of genes used for clustering calculations.
verbose a logical whether to display additional messages
log_transform boolean whether log transform should be computed

Value

a list with clustering results of all iterations, and a selected optimal resolution

Author(s)

Quan Nguyen, 2017-11-25

Examples

day5 <- day_5_cardio_cell_sample
#day5$dat5_counts needs to be in a matrix format
cellnames <- colnames(day5$dat5_counts)
cluster <- day5$dat5_clusters
cellnames <- data.frame('Cluster' = cluster, 'cellBarcodes' = cellnames)
mixedpop2 <- new_summarized_scGPS_object(ExpressionMatrix = day5$dat5_counts,
  GeneMetadata = day5$dat5geneInfo, CellMetadata = day5$dat5_clusters)
test <- CORE_clustering(mixedpop2, remove_outlier = c(0), PCA=FALSE, nPCs=20,
  ngenes = 1500)
CORE_subcluster

Description

CORE_subcluster allows re-cluster the CORE clustering result.

Usage

CORE_subcluster(
  mixedpop = NULL,
  windows = seq(from = 0.025, to = 1, by = 0.025),
  select_cell_index = NULL,
  ngenes = 1500
)

Arguments

- **mixedpop**: is a SingleCellExperiment object from the train mixed population.
- **windows**: a numeric specifying the number of windows to test.
- **select_cell_index**: a vector containing indexes for cells in selected clusters to be reclustered.
- **ngenes**: number of genes used for clustering calculations.

Value

a list with clustering results of all iterations, and a selected optimal resolution.

Author(s)

Quan Nguyen, 2017-11-25

Examples

day5 <- day_5_cardio_cell_sample
mixedpop2 <- new_summarized_scGPS_object(ExpressionMatrix = day5$dat5_counts,
  GeneMetadata = day5$dat5geneInfo, CellMetadata = day5$dat5_clusters)
test <- CORE_clustering(mixedpop2, remove_outlier = c(0))
day_2_cardio_cell_sample

One of the two example single-cell count matrices to be used for training scGPS model

Description
The count data set contains counts for 16990 genes for 590 cells randomly subsampled from day-2 cardio-differentiation population. The vector of clustering information contains corresponding to cells in the count matrix.

Usage
day_2_cardio_cell_sample

Format
a list instance, containing a count matrix and a vector with clustering information

Value
a list, with the name day2

Author(s)
Quan Nguyen, 2017-11-25

Source
Dr Joseph Powell’s laboratory, IMB, UQ

day_5_cardio_cell_sample

One of the two example single-cell count matrices to be used for scGPS prediction

Description
The count data set contains counts for 17402 genes for 983 cells (1 row per gene) randomly subsampled from day-5 cardio-differentiation population. The vector of clustering information contains corresponding to cells in the count matrix.

Usage
day_5_cardio_cell_sample
distvec

Format

a list instance, containing a count matrix and a vector with clustering information.

Value

a list, with the name day5

Author(s)

Quan Nguyen, 2017-11-25

Source

Dr Joseph Powell’s laboratory, IMB, UQ

distvec  Compute Distance between two vectors

Description

Compute Distance between two vectors

Usage

distvec(x, y)

Arguments

x  A numeric vector
y  A numeric vector

Value

a numeric distance

Examples

x <- matrix(rnbinom(1000, mu=0.01, size=10), nrow=1000)
x <- x[1,]
y <- matrix(rnbinom(1000, mu=0.01, size=10), nrow=1000)
y <- y[1,]
distvec(x, y)
find_markers

Description

Find DE genes from comparing one clust vs remaining

Usage

find_markers(
  expression_matrix = NULL,
  cluster = NULL,
  selected_cluster = NULL,
  fitType = "local",
  dispersion_method = "per-condition",
  sharing_Mode = "maximum"
)

Arguments

expression_matrix
  is a normalised expression matrix.
cluster
  corresponding cluster information in the expression_matrix by running CORE clustering or using other methods.
selected_cluster
  a vector of unique cluster ids to calculate
fitType
  string specifying 'local' or 'parametric' for DEseq dispersion estimation
dispersion_method
  one of the options c('pooled', 'pooled-CR', 'per-condition', 'blind')
sharing_Mode
  one of the options c("maximum", "fit-only", "gene-est-only")

Value

a list containing sorted DESeq analysis results

Author(s)

