Package ‘monocle’

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Type Package

Title Clustering, differential expression, and trajectory analysis for single-cell RNA-Seq

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Description Monocle performs differential expression and time-series analysis for single-cell expression experiments. It orders individual cells according to progress through a biological process, without knowing ahead of time which genes define progress through that process. Monocle also performs differential expression analysis, clustering, visualization, and other useful tasks on single cell expression data. It is designed to work with RNA-Seq and qPCR data, but could be used with other types as well.

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BEAM
branchTest .................................................. 4
buildBranchCellDataSet .................................. 5
calABCs ....................................................... 6
calibrate_per_cell_total_proposal ......................... 7
calILRs ....................................................... 7
CellDataSet .................................................. 8
CellDataSet-methods ......................................... 9
cellPairwiseDistances ....................................... 10
cellPairwiseDistances<- .................................... 11
CellType .................................................... 11
CellTypeHierarchy ........................................... 12
clusterCells .................................................. 12
clusterGenes .................................................. 13
compareModels ............................................... 13
detectBifurcationPoint ...................................... 14
detectGenes ................................................... 15
differentialGeneTest ........................................ 16
diff_test_helper ............................................. 17
dispersionTable ............................................. 17
estimateDispersionsForCellDataSet ......................... 18
estimateSizeFactorsForMatrix ............................... 18
estimate_t .................................................... 19
extract_good_branched_ordering .............................. 20
fitModel ...................................................... 20
fit_model_helper ............................................ 21
genSmoothCurveResiduals ................................... 21
genSmoothCurves ........................................... 22
get_classic_muscle_markers .................................. 23
load_HSMM .................................................... 23
load_HSMM_markers .......................................... 23
load_lung ..................................................... 23
markerDiffTable ............................................. 24
mcesApply ...................................................... 24
minSpanningTree ............................................ 25
minSpanningTree<- .......................................... 26
newCellDataSet ............................................. 26
newCellTypeHierarchy ....................................... 27
orderCells .................................................... 29
order_p_node .................................................. 30
plot_cell_trajectory ......................................... 31
plot_clusters ................................................ 32
plot_coexpression_matrix ................................... 33
plot_genes_branched_heatmap ................................ 33
plot_genes_branched_pseudotime ............................. 35
plot_genes_in_pseudotime .................................... 36
plot_genes_jitter ............................................. 37
plot_genes_positive_cells ................................... 38
plot_ordering_genes ......................................... 39
plot_pseudotime_heatmap .................................... 39
plot_spanning_tree .......................................... 40
pq_helper ...................................................... 41
reducedDimA .................................................. 42
BEAM

### Branched expression analysis modeling (BEAM)

#### Description
Identify genes with branch-dependent expression

#### Usage
```r
BEAM(cds, fullModelFormulaStr = "~sm.ns(Pseudotime, df = 3)*Branch",
reducedModelFormulaStr = "~sm.ns(Pseudotime, df = 3)",
branch_states = NULL, branch_point = 1, relative_expr = TRUE,
branch_labels = NULL, verbose = FALSE, cores = 1, ...)
```

#### Arguments
- **cds**: a `CellDataSet` object upon which to perform this operation
- **fullModelFormulaStr**: a formula string specifying the full model in differential expression tests (i.e. likelihood ratio tests) for each gene/feature.
- **reducedModelFormulaStr**: a formula string specifying the reduced model in differential expression tests (i.e. likelihood ratio tests) for each gene/feature.
- **branch_states**: ids for the immediate branch branch which obtained from branch construction based on MST
- **branch_point**: The ID of the branch point to analyze. Can only be used when reduceDimension is called with method = "DDRTree".
- **relative_expr**: a logic flag to determine whether or not the relative gene expression should be used
- **branch_labels**: the name for each branch, for example, "AT1" or "AT2"
Whether to generate verbose output

the number of cores to be used while testing each gene for differential expression

additional arguments to be passed to differentialGeneTest

Details

Branches in single-cell trajectories are generated by cell fate decisions in development and also arise when analyzing genetic, chemical, or environmental perturbations. Branch expression analysis modeling is a statistical approach for finding genes that are regulated in a manner that depends on the branch. Consider a progenitor cell that generates two distinct cell types. A single-cell trajectory that includes progenitor cells and both differentiated cell types will capture the “decision” as a branch point, with progenitors upstream of the branch and the differentiated cells positioned along distinct branches. These branches will be characterized by distinct gene expression programs. BEAM aims to find all genes that differ between the branches. Such “branch-dependent” genes can help identify the mechanism by which the fate decision is made.

BEAM() Takes a CellDataSet and either a specified branch point, or a pair of trajectory outcomes (as States). If a branch point is provided, the function returns a dataframe of test results for dependence on that branch. If a pair of outcomes is provided, it returns test results for the branch that unifies those outcomes into a common path to the trajectory’s root state.

BEAM() compares two models with a likelihood ratio test for branch-dependent expression. The full model is the product of smooth Pseudotime and the Branch a cell is assigned to. The reduced model just includes Pseudotime. You can modify these to include arbitrary additional effects in the full or both models.

Value

a data frame containing the p values and q-values from the BEAM test, with one row per gene.

Description

Testing for branch-dependent expression with BEAM() first involves constructing a CellDataSet that assigns each cell to a branch, and then performing a likelihood ratio test to see if the branch assignments significantly improves the fit over a null model that does not split the cells. branchTest() implements these two steps.

Usage

```r
branchTest(cds, fullModelFormulaStr = "~sm.ns(Pseudotime, df = 3)*Branch", reducedModelFormulaStr = "~sm.ns(Pseudotime, df = 3)", branch_states = NULL, branch_point = 1, relative_expr = TRUE, cores = 1, branch_labels = NULL, verbose = FALSE, ...)
```
**Arguments**

- **cds**
  - a CellDataSet object upon which to perform this operation

- **fullModelFormulaStr**
  - a formula string specifying the full model in differential expression tests (i.e. likelihood ratio tests) for each gene/feature.

- **reducedModelFormulaStr**
  - a formula string specifying the reduced model in differential expression tests (i.e. likelihood ratio tests) for each gene/feature.

- **branch_states**
  - states corresponding to two branches

- **branch_point**
  - The ID of the branch point to analyze. Can only be used when reduceDimension is called with method = "DDRTree".

