Package ‘SC.MEB’

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Type Package

Title Spatial Clustering with Hidden Markov Random Field using Empirical Bayes

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Description Spatial clustering with hidden markov random field fitted via EM algorithm, details of which can be found in Yi Yang (2021) <doi:10.1101/2021.06.05.447181>. It is not only computationally efficient and scalable to the sample size increment, but also is capable of choosing the smoothness parameter and the number of clusters as well.

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Depends mclust,parallel,ggplot2, Matrix, R (>= 3.5)

Imports Rcpp (>= 1.0.6), SingleCellExperiment, purrr,BiocSingular, SummarizedExperiment, scater, scran, S4Vectors

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Author Yi Yang [aut, cre],
   Xingjie Shi [aut],
   Jin Liu [aut]

Maintainer Yi Yang <yygaosansiban@sina.com>

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ClusterPlot

Description

The function ClusterPlot is used to Visualize spatial clusters.

Usage

ClusterPlot(out, pos, size = 5, shape = 15)

Arguments

out is the output of function selectK.
pos is a n-by-2 matrix of position.
size is a positive value for characterizing the size of point in the plot, which is the same as size in ggplot2.
shape is a positive value for characterizing the shape of point in the plot, which is the same as shape in ggplot2.

Details

The function ClusterPlot is used to Visualize spatial clusters.

Value

a ggplot2 object.

Examples

pos = cbind(rep(1:5, each=5), rep(1:5, 5))
out = list()
out[[1]] = ""
out[[2]] = rep(1:5, each = 5)
ClusterPlot(out, pos)
**find_neighbors2**

**Description**

`find_neighbors2` was used to find the neighborhood of spot.

**Usage**

```r
find_neighbors2(sce, platform)
```

**Arguments**

- `sce` is a `SingleCellExperiment` object containing PCA and position information.
- `platform` is the name of spatial transcriptomic platform. Specify 'Visium' for hex lattice geometry or 'ST' for square lattice geometry. Specifying this parameter is optional as this information is included in their metadata.

**Details**

`find_neighbors2` was used to find the neighborhood of spot.

**Value**

- a sparse matrix recording the information of neighborhood.

**Examples**

```r
data(sce)
platform = "ST"
Adj <- find_neighbors2(sce, platform)
```

---

**getneighborhood_fast**

**Description**

an efficient function to find the neighborhood based on the matrix of position and a pre-defined cutoff

**Usage**

```r
getneighborhood_fast(x, cutoff)
```
Arguments

x is a n-by-2 matrix of position.
cutoff is a threshold of Euclidean distance to decide whether a spot is a neighborhood of another spot. For example, if the Euclidean distance between spot A and B is less than cutoff, then A is taken as the neighbourhood of B.

Value

A sparse matrix containing the neighbourhood

Examples

pos = cbind(rep(1:5, each=5), rep(1:5, 5))
Adj = getneighborhood_fast(pos, 2)

Description

The function ICMEM was used to conduct spatial clustering with hidden Markov random field for a sequence of beta and fixed number of clusters

Usage

ICMEM(
  y,
  x_int,
  Adj,
  mu_int,
  sigma_int,
  alpha,
  beta_grid,
  PX,
  maxIter_ICM,
  maxIter
)

Arguments

y is a matrix of PCs containing gene expression.
x_int is a vector of initial cluster label.
Adj is a matrix containing neighborhood information generated by find_neighbors2.
mu_int is a initial mean vector. we often generated it by Gaussian mixture model.
sigma_int is a initial co-variance matrix. we often generated it by Gaussian mixture model.
alpha is a intercept.
beta_grid is a sequence of smoothing parameter that can be specified by user.
PX is a logical value specifying the parameter expansion in EM algorithm.
maxIter_ICM is the maximum iteration of ICM algorithm.
maxIter is the maximum iteration of EM algorithm.

Details

The function ICMEM was used to conduct spatial clustering with hidden Markov random field for fixed beta and fixed number of clusters

Value

a list.
The item 'x' is the clustering result.
The item 'gam' is the posterior probability matrix.
The item 'ell' is the opposite log-likelihood.
The item 'mu' is the mean of each component.
The item 'sigma' is the variance of each component.