Quan Nguyen, 2017-11-25

Examples

day2 <- day_2_cardio_cell_sample
mixedpop1 <- new_scGPS_object(ExpressionMatrix = day2$dat2_counts,
  GeneMetadata = day2$dat2geneInfo, CellMetadata = day2$dat2_clusters)
# depending on the data, the DESeq::estimateDispersions function requires
# suitable fitType
# and dispersion_method options
find_optimal_stability

DEgenes <- find_markers(expression_matrix=assay(mixedpop1),
cluster = colData(mixedpop1)[,1],
selected_cluster=c(1), #can also run for more
#than one clusters, e.g.selected_cluster = c(1,2)
fitType = "parametric",
dispersion_method = "blind",
sharing_Mode="fit-only"
)

names(DEgenes)

find_optimal_stability

Find the optimal cluster

Description

from calculated stability based on Rand indexes for consecutive clustering run, find the resolution
(window), where the stability is the highest

Usage

find_optimal_stability(
  list_clusters,
  run_RandIdx,
  bagging = FALSE,
  windows = seq(from = 0.025, to = 1, by = 0.025)
)

Arguments

list_clusters is a list object containing 40 clustering results
run_RandIdx is a data frame object from iterative clustering runs
bagging is a logical that is true if bagging is to be performed, changes return
windows a numeric vector specifying the ranges of each window.

Value

bagging == FALSE => a list with optimal stability, cluster count and summary stats bagging ==
TRUE => a list with high res cluster count, optimal cluster count and keystats

Author(s)

Quan Nguyen, 2017-11-25
Examples

day5 <- day_5_cardio_cell_sample
mixedpop2 <- new_summarized_scGPS_object(ExpressionMatrix = day5$dat5_counts,
GeneMetadata = day5$dat5geneInfo, CellMetadata = day5$dat5_clusters)
cluster_all <- clustering(object=mixedpop2)
stab_df <- find_stability(list_clusters=cluster_all$list_clusters,
cluster_ref = cluster_all$cluster_ref)
optimal_stab <- find_optimal_stability(list_clusters =
cluster_all$list_clusters, stab_df, bagging = FALSE)

find_stability

Calculate stability index

Description

from clustering results, compare similarity between clusters by adjusted Randindex

Usage

find_stability(list_clusters = NULL, cluster_ref = NULL)

Arguments

list_clusters is a object from the iterative clustering runs
cluster_ref is a object from the reference cluster

Value

da data frame with stability scores and rand_index results

Author(s)

Quan Nguyen, 2017-11-25

Examples

day5 <- day_5_cardio_cell_sample
mixedpop2 <- new_summarized_scGPS_object(ExpressionMatrix = day5$dat5_counts,
GeneMetadata = day5$dat5geneInfo, CellMetadata = day5$dat5_clusters)
cluster_all <- clustering(object=mixedpop2)
stab_df <- find_stability(list_clusters=cluster_all$list_clusters,
cluster_ref = cluster_all$cluster_ref)
mean_cpp

Calculate mean

Description

Calculate mean

Usage

mean_cpp(x)

Arguments

x integer.

Value

a scalar value

Examples

mean_cpp(seq_len(10^6))

new_scGPS_object

new_scGPS_object

Description

new_scGPS_object generates a scGPS object in the SingleCellExperiment class for use with the scGPS package. This object contains an expression matrix, associated metadata (cells, genes, clusters). The data are expected to be normalised counts.

Usage

new_scGPS_object(
    ExpressionMatrix = NULL,
    GeneMetadata = NULL,
    CellMetadata = NULL,
    LogMatrix = NULL
)
Arguments

ExpressionMatrix
An expression matrix in data.frame or matrix format. Rows should represent a transcript and its normalised counts, while columns should represent individual cells.

GeneMetadata
A data frame or vector containing gene identifiers used in the expression matrix. The first column should hold the gene identifiers you are using in the expression matrix. Other columns contain information about the genes, such as their corresponding ENSEMBL transcript identifiers.

CellMetadata
A data frame containing cell identifiers (usually barcodes) and an integer representing which batch they belong to. The column containing clustering information needs to be the first column in the CellMetadata dataframe. If clustering information is not available, users can run CORE function and add the information to the scGPS before running scGPS prediction.

LogMatrix
Optional input for a log matrix of the data. If no log matrix is supplied one will be created for the object.

Value
This function generates an scGPS object belonging to the SingleCellExperiment.