- **relative_expr**
  - a logic flag to determine whether or not the relative gene expression should be used

- **cores**
  - the number of cores to be used while testing each gene for differential expression

- **branch_labels**
  - the name for each branch, for example, AT1 or AT2

- **verbose**
  - Whether to show VGAM errors and warnings. Only valid for cores = 1.

- **...**
  - Additional arguments passed to differentialGeneTest

**Value**

- a data frame containing the p values and q-values from the likelihood ratio tests on the parallel arrays of models.

---

**Build a CellDataSet that splits cells among two branches**

**Description**

Analyzing branches with BEAM() requires fitting two models to the expression data for each gene. The full model assigns each cell to one of the two outcomes of the branch, and the reduced model excludes this assignment. buildBranchCellDataSet() takes a CellDataSet object and returns a version where the cells are assigned to one of two branches. The branch for each cell is encoded in a new column, "Branch", in the pData table in the returned CellDataSet.

**Usage**

```r
buildBranchCellDataSet(cds, progenitor_method = c("sequential_split", "duplicate"), branch_states = NULL, branch_point = 1, branch_labels = NULL, stretch = TRUE)
```

**Arguments**

- **cds**
  - CellDataSet for the experiment

- **progenitor_method**
  - The method to use for dealing with the cells prior to the branch

- **branch_states**
  - The states for two branching branches
calABCs

**branch_point**  The ID of the branch point to analyze. Can only be used when `reduceDimension()` is called with `reduction_method = "DDRTree"`.

**branch_labels**  The names for each branching branch

**stretch**  A logical flag to determine whether or not the pseudotime trajectory for each branch should be stretched to the same range or not

**Value**

a CellDataSet with the duplicated cells and stretched branches

---

**calABCs**  *Compute the area between curves (ABC) for branch-dependent genes*

**Description**

This function is used to calculate the ABC score based on the the nature spline curves fitted for each branch. ABC score is used to quantify the total magnitude of divergence between two branches. By default, the ABC score is the area between two fitted spline curves. The ABC score can be used to rank gene divergence. When coupled with p-val calculated from the branchTest, it can be used to identify potential major regulators for branch bifurcation.

**Usage**

`calABCs(cds, trend_formula = "~sm.ns(Pseudotime, df = 3)*Branch", trajectory_states = c(2, 3), relative_expr = TRUE, stretch = TRUE, cores = 1, verbose = F, min_expr = 0.5, integer_expression = FALSE, num = 5000, branch_labels = NULL, ...)`

**Arguments**

- `cds`  a CellDataSet object upon which to perform this operation
- `trend_formula`  a formula string specifying the full model in differential expression tests (i.e. likelihood ratio tests) for each gene/feature.
- `trajectory_states`  States corresponding to two branches
- `relative_expr`  a logic flag to determine whether or not the relative gene expression should be used
- `stretch`  a logic flag to determine whether or not each branch should be stretched
- `cores`  the number of cores to be used while testing each gene for differential expression
- `verbose`  a logic flag to determine whether or not we should output detailed running information
- `min_expr`  the lower limit for the expressed gene
- `integer_expression`  the logic flag to determine whether or not the integer numbers are used for calculating the ABCs. Default is False.
- `num`  number of points on the fitted branch trajectories used for calculating the ABCs. Default is 5000.
- `branch_labels`  the name for each branch, for example, AT1 or AT2
- `...`  Additional arguments passed to `buildBranchCellDataSet`
**calibrate_per_cell_total_proposal**

*Calibrate_per_cell_total_proposal*

**Description**

Calibrate_per_cell_total_proposal

**Usage**

```r
calibrate_per_cell_total_proposal(relative_exprs_matrix, t_estimate, expected_capture_rate)
```

**Arguments**

- `relative_exprs_matrix`  
  The matrix of relative TPM expression values
- `t_estimate`  
  the TPM value that corresponds to 1 cDNA copy per cell
- `expected_capture_rate`  
  The fraction of mRNAs captured as cDNAs

**calILRs**  
*Calculate the Instantaneous Log Ratio between two branches*

**Description**

This function is used to calculate the Instant Log Ratio between two branches which can be used to prepare the heatmap demonstrating the branch gene expression divergence hierarchy. If "stretch" is specified, each branch will be firstly stretched into maturation level from 0-100. Since the results when we use "stretching" are always better and IRLs for non-stretched spline curves are often mismatched, we may only turn down "non-stretch" functionality in future versions. Then, we fit two separate nature spline curves for each individual lineages. The log-ratios of the value on each spline curve corresponding to each branch are calculated, which can be used as a measure for the magnitude of divergence between two branching branches.

**Usage**

```r
calILRs(cds, trend_formula = "~sm.ns(Pseudotime, df = 3)*Branch", trajectory_states = c(2, 3), relative_expr = TRUE, stretch = TRUE, cores = 1, ILRs_limit = 3, label_by_short_name = TRUE, useVST = FALSE, round_exprs = FALSE, output_type = "all", branch_labels = NULL, file = NULL, return_all = F, verbose = FALSE, ...)
```
Arguments

- **cds**: CellDataSet for the experiment
- **trend_formula**: A formula string specifying the full model in differential expression tests (i.e. likelihood ratio tests) for each gene/feature.
- **trajectory_states**: States corresponding to two branches
- **relative_expr**: A logic flag to determine whether or not the relative expressed should be used when we fitting the spline curves
- **stretch**: A logic flag to determine whether or not each branch should be stretched
- **cores**: Number of cores when fitting the spline curves
- **ILRs_limit**: The minimum Instant Log Ratio used to make the heatmap plot
- **label_by_short_name**: Label the rows of the returned matrix by gene_short_name (TRUE) or feature id (FALSE)
- **useVST**: A logic flag to determine whether or not the Variance Stabilization Transformation should be used to stabilize the gene expression. When VST is used, the difference between two branches are used instead of the log-ratio.
- **round_exprs**: A logic flag to determine whether or not the expression value should be rounded into integer
- **output_type**: A character either of "all" or "after_bifurcation". If "after_bifurcation" is used, only the time points after the bifurcation point will be selected
- **branch_labels**: The name for each branch, for example, AT1 or AT2
- **file**: The name for storing the data. Since the calculation of the Instant Log Ratio is very time consuming, so by default the result will be stored
- **return_all**: A logic flag to determine whether or not all the results from the analysis should be returned, this includes a dataframe for the log fold change, normalized log fold change, raw divergence, normalized divergence, fitting curves for each branch
- **verbose**: Whether or not detailed running information should be returned
- **...**: Additional arguments passed to buildBranchCellDataSet

Value

- a ggplot2 plot object

---

**CellDataSet**

*The CellDataSet class*

**Description**

The main class used by Monocle to hold single cell expression data. CellDataSet extends the basic Bioconductor ExpressionSet class.