Examples

```r
y = matrix(rnorm(50, 0, 1), 25,2)
pos = cbind(rep(1:5, each=5), rep(1:5, 5))
Adj = getneighborhood_fast(pos, 1.2)
beta_grid = c(0.5,1)
G = 2
fit_int = Mclust(y, G = G)
x_gmm <- fit_int$classification
mu_int <- unname(fit_int$parameter$mean)
sigma_int <- unname(fit_int$parameter$variance$sigma)
alpha <- -log(fit_int$parameter$pro)*0
reslist <- ICMEM(y = y, x_int = x_gmm, Adj = Adj, mu_int = mu_int, sigma_int = sigma_int,
alpha = alpha, beta_grid = beta_grid,
PX = TRUE, maxIter_ICM = 10, maxIter = 50)
```

Description

The function parafun implements the model SC-MEB for fixed number of clusters and a sequence of beta with initial value from Gaussian mixture model
Usage

parafun(
  y,
  Adj,
  G,
  beta_grid = seq(0, 4, 0.2),
  PX = TRUE,
  maxIter_ICM = 10,
  maxIter = 50
)

Arguments

y is n-by-d PCs.
Adj is a sparse matrix of neighborhood.
G is an integer specifying the numbers of clusters.
beta_grid is a numeric vector specifying the smoothness parameter of Random Markov Field. The default is seq(0,4,0.2).
PX is a logical value specifying the parameter expansion in EM algorithm.
maxIter_ICM is the maximum iteration of ICM algorithm. The default is 10.
maxIter is the maximum iteration of EM algorithm. The default is 50.

Details

The function parafun implements the model SC-MEB for fixed number of clusters and a sequence of beta with initial value from Gaussian mixture model

Value

a list. We briefly explain the output of the SC.MEB.
The item ‘x’ storing clustering results.
The item ‘gam’ is the posterior probability matrix.
The item ‘ell’ is the opposite log-likelihood.
The item ‘mu’ is the mean of each component.
The item ‘sigma’ is the variance of each component.

Examples

y = matrix(rnorm(50, 0, 1), 25,2)
pos = cbind(rep(1:5, each=5), rep(1:5, 5))
Adj_sp = getneighborhood_fast(pos, 1.2)
beta_grid = c(0.5,1)
G = 2
out = parafun(y, Adj_sp, G, beta_grid)
### Description

A dataset containing PCs

### Usage

```r
data(PC)
```

### Format

It is a matrix containing 5 PCs

the variables are listed as following

- **PC1** The 1th PC
- **PC2** The 2th PC ...
- **PC5** The 5th PC

### Examples

```r
## run the PC with the Gaussian mixture model
data(PC)
out1 = mclust::Mclust(PC,G = 2)
```

---

### Description

SC.MEB implements the model SC-MEB, spatial clustering with hidden Markov random field using empirical Bayes.

### Usage

```r
SC.MEB(
  y,
  Adj_sp,
  beta_grid = seq(0, 4, 0.2),
  K_set = 2:10,
  parallel = TRUE,
  num_core = 5,
  PX = TRUE,
  maxIter_ICM = 10,
  maxIter = 50
)
```
Arguments

- **y**: n-by-d PCs.
- **Adj_sp**: a sparse matrix of neighborhood. It is often generated from function `find_neighbors2` or `getneighborhood_fast`.
- **beta_grid**: a numeric vector specifying the smoothness parameter of Random Markov Field. The default is `seq(0,4,0.2)`.
- **K_set**: an integer vector specifying the numbers of mixture components (clusters) for which the BIC is to be calculated. The default is `K = 2:10`.
- **parallel**: is a logical value to decide whether the function SC.MEB run in parallel. The default is TRUE.
- **num_core**: is an integer value to decide how many cores are used to run SC.MEB in parallel.
- **PX**: is a logical value to decide whether to use parameter expansion in EM algorithm.
- **maxIter_ICM**: is the maximum iteration of ICM algorithm. The default is 10.
- **maxIter**: is the maximum iteration of EM algorithm. The default is 50.

Details

SC.MEB can implements the model SC-MEB in parallel which can improve the speed of the computation.

Value

- a list, We briefly explain the output of the SC.MEB.
- The item 'x' contains clustering results.
- The item 'gam' is the posterior probability matrix.
- The item 'ell' is the opposite log-likelihood.
- The item 'mu' is the mean of each component.
- The item 'sigma' is the variance of each component.

References


Examples

```r
y = matrix(rnorm(50, 0, 1), 25,2)
pos = cbind(rep(1:5, each=5), rep(1:5, 5))
Adj_sp = getneighborhood_fast(pos, 1.2)
beta_grid = c(0.5,1)
K_set = 2:3
out = SC.MEB(y, Adj_sp, beta_grid, K_set, TRUE, 2)
```
Description

A simulated SingleCellExperiment

Usage

data(sce)

Format

It is a SingleCellExperiment object with gene expression and meta information

References


Examples

```r
## find the neighborhood of spots in SingleCellExperiment
data(sce)
out = find_neighbors2(sce, "ST")
```

selectK

Description

The function selectK is used to select the best K according to BIC or Modified BIC criterion.