Author(s)
Quan Nguyen, 2018-04-06

See Also
SingleCellExperiment

Examples

day2 <- day_2_cardio_cell_sample
t <- new_scGPS_object(ExpressionMatrix = day2$dat2_counts,
  GeneMetadata = day2$dat2geneInfo, CellMetadata = day2$dat2_clusters)
colData(t); show(t); colnames(t)

Description

new_scGPS_object generates a scGPS object in the SingleCellExperiment class for use with the scGPS package. This object contains an expression matrix, associated metadata (cells, genes, clusters). The data are expected to be normalised counts.
new_summarized_scGPS_object

Usage

new_summarized_scGPS_object(
  ExpressionMatrix = NULL,
  GeneMetadata = NULL,
  CellMetadata = NULL
)

Arguments

ExpressionMatrix
An expression dataset in matrix format. Rows should represent a transcript and its normalised counts, while columns should represent individual cells.

GeneMetadata
A data frame or vector containing gene identifiers used in the expression matrix. The first column should hold the cell identifiers you are using in the expression matrix. Other columns contain information about the genes, such as their corresponding ENSEMBL transcript identifiers.

CellMetadata
A data frame containing cell identifiers (usually barcodes) and clustering information (the first column of the data frame contains clustering information). The column containing clustering information needs to be named as 'Cluster'. If clustering information is not available, users can run CORE function and add the information to the scGPS before running scGPS prediction.

Value

This function generates an scGPS object belonging to the SingleCellExperiment.

Author(s)

Quan Nguyen, 2017-11-25

See Also

SingleCellExperiment

Examples

day2 <- day_2_cardio_cell_sample
t <- new_summarized_scGPS_object(ExpressionMatrix = day2$dat2_counts,
  GeneMetadata = day2$dat2geneInfo, CellMetadata = day2$dat2_clusters)
colData(t); show(t); colnames(t)
**Description**

Select top variable genes and perform prcomp

**Usage**

```r
PCA(expression.matrix = NULL, ngenes = 1500, scaling = TRUE, npcs = 50)
```

**Arguments**

- `expression.matrix`
  - An expression matrix, with genes in rows
- `ngenes`
  - Number of genes used for clustering calculations.
- `scaling`
  - A logical of whether we want to scale the matrix
- `npcs`
  - An integer specifying the number of principal components to use.

**Value**

A list containing PCA results and variance explained

**Examples**

```r
day2 <- day_2_cardio_cell_sample
mixedpop1 <- new_scGPS_object(ExpressionMatrix = day2$dat2_counts,
                               GeneMetadata = day2$dat2geneInfo, CellMetadata = day2$dat2_clusters)
t <- PCA(expression.matrix = assay(mixedpop1))
```

---

**plot_CORE**

**Description**

This function plots CORE and all clustering results underneath

**Usage**

```r
plot_Core(original.tree, list_clusters = NULL, color_branch = NULL)
```
**Arguments**

- `original.tree`: the original dendrogram before clustering
- `list_clusters`: a list containing clustering results for each of the
- `color_branch`: is a vector containing user-specified colors (the number of unique colors should be equal or larger than the number of clusters). This parameter allows better selection of colors for the display.

**Value**

a plot with clustering bars underneath the tree

**Examples**

```r
day5 <- day_5_cardio_cell_sample
cellnames <- colnames(day5$dat5_counts)
cluster <- day5$dat5_clusters
cellnames <- data.frame('Cluster'=cluster, 'cellBarcodes' = cellnames)
mixedpop2 <- new_summarized_scGPS_object(ExpressionMatrix = day5$dat5_counts,
                                        GeneMetadata = day5$dat5geneInfo, CellMetadata = cellnames)
CORE_cluster <- CORE_clustering(mixedpop2, remove_outlier = c(0))
plot_CORE(CORE_cluster$tree, CORE_cluster$Cluster)
```

---

**Description**

after an optimal cluster has been identified, users may use this function to plot the resulting dendrogram with the branch colors represent clustering results

**Usage**

```r
plot_optimal_CORE(
    original_tree,
    optimal_cluster = NULL,
    shift = -100,
    values = NULL
)
```

**Arguments**

- `original_tree`: a dendrogram object
- `optimal_cluster`: a vector of cluster IDs for cells in the dendrogram
- `shift`: a numer specifying the gap between the dendrogram and the colored
- `values`: a vector containing color values of the branches and the colored bar underneath the tree bar underneath the dendrogram. This parameter allows better selection of colors for the display.
Value

a plot with colored branches and bars for the optimal clustering result

Author(s)