**Details**

This class is initialized from a matrix of expression values. Methods that operate on CellDataSet objects constitute the basic Monocle workflow.
Slots

reducedDimS  Matrix of class numeric, containing the source values computed by Independent Components Analysis.

reducedDimW  Matrix of class numeric, containing the whitened expression values computed during Independent Components Analysis.

reducedDimA  Matrix of class numeric, containing the weight values computed by Independent Components Analysis.

reducedDimK  A Matrix of class numeric, containing the pre-whitening matrix computed by Independent Components Analysis.

minSpanningTree  An Object of class igraph, containing the minimum spanning tree used by Monocle to order cells according to progress through a biological process.

cellPairwiseDistances  A Matrix of class numeric, containing the pairwise distances between cells in the reduced dimension space.

expressionFamily  An Object of class vglmff, specifying the VGAM family function used for expression responses.

lowerDetectionLimit  A numeric value specifying the minimum expression level considered to be true expression.

dispFitInfo  An environment containing lists, one for each set of estimated dispersion values. See estimateDispersions.

dim_reduce_type  A string encoding how this CellDataSet has been reduced in dimensionality.

auxOrderingData  An environment of auxilliary data structures used by various steps in Monocle. Not to be accessed by users directly.

---

CellDataSet-methods  Methods for the CellDataSet class

Description

Methods for the CellDataSet class

Usage

```r
## S4 method for signature 'CellDataSet'
sizeFactors(object)

## S4 replacement method for signature 'CellDataSet,numeric'
sizeFactors(object) <- value

## S4 method for signature 'CellDataSet'
estimateSizeFactors(object, locfunc = median, ...)

## S4 method for signature 'CellDataSet'
estimateDispersions(object, modelFormulaStr = "~ 1",
                            relative_expr = TRUE, min_cells_detected = 1, remove_outliers = TRUE,
                            cores = 1, ...)
```
Arguments

object  The CellDataSet object
value   A vector of size factors, with length equal to the cells in object
loefunc A function applied to the geometric-mean-scaled expression values to derive the size factor.
...    Additional arguments to be passed to estimateSizeFactorsForMatrix
modelFormulaStr A model formula, passed as a string, specifying how to group the cells prior to estimated dispersion. The default groups all cells together.
relative_expr Whether to transform expression into relative values
min_cells_detected Only include genes detected above lowerDetectionLimit in at least this many cells in the dispersion calculation
remove_outliers Whether to remove outliers (using Cook’s distance) when estimating dispersions
cores   The number of cores to use for computing dispersions

cellPairwiseDistances  Get the matrix of pairwise distances between cells

Description

Retrieves a matrix capturing distances between each cell used during cell ordering.

Usage

cellPairwiseDistances(cds)

Arguments

cds    expression data matrix for an experiment

Value

A square, symmetric matrix containing the distances between each cell in the reduced-dimensionality space.

Examples

## Not run:
D <- cellPairwiseDistances(HSMM)

## End(Not run)
cellPairwiseDistances<-  

Sets the matrix containing distances between each pair of cells used by Monocle during cell ordering. Not intended to be called directly.

Description

Sets the matrix containing distances between each pair of cells used by Monocle during cell ordering. Not intended to be called directly.

Usage

cellPairwiseDistances(cds) <- value

Arguments

cds A CellDataSet object.
value a square, symmetric matrix containing pairwise distances between cells.

Value

An updated CellDataSet object

Examples

```r
## Not run:
cds <- cellPairwiseDistances(D)
## End(Not run)
```

CellType  

The CellType class

Description

Classifies cells using a criterion function.

Details

Classifies cells via a user-defined gating function. The gating function accepts as input the entire matrix of expression data from a CellDataSet, and return TRUE or FALSE for each cell in it, depending on whether each meets the criteria in the gating function

Slots

classify_func: A function that accepts a matrix of expression values as input, and returns a logical vector (of length equal to the number of columns in the matrix) as output
**ClusterCells**

**The CellTypeHierarchy class**

**Description**
Classifies cells according to a hierarchy of types.

**Details**
Classifies cells according to a hierarchy of types via user-defined gating functions.

**Slots**
- `classificationTree`: Object of class "igraph"

**clusterCells**
Cluster cells into a specified number of groups.

**Description**
Unsupervised clustering of cells is a common step in many single-cell expression workflows. In an experiment containing a mixture of cell types, each cluster might correspond to a different cell type. This method takes a CellDataSet as input along with a requested number of clusters, clusters them with an unsupervised algorithm, and then returns the CellDataSet with the cluster assignments stored in the pData table.

**Usage**
```r
clusterCells(cds, num_clusters, cell_type_hierarchy = NULL, 
frequency_thresh = 0.1, clustering_genes = NULL, max_components = 10, 
residualModelFormulaStr = NULL, param.gamma = 100, verbose = F, ...)
```

**Arguments**
- `cds`: the CellDataSet upon which to perform this operation
- `num_clusters`: number of desired cell clusters
- `cell_type_hierarchy`: the CellTypeHierarchy that divides the cells from cds into different types of cells
- `frequency_thresh`: When a CellTypeHierarchy is provided, cluster cells will impute cell types in clusters that are composed of at least this much of exactly one cell type.
- `clustering_genes`: a vector of genes used to differentiate between the cell types in the CellType-Hierarchy
- `max_components`: number of dimensions to project the data into via `reduceDimension()`
- `residualModelFormulaStr`: A model formula specifying the effects to subtract from the data before clustering.
- `param.gamma`: gamma parameter for DDRTree
- `verbose`: Verbos parameter for DDRTree
- `...`: Additional arguments passed to `reduceDimension()`
clusterGenes

Description
This function takes a matrix of expression values and performs k-means clustering on the genes.