Usage

`selectK(ScObject, K_set = 2:10, criterion = "BIC", c = 1)`

Arguments

- `ScObject`: is an object generated from SC.MEB function.
- `K_set`: is an integer vector used in SC.MEB. The default is 2:10.
- `criterion`: is a character specifying the criterion for selecting K. The default value is BIC. The alternative value MBIC can also be used.
is a positive value in the modified BIC. The default is 1. Here we briefly explain
how to choose the parameter c in the modified BIC. In general, For the ST or
Visium dataset, it often ranges from 0.4 to 1 while for the MERFISH dataset
with large number of cells, it often becomes larger, for example 10,20. Most
importantly, SC-MEB is fast, scaling well in terms of sample size, which allow
the user to tune the c based on their prior knowledge about the tissues or cells.

Details

The function selectK is used to select the best K according to BIC or Modified BIC criterion.

Value

a list contains two items. one is for the best K and the other is the clustering labels of n spots.

Examples

```
y = matrix(rnorm(50, 0, 1), 25, 2)
pos = cbind(rep(1:5, each=5), rep(1:5, 5))
Adj_sp = getneighborhood_fast(pos, 1.2)
beta_grid = c(0.5, 1)
K_set = 2:3
out = SC.MEB(y, Adj_sp, beta_grid, K_set, TRUE, 2)
selectK(out, K_set)
```

Description

The function selectKPlot is used to demonstrate the scatter plot of BIC or Modified BIC vs K for
selecting the best K.

Usage

![](selectKPlot)

Arguments

- **SObject** is a object generated from SC.MEB function.
- **K_set** is the corresponding K_set used in your previous function SC.MEB.
- **criterion** is a character specifying the criterion for selecting K. The default is BIC, the
  alternative criterion MBIC can also be used.
- **c** is a positive value in modified BIC. The default is 1. Here we briefly explain
  how to choose the parameter c in the modified BIC. In general, For the ST or
  Visium dataset, it often ranges from 0.4 to 1 while for the MERFISH dataset
  with large number of cells, it often becomes larger, for example 10,20. Most
  importantly, SC-MEB is fast, scaling well in terms of sample size, which allow
  the user to tune the c based on their prior knowledge about the tissues or cells.
**Details**

The function `selectKPlot` is used to demonstrate the scatter plot of BIC or Modified BIC vs K for selecting the best K.

**Value**

a ggplot2 object.

**Examples**

```r
y = matrix(rnorm(50, 0, 1), 25, 2)
pos = cbind(rep(1:5, each=5), rep(1:5, 5))
Adj_sp = getneighborhood_fast(pos, 1.2)
beta_grid = c(0.5, 1)
K_set = 2:3
out = SC.MEB(y, Adj_sp, beta_grid, K_set, TRUE, 2)
selectKPlot(out, K_set)
```

---

**spatialPreprocess**  
*Preprocess a spatial dataset for SC-MEB*

**Description**

Adds metadata required for downstream analyses, and (optionally) performs PCA on log-normalized expression of top HVGs.

**Usage**

```r
spatialPreprocess(
  sce,  
  platform = c("Visium", "ST"),  
  n.PCs = 15,  
  n.HVGs = 2000,  
  skip.PCA = FALSE,  
  log.normalize = TRUE,  
  assay.type = "logcounts",  
  BSPARAM = BiocSingular::ExactParam()
)
```

**Arguments**

- **sce**  
  SingleCellExperiment to preprocess

- **platform**  
  Spatial sequencing platform. Used to determine spot layout and neighborhood structure (Visium = hex, ST = square).

- **n.PCs**  
  Number of principal components to compute. We suggest using the top 15 PCs in most cases.

- **n.HVGs**  
  Number of highly variable genes to run PCA upon.
skip.PCA Skip PCA (if dimensionality reduction was previously computed.)
log.normalize Whether to log-normalize the input data with scater. May be omitted if log-normalization previously computed.
assay.type Name of assay in sce containing normalized counts. Leave as "logcounts" unless you explicitly pre-computed a different normalization and added it to sce under another assay. Note that we do not recommend running BayesSpace on PCs computed from raw counts.
BSPARAM A BiocSingularParam object specifying which algorithm should be used to perform the PCA. By default, an exact PCA is performed, as current spatial datasets are generally small (<10,000 spots). To perform a faster approximate PCA, please specify FastAutoParam() and set a random seed to ensure reproducibility.

Value

SingleCellExperiment with PCA and SC.MEB metadata

Examples

```r
## read the simulated data
data(sce)
platform = "ST"
out = find_neighbors2(sce, platform)
```
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