Quan Nguyen, 2017-11-25

Examples

day5 <- day_5_cardio_cell_sample
mixedpop2 <- new_summarized_scGPS_object(ExpressionMatrix = day5$dat5_counts,
    GeneMetadata = day5$dat5geneInfo, CellMetadata = day5$dat5_clusters)
CORE_cluster <- CORE_clustering(mixedpop2, remove_outlier = c(0))
key_height <- CORE_cluster$optimalClust$KeyStats$Height
optimal_res <- CORE_cluster$optimalClust$OptimalRes
optimal_index = which(key_height == optimal_res)
plot_optimal_CORE(original_tree= CORE_cluster$tree,
    optimal_cluster = unlist(CORE_cluster$Cluster[optimal_index]),
    shift = -2000)

plot_reduced

Description

plot PCA, tSNE, and CIDR reduced datasets

Usage

plot_reduced(
    reduced_dat,
    color_fac = NULL,
    dims = c(1, 2),
    dimNames = c("Dim1", "Dim2"),
    palletes = NULL,
    legend_title = "Cluster"
)

Arguments

reduced_dat is a matrix with genes in rows and cells in columns

color_fac is a vector of colors corresponding to clusters to determine colors of scattered plots

dims an integer of the number of dimensions

dimNames a vector of the names of the dimensions
predicting can be a customised color pallete that determine colors for density plots, if NULL it will use RColorBrewer colorRampPalette(RColorBrewer::brewer.pal(sample_num, 'Set1'))(sample_num)

legend_title title of the plot's legend

Value

a matrix with the top 20 CIDR dimensions

Examples

day2 <- day_2_cardio_cell_sample
mixedpop1 <- new_scGPS_object(ExpressionMatrix = day2$dat2_counts,
   GeneMetadata = day2$dat2geneInfo, CellMetadata = day2$dat2_clusters)
#CIDR_dim <- CIDR(expression.matrix=assay(mixedpop1))
#p <- plot_reduced(CIDR_dim, color_fac = factor(colData(mixedpop1)[[,1]],
#   palletes = seq_len(length(unique(colData(mixedpop1)[[,1]]))))
#plot(p)
tSNE_dim <- tSNE(expression.mat=assay(mixedpop1))
p2 <- plot_reduced(tSNE_dim, color_fac = factor(colData(mixedpop1)[[,1]],
   palletes = seq_len(length(unique(colData(mixedpop1)[[,1]]))))
plot(p2)

---

predicting Main prediction function applying the optimal ElasticNet and LDA models

Description

Predict a new mixed population after training the model for a subpopulation in the first mixed population. All subpopulations in the new target mixed population will be predicted, where each targeted subpopulation will have a transition score from the original subpopulation to the new subpopulation.

Usage

predicting(
   listData = NULL,
   cluster_mixedpop2 = NULL,
   mixedpop2 = NULL,
   out_idx = NULL,
   standardize = TRUE,
   LDA_run = FALSE,
   c_selectID = NULL,
   log_transform = FALSE
)

Predicting

Arguments

- **listData**: a list object containing trained results for the selected subpopulation in the first mixed population
- **cluster_mixedpop2**: a vector of cluster assignment for mixedpop2
- **mixedpop2**: a `SingleCellExperiment` object from the target mixed population of importance, e.g. differentially expressed genes that are most significant
- **out_idx**: a number to specify index to write results into the list output. This is needed for running bootstrap.
- **standardize**: a logical of whether to standardize the data
- **LDA_run**: logical, if the LDA prediction is added to compare to ElasticNet, the LDA model needs to be trained from the training before inputting to this prediction step
- **c_selectID**: a number to specify the trained cluster used for prediction
- **log_transform**: boolean whether log transform should be computed

Value

a list with prediction results written in to the index `out_idx`

Author(s)

Quan Nguyen, 2017-11-25

Examples

```r
library(scGPS)

c_selectID<-1
out_idx<-1
day2 <- day_2_cardio_cell_sample
mixedpop1 <- new_scGPS_object(ExpressionMatrix = day2$dat2_counts,
   GeneMetadata = day2$dat2geneInfo, CellMetadata = day2$dat2_clusters)
day5 <- day_5_cardio_cell_sample
mixedpop2 <- new_scGPS_object(ExpressionMatrix = day5$dat5_counts,
   GeneMetadata = day5$dat5geneInfo, CellMetadata = day5$dat5_clusters)
genes <- training_gene_sample
genes <- genes$Merged_unique
listData <- training(genes,
   cluster_mixedpop1 = colData(mixedpop1)[, 1],
   mixedpop1 = mixedpop1,
   mixedpop2 = mixedpop2, c_selectID, listData =list(), out_idx=out_idx)

listData <- predicting(listData =listData, mixedpop2 = mixedpop2,
   out_idx=out_idx, cluster_mixedpop2 = colData(mixedpop2)[, 1],
   c_selectID = c_selectID)
```
PrinComp_cpp

Principal component analysis

Description
This function provides significant speed gain if the input matrix is big.