Usage
`clusterGenes(expr_matrix, k, method = function(x) { as.dist((1 - cor(Matrix::t(x)))/2)}, ...)`

Arguments
- `expr_matrix`: A matrix of expression values to cluster together. Rows are genes, columns are cells.
- `k`: How many clusters to create
- `method`: The distance function to use during clustering
- `...`: Extra parameters to pass to `pam()` during clustering

Value
a `pam` cluster object

Examples
```r
## Not run:
full_model_fits <- fitModel(HSMM[,sample(nrow(fData(HSMM_filtered)), 100),],
                           modelFormulaStr="sm.ns(Pseudotime)"
expression_curve_matrix <- responseMatrix(full_model_fits)
clusters <- clusterGenes(expression_curve_matrix, k=4)
plot_clusters(HSMM_filtered[ordering_genes,], clusters)
## End(Not run)
```

compareModels

Description
Performs likelihood ratio tests on nested vector generalized additive models

Usage
`compareModels(full_models, reduced_models)`
### Arguments

- `full_models`: a list of models, e.g. as returned by `fitModels()`, forming the numerators of the L.R.Ts.
- `reduced_models`: a list of models, e.g. as returned by `fitModels()`, forming the denominators of the L.R.Ts.

#### Value

A data frame containing the p values and q-values from the likelihood ratio tests on the parallel arrays of models.

---

**detectBifurcationPoint**

*Calculate divergence times for branch-dependent genes*

#### Description

Branch-dependent genes may diverge at different points in pseudotime. `detectBifurcationPoint()` calculates these times. Although the branch times will be shaped by and distributed around the branch point in the trajectory, upstream regulators tend to branch earlier in pseudotime than their targets.

#### Usage

```r
detectBifurcationPoint(str_log_df = NULL, ILRs_threshold = 0.1, 
detect_all = T, cds = cds, Branch = "Branch", branch_point = NULL, 
branch_states = c(2, 3), stretch = T, cores = 1, 
trend_formula = "~sm.ns(Pseudotime, df = 3)", ILRs_limit = 3, 
relative_expr = TRUE, label_by_short_name = TRUE, useVST = FALSE, 
round_exprs = FALSE, output_type = "all", return_cross_point = T, 
file = "bifurcation_heatmap", verbose = FALSE, ...)
```

#### Arguments

- `str_log_df`: the ILRs dataframe calculated from `calILRs` function. If this data frame is provided, all the following parameters are ignored. Note that we need to only use the ILRs after the bifurcation point if we duplicated the progenitor cell state.
- `ILRs_threshold`: the ILR value used to determine the earliest divergence time point
- `detect_all`: a logic flag to determine whether or not genes without ILRs pass the threshold will still report a bifurcation point
- `cds`: CellDataSet for the experiment
- `Branch`: The column in pData used for calculating the ILRs (If not equal to "Branch", a warning will report)
- `branch_point`: The ID of the branch point to analyze. Can only be used when `reduceDimension` is called with method = "DDRTree".
- `branch_states`: The states for two branching branches
- `stretch`: a logic flag to determine whether or not each branch should be stretched
- `cores`: Number of cores when fitting the spline curves
**Value**

A vector containing the time for the bifurcation point with gene names for each value

---

**detectGenes**

Sets the global expression detection threshold to be used with this CellDataSet. Counts how many cells each feature in a CellDataSet object that are detectably expressed above a minimum threshold. Also counts the number of genes above this threshold are detectable in each cell.

**Description**

Sets the global expression detection threshold to be used with this CellDataSet. Counts how many cells each feature in a CellDataSet object that are detectably expressed above a minimum threshold. Also counts the number of genes above this threshold are detectable in each cell.

**Usage**

detectGenes(cds, min_expr = NULL)

**Arguments**

cds the CellDataSet upon which to perform this operation

min_expr the expression threshold
Value

an updated CellDataSet object

Examples

```r
## Not run:
HSMM <- detectGenes(HSMM, min_expr=0.1)
## End(Not run)
```

differentialGeneTest(differentialGeneTest

Test genes for differential expression

Description

Tests each gene for differential expression as a function of pseudotime or according to other co-

variants as specified. differentialGeneTest is Monocle’s main differential analysis routine. It

accepts a CellDataSet and two model formulae as input, which specify generalized lineage models

as implemented by the VGAM package.

Usage

```r
differentialGeneTest(cds, fullModelFormulaStr = "~sm.ns(Pseudotime, df=3)",
reducedModelFormulaStr = "~1", relative_expr = TRUE, cores = 1,
verbose = FALSE)
```

Arguments

- **cds**: a CellDataSet object upon which to perform this operation
- **fullModelFormulaStr**: a formula string specifying the full model in differential expression tests (i.e. likelihood ratio tests) for each gene/feature.
- **reducedModelFormulaStr**: a formula string specifying the reduced model in differential expression tests (i.e. likelihood ratio tests) for each gene/feature.
- **relative_expr**: Whether to transform expression into relative values.
- **cores**: the number of cores to be used while testing each gene for differential expression.
- **verbose**: Whether to show VGAM errors and warnings. Only valid for cores = 1.

Value

a data frame containing the p values and q-values from the likelihood ratio tests on the parallel

arrays of models.

See Also

- vglm
**diff_test_helper**  
*Helper function for parallel differential expression testing*

**Description**

test

**Usage**

diff_test_helper(x, fullModelFormulaStr, reducedModelFormulaStr, expressionFamily, relative_expr, weights, disp_func = NULL, verbose = FALSE)

**Arguments**

- `x` (test)
- `fullModelFormulaStr` (a formula string specifying the full model in differential expression tests (i.e. likelihood ratio tests) for each gene/feature.)
- `reducedModelFormulaStr` (a formula string specifying the reduced model in differential expression tests (i.e. likelihood ratio tests) for each gene/feature.)
- `expressionFamily` (specifies the VGAM family function used for expression responses)
- `relative_expr` (Whether to transform expression into relative values)
- `weights` (test)
- `disp_func` (test)
- `verbose` (Whether to show VGAM errors and warnings. Only valid for cores = 1.)

**dispersionTable**  
*Retrieve a table of values specifying the mean-variance relationship*

**Description**

Calling estimateDispersions computes a smooth function describing how variance in each gene’s expression across cells varies according to the mean. This function only works for CellDataSet objects containing count-based expression data, either transcripts or reads.

**Usage**

dispersionTable(cds)

**Arguments**

- `cds` (The CellDataSet from which to extract a dispersion table.)