Usage
PrinComp_cpp(X)

Arguments
X: an R matrix (expression matrix), rows are genes, columns are cells

Value
a list with three list pca lists

Examples
mat_test <- matrix(rnbinom(1000000, mu=0.01, size=10), nrow=1000)
#library(microbenchmark)
#microbenchmark(PrinComp_cpp(mat_test), prcomp(mat_test), times=3)

rand_index
Calculate rand index

Description
Comparing clustering results Function for calculating randindex (adapted from the function by Steve Horvath and Luohua Jiang, UCLA, 2003)

Usage
rand_index(tab, adjust = TRUE)

Arguments
tab: a table containing different clustering results in rows
adjust: a logical of whether to use the adjusted rand index

Value
a rand_index value
**rcpp_Eucl_distance_NotPar**

*Function to calculate Euclidean distance matrix without parallelisation*

**Description**

Function to calculate Euclidean distance matrix without parallelisation

**Usage**

```r
rcpp_Eucl_distance_NotPar(mat)
```

**Arguments**

| mat       | an R matrix (expression matrix), with cells in rows and genes in columns |

**Value**

a distance matrix

**Examples**

```r
mat_test <- matrix(rnbinom(100000, mu=0.01, size=10), nrow=1000)
#library(microbenchmark)
#microbenchmark(rcpp_Eucl_distance_NotPar(mat_test), dist(mat_test), times=3)
```

---

**Author(s)**

Quan Nguyen and Michael Thompson, 2018-05-11

**Examples**

```r
day5 <- day_5_cardio_cell_sample
mixedpop2 <- new_summarized_scGPS_object(ExpressionMatrix = day5$dat5_counts,
GeneMetadata = day5$dat5geneInfo, CellMetadata = day5$dat5_clusters)
cluster_all <- clustering(object=mixedpop2)

rand_index(table(unlist(cluster_all$list_clusters[[1]]),
cluster_all$cluster_ref))
```
Description

This function provides fast and memory efficient distance matrix calculation.

Usage

cpp_parallel_distance(mat)

Arguments

mat an R matrix (expression matrix), rows are genes, columns are cells

Value

a distance matrix

Examples

mat_test <- matrix(rnbinom(1000000, mu=0.01, size=10), nrow=10000)
#library(microbenchmark)
#microbenchmark(rcpp_parallel_distance(mat_test), dist(mat_test), times=3)

Description

summarise bootstrap runs for Lasso model, from n bootstraps

Usage

reformat_LASSO(c_selectID = NULL, mp_selectID = NULL, LSOLDA_dat = NULL, nPredSubpop = NULL, Nodes_group = "#7570b3", nboots = 2)
### subset_cpp

**Subset a matrix**

**Description**

Subset a matrix

**Usage**

```r
subset_cpp(m1in, rowidx_in, colidx_in)
```
sub_clustering

**Arguments**

- `m1in` an R matrix (expression matrix)
- `rowidx_in` a numeric vector of rows to keep
- `colidx_in` a numeric vector of columns to keep

**Value**

- a subsetted matrix

**Examples**

```r
mat_test <- matrix(rnbinom(1000000, mu=0.01, size=10), nrow=100)
subset_mat <- subset_cpp(mat_test, rowidx_in=c(1:10), colidx_in=c(100:500))
dim(subset_mat)
```

---

**sub_clustering**  
**sub_clustering for selected cells**

**Description**

performs 40 clustering runs or more depending on windows

**Usage**

```r
sub_clustering(
  object = NULL,
  ngenes = 1500,
  windows = seq(from = 0.025, to = 1, by = 0.025),
  select_cell_index = NULL
)
```

**Arguments**

- `object` is a `SingleCellExperiment` object from the train mixed population
- `ngenes` number of genes used for clustering calculations.
- `windows` a numeric vector specifying the ranges of each window.
- `select_cell_index` a vector containing indexes for cells in selected clusters to be reclustered

**Value**

- clustering results

**Author(s)**

Quan Nguyen, 2018-01-31
Examples

day5 <- day_5_cardio_cell_sample
mixedpop2 <- new_summarized_scGPS_object(ExpressionMatrix = day5$dat5_counts,
   GeneMetadata = day5$dat5geneInfo, CellMetadata = day5$dat5_clusters)
test_sub_clustering <- sub_clustering(mixedpop2,
   select_cell_index = c(seq_len(100)))

summary_accuracy
get percent accuracy for Lasso model, from n bootstraps

Description

The training results from training were written to

Usage

summary_accuracy(object = NULL)