**Value**

A data frame containing the empirical mean expression, empirical dispersion, and the value estimated by the dispersion model.
estimateDispersionsForCellDataSet

*Helper function to estimate dispersions*

**Description**
Helper function to estimate dispersions

**Usage**
```
estimateDispersionsForCellDataSet(cds, modelFormulaStr, relative_expr, min_cells_detected, removeOutliers, cores)
```

**Arguments**
- `cds`: a CellDataSet that contains all cells user wants evaluated
- `modelFormulaStr`: a formula string specifying the model to fit for the genes.
- `relative_expr`: Whether to transform expression into relative values
- `min_cells_detected`: Only include genes detected above lowerDetectionLimit in at least this many cells in the dispersion calculation
- `removeOutliers`: a boolean it determines whether or not outliers from the data should be removed
- `cores`: the number of cores to be used while testing each gene for differential expression.

estimateSizeFactorsForMatrix

*Function to calculate the size factor for the single-cell RNA-seq data*

@importFrom stats median

**Description**
Function to calculate the size factor for the single-cell RNA-seq data

@importFrom stats median

**Usage**
```
estimateSizeFactorsForMatrix(counts, locfunc = median, round_exprs = TRUE, method = "mean-geometric-mean-total")
```

**Arguments**
- `counts`: The matrix for the gene expression data, either read counts or FPKM values or transcript counts
- `locfunc`: The location function used to find the representative value
- `round_exprs`: A logic flag to determine whether or not the expression value should be rounded
- `method`: A character to specify the size factor calculation approaches. It can be either "mean-geometric-mean-total" (default), "weighted-median", "median-geometric-mean", "median", "mode", "geometric-mean-total".
Description

Converting relative expression values to mRNA copies per cell requires knowing the most commonly occurring relative expression value in each cell. This value typically corresponds to an RPC value of 1. This function finds the most commonly occurring (log-transformed) relative expression value for each column in the provided expression matrix.

Usage

```r
estimate_t(relative_expr_matrix, relative_expr_thresh = 0.1)
```

Arguments

- `relative_expr_matrix`: a matrix of relative expression values for values with each row and column representing genes/isoforms and cells, respectively. Row and column names should be included. Expression values should not be log-transformed.
- `relative_expr_thresh`: Relative expression values below this threshold are considered zero.

Details

This function estimates the most abundant relative expression value \( (t^*) \) using a gaussian kernel density function. It can also optionally output the \( t^* \) based on a two gaussian mixture model based on the `smsn.mixture` from `mixsmsn` package.

Value

- An vector of most abundant relative_expr value corresponding to the RPC 1.

Examples

```r
## Not run:
HSMM_fpkm_matrix <- exprs(HSMM)
t_estimate = estimate_t(HSMM_fpkm_matrix)
## End(Not run)
```
extract_good_branched_ordering

Extract a linear ordering of cells from a PQ tree

Description

Extract a linear ordering of cells from a PQ tree

Usage

extract_good_branched_ordering(orig_pq_tree, curr_node, dist_matrix, 
num_branches, reverse_main_path = FALSE)

Arguments

orig_pq_tree  The PQ object to use for ordering
curr_node    The node in the PQ tree to use as the start of ordering
dist_matrix  A symmetric matrix containing pairwise distances between cells
num_branches The number of outcomes allowed in the trajectory.
reverse_main_path Whether to reverse the direction of the trajectory

fitModel

Fits a model for each gene in a CellDataSet object.

Description

Fits a model for each gene in a CellDataSet object.

Usage

fitModel(cds, modelFormulaStr = "~sm.ns(Pseudotime, df=3)",
relativeExpr = TRUE, cores = 1)

Arguments

cds                    the CellDataSet upon which to perform this operation
modelFormulaStr       a formula string specifying the model to fit for the genes.
relativeExpr          Whether to fit a model to relative or absolute expression. Only meaningful for count-based expression data. If TRUE, counts are normalized by Size_Factor prior to fitting.
cores                  the number of processor cores to be used during fitting.
Details
This function fits a vector generalized additive model (VGAM) from the VGAM package for each gene in a CellDataSet. By default, expression levels are modeled as smooth functions of the Pseudo-time value of each cell. That is, expression is a function of progress through the biological process. More complicated formulae can be provided to account for additional covariates (e.g. day collected, genotype of cells, media conditions, etc).

Value
a list of VGAM model objects

Description
Helper function for parallel VGAM fitting

Usage
fit_model_helper(x, modelFormulaStr, expressionFamily, relative_expr, disp_func = NULL, verbose = FALSE, ...)

Arguments
x
modelFormulaStr	a formula string specifying the model to fit for the genes.
expressionFamily
specifies the VGAM family function used for expression responses
relative_expr
Whether to transform expression into relative values
disp_func
test
verbose
Whether to show VGAM errors and warnings. Only valid for cores = 1.
...
test

Description
Fit smooth spline curves and return the residuals matrix

Usage
genSmoothCurveResiduals(cds, trend_formula = "~sm.ns(Pseudotime, df = 3)", relative_expr = T, residual_type = "response", cores = 1)
genSmoothCurves

Arguments

cds a CellDataSet object upon which to perform this operation
trend_formula a formula string specifying the model formula used in fitting the spline curve for each gene/feature.
relative_expr a logic flag to determine whether or not the relative gene expression should be used
residual_type the response desired, as accepted by VGAM's predict function
cores the number of cores to be used while testing each gene for differential expression

Value

a data frame containing the data for the fitted spline curves.

description

This function will fit smooth spline curves for the gene expression dynamics along pseudotime in a gene-wise manner and return the corresponding response matrix. This function is build on other functions (fit_models and responseMatrix) and used in calILRs and calABCs functions

Usage

genSmoothCurves(cds, new_data, trend_formula = "~sm.ns(Pseudotime, df = 3)",
relative_expr = T, response_type = "response", cores = 1)

Arguments

cds a CellDataSet object upon which to perform this operation
new_data a data.frame object including columns (for example, Pseudotime) with names specified in the model formula. The values in the data.frame should be consist with the corresponding values from cds object.
trend_formula a formula string specifying the model formula used in fitting the spline curve for each gene/feature.
relative_expr a logic flag to determine whether or not the relative gene expression should be used
response_type the response desired, as accepted by VGAM’s predict function
cores the number of cores to be used while testing each gene for differential expression

Value

a data frame containing the data for the fitted spline curves.
get_classic_muscle_markers