Arguments

object

is a list containing the training results from the summary_accuracy summarise

n bootstraps

Value

a vector of percent accuracy for the selected subpopulation

Author(s)

Quan Nguyen, 2017-11-25

Examples

c_selectID<-1
day2 <- day_2_cardio_cell_sample
mixedpop1 <- new_scGPS_object(ExpressionMatrix = day2$dat2_counts,
   GeneMetadata = day2$dat2geneInfo, CellMetadata = day2$dat2_clusters)
day5 <- day_5_cardio_cell_sample
mixedpop2 <- new_scGPS_object(ExpressionMatrix = day5$dat5_counts,
   GeneMetadata = day5$dat5geneInfo, CellMetadata = day5$dat5_clusters)
genes <- training_gene_sample
genes <- genes$Merged_unique
LSOLDA_dat <- bootstrap_prediction(nboots = 1, mixedpop1 = mixedpop1,
   mixedpop2 = mixedpop2, genes=genes, c_selectID, listData =list(),
   cluster_mixedpop1 = colData(mixedpop1)[,1],
   cluster_mixedpop2=colData(mixedpop2)[,1])
summary_accuracy(LSOLDA_dat)
summary_deviance(LSOLDA_dat)
summary_deviance

get percent deviance explained for Lasso model, from n bootstraps

Description

the training results from training were written to the object LSOLDA_dat, the summary_devidance summarises deviance explained for n bootstrap runs and also returns the best deviance matrix for plotting, as well as the best matrix with Lasso genes and coefficients

Usage

summary_deviance(object = NULL)

Arguments

object is a list containing the training results from training

Value

a list containing three elements, with a vector of percent maximum deviance explained, a dataframe containing information for the full deviance, and a dataframe containing gene names and coefficients of the best model

Author(s)

Quan Nguyen, 2017-11-25

Examples

c_selectID<-1
day2 <- day_2_cardio_cell_sample
mixedpop1 <- new_scGPS_object(ExpressionMatrix = day2$dat2_counts,
    GeneMetadata = day2$dat2geneInfo, CellMetadata = day2$dat2_clusters)
day5 <- day_5_cardio_cell_sample
mixedpop2 <- new_scGPS_object(ExpressionMatrix = day5$dat5_counts,
    GeneMetadata = day5$dat5geneInfo,
    CellMetadata = day5$dat5_clusters)
genes <- training_gene_sample
genes <- genes$Merged_unique
LSOLDA_dat <- bootstrap_prediction(nboots = 2, mixedpop1 = mixedpop1,
    mixedpop2 = mixedpop2, genes=genes, c_selectID, listData = list(),
    cluster_mixedpop1 = colData(mixedpop1)[,1],
    cluster_mixedpop2=colData(mixedpop2)[,1])
summary_deviance(LSOLDA_dat)
**summary_prediction_lasso**

*get percent deviance explained for Lasso model, from n bootstraps*

**Description**

The training results from training were written to the object LSOLDA_dat, the `summary_prediction` summarises prediction for n bootstrap runs.

**Usage**

```r
summary_prediction_lasso(LSOLDA_dat = NULL, nPredSubpop = NULL)
```

**Arguments**

- **LSOLDA_dat** is a list containing the training results from training.
- **nPredSubpop** is the number of subpopulations in the target mixed population.

**Value**

A dataframe containing information for the Lasso prediction results, each column contains prediction results for all subpopulations from each bootstrap run.

**Examples**

```r
c_selectID<-1
day2 <- day_2_cardio_cell_sample
mixedpop1 <- new_scGPS_object(ExpressionMatrix = day2$dat2_counts,
   GeneMetadata = day2$dat2geneInfo, CellMetadata = day2$dat2_clusters)
day5 <- day_5_cardio_cell_sample
mixedpop2 <- new_scGPS_object(ExpressionMatrix = day5$dat5_counts,
   GeneMetadata = day5$dat5geneInfo, CellMetadata = day5$dat5_clusters)
genes <- training_gene_sample
genes <- genes$Merged_unique
LSOLDA_dat <- bootstrap_prediction(nboots = 1, mixedpop1 = mixedpop1,
   mixedpop2 = mixedpop2, genes = genes, c_selectID, listData = list(),
   cluster_mixedpop1 = colData(mixedpop1)[,1],
   cluster_mixedpop2 = colData(mixedpop2)[,1])
summary_prediction_lasso(LSOLDA_dat=LSOLDA_dat, nPredSubpop=4)
```
The training results from training were written to the object LSOLDA_dat, the `summary_prediction` summarises prediction explained for n bootstrap runs and also returns the best deviance matrix for plotting, as well as the best matrix with Lasso genes and coefficients.