Return the names of classic muscle genes

Description
Return the names of classic muscle genes

Usage
get_classic_muscle_markers()

load_HSMM

Build a CellDataSet from the HSMMSingleCell package

Description
Build a CellDataSet from the HSMMSingleCell package

Usage
load_HSMM()

load_HSMM_markers

Return a CellDataSet of classic muscle genes

Description
Return a CellDataSet of classic muscle genes

Usage
load_HSMM_markers()

Value
A CellDataSet object

load_lung

Build a CellDataSet from the data stored in inst/extdata directory

Description
Build a CellDataSet from the data stored in inst/extdata directory

Usage
load_lung()
markerDiffTable

Test genes for cell type-dependent expression

**Description**

Test genes for cell type-dependent expression

**Usage**

```r
markerDiffTable(cds, cth, residualModelFormulaStr = "~1", balanced = FALSE,
                reclassify_cells = TRUE, remove_ambig = TRUE, remove_unknown = TRUE,
                verbose = FALSE, cores = 1)
```

**Arguments**

- **cds**: A CellDataSet object containing cells to classify
- **cth**: The CellTypeHierarchy object to use for classification
- **residualModelFormulaStr**: A model formula string specify effects you want to exclude when testing for cell type dependent expression
- **balanced**: Whether to downsample the cells so that there’s an equal number of each type prior to performing the test
- **reclassify_cells**: a boolean that indicates whether or not the cds and cth should be run through classifyCells again
- **remove_ambig**: a boolean that indicates whether or not ambiguous cells should be removed the cds
- **remove_unknown**: a boolean that indicates whether or not unknown cells should be removed from the cds
- **verbose**: Whether to emit verbose output during the the search for cell-type dependent genes
- **cores**: The number of cores to use when testing

**Value**

A table of differential expression test results

---

mcesApply

Multicore apply-like function for CellDataSet

**Description**

mcesApply computes the row-wise or column-wise results of FUN, just like esApply. Variables in pData from X are available in FUN.
**Usage**

```
mcasApply(X, MARGIN, FUN, required_packages, cores = 1,
        convert_to_dense = TRUE, ...)
```

**Arguments**

- **X**: a `CellDataSet` object
- **MARGIN**: The margin to apply to, either 1 for rows (samples) or 2 for columns (features)
- **FUN**: Any function
- **required_packages**: A list of packages `FUN` will need. Failing to provide packages needed by `FUN` will generate errors in worker threads.
- **cores**: The number of cores to use for evaluation
- **convert_to_dense**: Whether to force conversion a sparse matrix to a dense one before calling `FUN`
- **...**: Additional parameters for `FUN`

**Value**

The result of `with(pData(X) apply(exprs(X)), MARGIN, FUN, ...)`

---

**minSpanningTree**

Retrieves the minimum spanning tree generated by Monocle during cell ordering.

**Description**

Retrieves the minimum spanning tree (MST) that Monocle constructs during `orderCells()`. This MST is mostly used in `plot_spanning_tree` to help assess the accuracy of Monocle’s ordering.

**Usage**

```
minSpanningTree(cds)
```

**Arguments**

- **cds**: expression data matrix for an experiment

**Value**

An igraph object representing the `CellDataSet`’s minimum spanning tree.

**Examples**

```r
## Not run:
T <- minSpanningTree(HSMM)
## End(Not run)
```
minSpanningTree<- function(cds) {  
  Set the minimum spanning tree generated by Monocle during cell ordering.
}

Description
Sets the minimum spanning tree used by Monocle during cell ordering. Not intended to be called directly.

Usage
minSpanningTree(cds) <- value

Arguments
- cds: A CellDataSet object.
- value: an igraph object describing the minimum spanning tree.

Value
An updated CellDataSet object

Examples
## Not run:
cds <- minSpanningTree(T)
## End(Not run)

newCellDataSet

Description
Creates a new CellDateSet object.

Usage
newCellDataSet(cellData, phenoData = NULL, featureData = NULL,  
lowerDetectionLimit = 0.1, expressionFamily = VGAM::tobit(Lower =  
log10(lowerDetectionLimit), lmu = "identitylink"))

Arguments
- cellData: expression data matrix for an experiment
- phenoData: data frame containing attributes of individual cells
- featureData: data frame containing attributes of features (e.g. genes)
- lowerDetectionLimit: the minimum expression level that constitutes true expression
- expressionFamily: the VGAM family function to be used for expression response variables
newCellTypeHierarchy

Value

a new CellDataSet object

Examples

```r
## Not run:
sample_sheet_small <- read.delim("../data/sample_sheet_small.txt", row.names=1)
sample_sheet_small$Time <- as.factor(sample_sheet_small$Time)
gene_annotations_small <- read.delim("../data/gene_annotations_small.txt", row.names=1)
fpkm_matrix_small <- read.delim("../data/fpkm_matrix_small.txt")
pd <- new("AnnotatedDataFrame", data = sample_sheet_small)
fd <- new("AnnotatedDataFrame", data = gene_annotations_small)
HSMM <- new("CellDataSet", exprs = as.matrix(fpkm_matrix_small), phenoData = pd, featureData = fd)
## End(Not run)
```

Description

CellTypeHierarchy objects are Monocle's mechanism for classifying cells into types based on known markers. To classify the cells in a CellDataSet object according to known markers, first construct a CellTypeHierarchy with newCellTypeHierarchy() and addCellType() and then provide both the CellDataSet and the CellTypeHierarchy to classifyCells(). Each call to addCellType() registers a classification function that accepts the expression data from a CellDataSet object as input, and returns a boolean vector indicating whether each cell is of the given type. When you call classifyCells(), each cell will be checked against the classification functions in the CellTypeHierarchy. If you wish to make a cell type a subtype of another that's already been registered with a CellTypeHierarchy object, make that one the "parent" type with the cell_type_name argument. If you want two types to be mutually exclusive, make them "siblings" by giving them the same parent.