**Usage**

```r
summary_prediction_lda(LSOLDA_dat = NULL, nPredSubpop = NULL)
```

**Arguments**

- `LSOLDA_dat` is a list containing the training results from training.
- `nPredSubpop` is the number of subpopulations in the target mixed population.

**Value**

A dataframe containing information for the LDA prediction results, each column contains prediction results for all subpopulations from each bootstrap run.

**Examples**

```r
c_selectID<-1
day2 <- day_2_cardio_cell_sample
mixedpop1 <- new_scGPS_object(ExpressionMatrix = day2$dat2_counts,
GeneMetadata = day2$dat2geneInfo, CellMetadata = day2$dat2_clusters)
day5 <- day_5_cardio_cell_sample
mixedpop2 <- new_scGPS_object(ExpressionMatrix = day5$dat5_counts,
GeneMetadata = day5$dat5geneInfo, CellMetadata = day5$dat5_clusters)
genes <- training_gene_sample
genes <- genes$Merged_unique
LSOLDA_dat <- bootstrap_prediction(nboots = 1,mixedpop1 = mixedpop1,
mixedpop2 = mixedpop2, genes=genes, c_selectID, listData = list(),
cluster_mixedpop1 = colData(mixedpop1)[,1],
cluster_mixedpop2 = colData(mixedpop2)[,1])
summary_prediction_lda(LSOLDA_dat=LSOLDA_dat, nPredSubpop=4)
```
### top_var

**select top variable genes**

**Description**

subset a matrix by top variable genes

**Usage**

```r
top_var(expression.matrix = NULL, ngenes = 1500)
```

**Arguments**

- `expression.matrix`
  - is a matrix with genes in rows and cells in columns
- `ngenes`
  - number of genes used for clustering calculations.

**Value**

a subsetted expression matrix with the top n most variable genes

**Examples**

```r
day2 <- day_2_cardio_cell_sample
mixedpop1 <- new_scGPS_object(ExpressionMatrix = day2$dat2_counts,
                               GeneMetadata = day2$dat2geneInfo, CellMetadata = day2$dat2_clusters)
SortedExprsMat <- top_var(expression.matrix=assay(mixedpop1))
```

---

### tp_cpp

**Transpose a matrix**

**Description**

Transpose a matrix

**Usage**

```r
tp_cpp(X)
```

**Arguments**

- `X`
  - an R matrix (expression matrix)

**Value**

a transposed matrix
Training a half of all cells to find optimal ElasticNet and LDA models to predict a subpopulation

### Usage

```r
training(
  genes = NULL,
  cluster_mixedpop1 = NULL,
  mixedpop1 = NULL,
  mixedpop2 = NULL,
  c_selectID = NULL,
  listData = list(),
  out_idx = 1,
  standardize = TRUE,
  trainset_ratio = 0.5,
  LDA_run = FALSE,
  log_transform = FALSE
)
```

### Arguments

- **genes**: a vector of gene names (for ElasticNet shrinkage); gene symbols must be in the same format with gene names in subpop2. Note that genes are listed by the order of importance, e.g. differentially expressed genes that are most significant, so that if the gene list contains too many genes, only the top 500 genes are used.
- **cluster_mixedpop1**: a vector of cluster assignment in mixedpop1
- **mixedpop1**: is a `SingleCellExperiment` object from the train mixed population
- **mixedpop2**: is a `SingleCellExperiment` object from the target mixed population
- **c_selectID**: a selected number to specify which subpopulation to be used for training
- **listData**: list to store output in
- **out_idx**: a number to specify index to write results into the list output. This is needed for running bootstrap.
- **standardize**: a logical value specifying whether or not to standardize the train matrix
- **trainset_ratio**: a number specifying the proportion of cells to be part of the training subpopulation
- **LDA_run**: logical, if the LDA run is added to compare to ElasticNet
- **log_transform**: boolean whether log transform should be computed

### Examples

```r
mat_test <- matrix(rnbinom(1000000, mu=0.01, size=10), nrow=100)
tp_mat <- tp_cpp(mat_test)
```
Value

A list with prediction results written into the indexed out_idx.

Author(s)

Quan Nguyen, 2017-11-25

Examples

c_selectID<-1
out_idx<-1
day2 <- day_2_cardio_cell_sample
mixedpop1 <- new_scGPS_object(ExpressionMatrix = day2$dat2_counts,
   GeneMetadata = day2$dat2geneInfo, CellMetadata = day2$dat2_clusters)
day5 <- day_5_cardio_cell_sample
mixedpop2 <- new_scGPS_object(ExpressionMatrix = day5$dat5_counts,
   GeneMetadata = day5$dat5geneInfo, CellMetadata = day5$dat5_clusters)
genes <- training_gene_sample
genes <- genes$Merged_unique
listData <- training(genes,
   cluster_mixedpop1 = colData(mixedpop1)[, 1],
   mixedpop1 = mixedpop1, mixedpop2 = mixedpop2, c_selectID,
   listData = list(), out_idx=out_idx, trainset_ratio = 0.5)
names(listData)
listData$Accuracy

training_gene_sample

Input gene list for training scGPS, e.g. differentially expressed genes

Description

Genes should be ordered from most to least important genes (1 row per gene)

Usage

training_gene_sample

Format

A list instance, containing a count matrix and a vector with clustering information.

Value

A vector containing gene symbols

Author(s)

Quan Nguyen, 2017-11-25
tSNE

Source
Dr Joseph Powell’s laboratory, IMB, UQ

Description
calculate tSNE from top variable genes

Usage
tSNE(
  expression.mat = NULL,
  topgenes = 1500,
  scale = TRUE,
  thet = 0.5,
  perp = 30
)

Arguments
expression.mat An expression matrix, with genes in rows

topgenes number of genes used for clustering calculations.

scale a logical of whether we want to scale the matrix

thet numeric; Speed/accuracy trade-off (increase for less accuracy)

perp numeric; Perplexity parameter (should not be bigger than $3 \times \text{perplexity} < \text{nrow}(X)$ - 1, see details for interpretation)

Value
a tSNE reduced matrix containing three tSNE dimensions

Examples
day2 <- day_2_cardio_cell_sample
mixedpop1 <- new_scGPS_object(ExpressionMatrix = day2$dat2_counts,
  GeneMetadata = day2$dat2geneInfo, CellMetadata = day2$dat2_clusters)
t <- tSNE(expression.mat = assay(mixedpop1))
Calculate variance

**Description**

Calculate variance

**Usage**

`var_cpp(x, bias = TRUE)`

**Arguments**

- `x` a vector of gene expression.
- `bias` degree of freedom

**Value**

a variance value

**Examples**

`var_cpp(seq_len(10^6))`
### Index

<table>
<thead>
<tr>
<th><em>datasets</em></th>
<th>page</th>
</tr>
</thead>
<tbody>
<tr>
<td>day_2_cardio_cell_sample</td>
<td>14</td>
</tr>
<tr>
<td>day_5_cardio_cell_sample</td>
<td>14</td>
</tr>
<tr>
<td>training_gene_sample</td>
<td>38</td>
</tr>
</tbody>
</table>

| add_import | 3 |
| annotate_clusters | 3 |

| bootstrap_parallel | 4, 6 |
| bootstrap_prediction | 5 |

| calcDist | 7 |
| calcDistArma | 7 |
| clustering | 8 |
| clustering_bagging | 9 |
| CORE_bagging | 10 |
| CORE_clustering | 11 |
| CORE_subcluster | 13 |

| day_2_cardio_cell_sample | 14 |
| day_5_cardio_cell_sample | 14 |
| distvec | 15 |

| find_markers | 16 |
| find_optimal_stability | 17 |
| find_stability | 18 |

| mean_cpp | 19 |

| new_scGPS_object | 19, 19, 20 |
| new_summarized_scGPS_object | 20 |

| PCA | 22 |
| plot_CORE | 22 |
| plot_optimal_CORE | 23 |
| plot_reduced | 24 |
| predicting | 25 |
| PrinComp_cpp | 27 |

| rand_index | 27 |
| rcpp_Eucl_distance_NotPar | 28 |

| rcpp_parallel_distance | 29 |
| reformat_LASSO | 29 |

| SingleCellExperiment | 4, 6, 8–10, 12, 13, 19–21, 26, 31, 37 |
| sub_clustering | 31 |
| subset_cpp | 30 |
| summary_accuracy | 32 |
| summary_deviance | 33 |
| summary_prediction_lasso | 34 |
| summary_prediction_lda | 35 |

| top_var | 36 |
| tp_cpp | 36 |
| training | 37 |
| training_gene_sample | 38 |
| tSNE | 39 |

| var_cpp | 40 |