Usage

```r
newCellTypeHierarchy()
addCellType(cth, cell_type_name, classify_func,
            parent_cell_type_name = "root")
classifyCells(cds, cth, frequency_thresh = NULL, ...)
calculateMarkerSpecificity(cds, cth, remove_ambig = TRUE,
                           remove_unknown = TRUE)
```

Arguments

- `cth`: The CellTypeHierarchy object
- `cell_type_name`: The name of the new cell type. Can’t already exist in cth
- `classify_func`: A function that returns true when a cell is of the new type
- `parent_cell_type_name`: If this cell type is a subtype of another, provide its name here
The CellDataSet you want to classify

If at least this fraction of group of cells meet a cell types marker criteria, impute them all to be of that type.

character strings that you wish to pass to dplyr’s group_by_ routine

a boolean that determines if ambiguous cells should be removed

a boolean that determines whether unknown cells should be removed

Details

The classification functions in a CellTypeHierarchy must take a single argument, a matrix of expression values, as input. Note that this matrix could either be a sparseMatrix or a dense matrix. Explicitly casting the input to a dense matrix inside a classification function is likely to drastically slow down classifyCells and other routines that use CellTypeHierarchy objects.

Successive calls to addCellType build up a tree of classification functions inside a CellTypeHierarchy. When two functions are siblings in the tree, classifyCells expects that a cell will meet the classification criteria for at most one of them. For example, you might place classification functions for T cells and B cells as siblings, because a cell cannot be both of these at the same time. When a cell meets the criteria for more than one function, it will be tagged as "Ambiguous". If classifyCells reports a large number of ambiguous cells, consider adjusting your classification functions. For example, some cells are defined by very high expression of a key gene that is expressed at lower levels in other cell types. Raising the threshold for this gene in a classification could resolve the ambiguities.

A classification function can also have child functions. You can use this to specify subtypes of cells. For example, T cells express the gene CD3, and there are many subtypes. You can encode each subset by first adding a general T cell classification function that recognizes CD3, and then adding an additional function that recognizes CD4 (for CD4+ helper T cells), one for CD8 (to identify CD8+ cytotoxic T cells), and so on. classifyCells will aim to assign each cell to its most specific subtype in the "CellType" column.

By default, classifyCells applies the classification functions to individual cells, but you can also apply it to cells in a "grouped" mode to impute the type of cells that are missing expression of your known markers. You can specify additional (quoted) grouping variables to classifyCells. The function will group the cells according to these factors, and then classify the cells. It will compute the frequency of each cell type in each group, and if a cell type is present at the frequency specified in frequency_thresh, all the cells in the group are classified as that type. If group contains more than one cell type at this frequency, all the cells are marked "Ambiguous". This allows you to impute cell type based on unsupervised clustering results (e.g. with clusterCells()) or some other grouping criteria.

Value

newCellTypeHierarchy and addCellType both return an updated CellTypeHierarchy object. classifyCells returns an updated CellDataSet with a new column, "CellType", in the pData table.

For a CellDataSet with N genes, and a CellTypeHierarchy with k types, returns a dataframe with N x k rows. Each row contains a gene and a specificity score for one of the types.

Functions

- addCellType: Add a cell type to a CellTypeHierarchy
- classifyCells: Add a cell type to a CellTypeHierarchy
orderCells

- **calculateMarkerSpecificity**: Calculate each gene's specificity for each cell type
  Computes the Jensen-Shannon distance between the distribution of a gene's expression across cells and a hypothetical gene that is perfectly restricted to each cell type. The Jensen-Shannon distance is an information theoretic metric between two probability distributions. It is a widely accepted measure of cell-type specificity. For a complete description see Cabili et al., Genes & Development (2011).

**Examples**

```r
## Not run:
# Initialize a new CellTypeHierarchy

# Register a set of classification functions. There are multiple types of T cells
# A cell cannot be both a B cell and a T cell, a T cell and a Monocyte, or
# a B cell and a Monocyte.
cth <- newCellTypeHierarchy()

cth <- addCellType(cth, "T cell",
  classify_func=function(x) {x["CD3D",] > 0})

cth <- addCellType(cth, "CD4+ T cell",
  classify_func=function(x) {x["CD4",] > 0},
  parent_cell_type_name = "T cell")

cth <- addCellType(cth, "CD8+ T cell",
  classify_func=function(x) {
    x["CD8A",] > 0 | x["CD8B",] > 0
  },
  parent_cell_type_name = "T cell")

cth <- addCellType(cth, "B cell",
  classify_func=function(x) {x["MS4A1",] > 0})

cth <- addCellType(cth, "Monocyte",
  classify_func=function(x) {x["CD14",] > 0})

# Classify each cell in the CellDataSet "mix" according to these types
mix <- classifyCells(mix, cth)

# Group the cells by the pData table column "Cluster". Apply the classification
# functions to the cells groupwise. If a group is at least 5% of a type, make
# them all that type. If the group is 5% one type, and 5% a different, mutually
# exclusive type, mark the whole cluster "Ambiguous"
mix <- classifyCells(mix, Cluster, 0.05)

## End(Not run)
```

**OrderCells**

*Orders cells according to pseudotime.*

Description

Learns a "trajectory" describing the biological process the cells are going through, and calculates where each cell falls within that trajectory. Monocle learns trajectories in two steps. The first step is reducing the dimensionality of the data with `reduceDimension()`. The second is this function, `orderCells()`. This function takes as input a CellDataSet and returns it with two new columns: Pseudotime and State, which together encode where each cell maps to the trajectory. `orderCells()` optionally takes a "root" state, which you can use to specify the start of the trajectory. If you don't provide a root state, one is selected arbitrarily.

Usage

`orderCells(cds, root_state = NULL, num_paths = NULL, reverse = NULL)`

Arguments

- `cds`: the CellDataSet upon which to perform this operation
- `root_state`: The state to use as the root of the trajectory. You must already have called `orderCells()` once to use this argument.
- `num_paths`: the number of end-point cell states to allow in the biological process.
- `reverse`: whether to reverse the beginning and end points of the learned biological process.

Details

The `reduction_method` argument to `reduceDimension()` determines which algorithm is used by `orderCells()` to learn the trajectory. If `reduction_method == "ICA"`, this function uses polygonal reconstruction to learn the underlying trajectory. If `reduction_method == "DDRTree"`, the trajectory is specified by the principal graph learned by the `DDRTree()` function.

Whichever algorithm you use, the trajectory will be composed of segments. The cells from a segment will share the same value of State. One of these segments will be selected as the root of the trajectory arbitrarily. The most distal cell on that segment will be chosen as the "first" cell in the trajectory, and will have a Pseudotime value of zero. `orderCells()` will then "walk" along the trajectory, and as it encounters additional cells, it will assign them increasingly large values of Pseudotime.

Value

an updated CellDataSet object, in which phenoData contains values for State and Pseudotime for each cell

---

**order_p_node**: Return an ordering for a P node in the PQ tree

Description

Return an ordering for a P node in the PQ tree

Usage

`order_p_node(q_level_list, dist_matrix)`
plot_cell_trajectory

Arguments

- **q_level_list**: A list of Q nodes in the PQ tree
- **dist_matrix**: A symmetric matrix of pairwise distances between cells

Description

Plots the minimum spanning tree on cells.

Usage

```r
plot_cell_trajectory(cds, x = 1, y = 2, color_by = "State",
                    show_tree = TRUE, show_backbone = TRUE, backbone_color = "black",
                    markers = NULL, show_cell_names = FALSE, cell_size = 1.5,
                    cell_link_size = 0.75, cell_name_size = 2, show_branch_points = TRUE)
```

Arguments

- **cds**: CellDataSet for the experiment
- **x**: the column of reducedDimS(cds) to plot on the horizontal axis
- **y**: the column of reducedDimS(cds) to plot on the vertical axis
- **color_by**: the cell attribute (e.g. the column of pData(cds)) to map to each cell’s color
- **show_tree**: whether to show the links between cells connected in the minimum spanning tree
- **show_backbone**: whether to show the diameter path of the MST used to order the cells
- **backbone_color**: the color used to render the backbone.
- **markers**: a gene name or gene id to use for setting the size of each cell in the plot
- **show_cell_names**: draw the name of each cell in the plot
- **cell_size**: The size of the point for each cell
- **cell_link_size**: The size of the line segments connecting cells (when used with ICA) or the principal graph (when used with DDRTree)
- **cell_name_size**: the size of cell name labels
- **show_branch_points**: Whether to show icons for each branch point (only available when reduceDimension was called with DDRTree)

Value

A ggplot2 plot object
plot_clusters

Plots kinetic clusters of genes.

**Usage**

```r
plot_clusters(cds, clustering, drawSummary = TRUE, sumFun = mean_cl_boot, 
ncol = NULL, nrow = NULL, row_samples = NULL, callout_ids = NULL)
```

**Arguments**

- `cds` CellDataSet for the experiment
- `clustering` a clustering object produced by clusterCells
- `drawSummary` whether to draw the summary line for each cluster
- `sumFun` whether the function used to generate the summary for each cluster
- `ncol` number of columns used to layout the faceted cluster panels
- `nrow` number of columns used to layout the faceted cluster panels
- `row_samples` how many genes to randomly select from the data
- `callout_ids` a vector of gene names or gene ids to manually render as part of the plot

**Value**

a ggplot2 plot object

**Examples**

```r
## Not run:
full_model_fits <- fitModel(HSMM_filtered[sample(nrow(fData(HSMM_filtered)), 100),], 
  modelFormulaStr="~VGAM::bs(Pseudotime)"
expression_curve_matrix <- responseMatrix(full_model_fits) 
clusters <- clusterGenes(expression_curve_matrix, k=4) 
plot_clusters(HSMM_filtered[ordering_genes,], clusters) 
## End(Not run)
```
plot_coexpression_matrix

Not sure we’re ready to release this one quite yet: Plot the branch genes in pseudotime with separate branch curves

Description

Not sure we’re ready to release this one quite yet: Plot the branch genes in pseudotime with separate branch curves

Usage

plot_coexpression_matrix(cds, rowgenes, colgenes, relative_expr = TRUE, min_expr = NULL, cell_size = 0.85, label_by_short_name = TRUE, show_density = TRUE, round_expr = FALSE)

Arguments

cds  CellDataSet for the experiment
rowgenes  Gene ids or short names to be arrayed on the vertical axis.
colgenes  Gene ids or short names to be arrayed on the horizontal axis
relative_expr  Whether to transform expression into relative values
min_expr  The minimum level of expression to show in the plot
cell_size  A number how large the cells should be in the plot
label_by_short_name  a boolean that indicates whether cells should be labeled by their short name
show_density  a boolean that indicates whether a 2D density estimation should be shown in the plot
round_expr  a boolean that indicates whether cds_expr values should be rounded or not

Value

a ggplot2 plot object

plot_genes_branched_heatmap

Create a heatmap to demonstrate the bifurcation of gene expression along two branches

Description

Create a heatmap to demonstrate the bifurcation of gene expression along two branches
plot_genes_branched_heatmap

Usage

plot_genes_branched_heatmap(cds_subset, branch_point = 1,
branch_states = NULL, branch_labels = c("Cell fate 1", "Cell fate 2"),
cluster_rows = TRUE, hclust_method = "ward.D2", num_clusters = 6,
hmcols = NULL, branch_colors = c("#979797", "#F05662", "#7990C8"),
add_annotation_row = NULL, add_annotation_col = NULL,
show_rownames = FALSE, use_gene_short_name = TRUE, scale_max = 3,
scale_min = -3, norm_method = c("vstExprs", "log"),
trend_formula = "~sm.ns(Pseudotime, df=3) * Branch",
return_heatmap = FALSE, cores = 1, ...)

Arguments

cds_subset CellDataSet for the experiment (normally only the branching genes detected with branchTest)
branch_point The ID of the branch point to visualize. Can only be used when reduceDimension is called with method = "DDRTree".
branch_states The two states to compare in the heatmap. Mutually exclusive with branch_point.
branch_labels The labels for the branches.
cluster_rows Whether to cluster the rows of the heatmap.
hclust_method The method used by pheatmap to perform hierarchical clustering of the rows.
num_clusters Number of clusters for the heatmap of branch genes
hmcols The color scheme for drawing the heatmap.
branch_colors The colors used in the annotation strip indicating the pre- and post-branch cells.
add_annotation_row Additional annotations to show for each row in the heatmap. Must be a dataframe with one row for each row in the fData table of cds_subset, with matching IDs.
add_annotation_col Additional annotations to show for each column in the heatmap. Must be a dataframe with one row for each cell in the pData table of cds_subset, with matching IDs.
show_rownames Whether to show the names for each row in the table.
use_gene_short_name Whether to use the short names for each row. If FALSE, uses row IDs from the fData table.
scale_max The maximum value (in standard deviations) to show in the heatmap. Values larger than this are set to the max.
scale_min The minimum value (in standard deviations) to show in the heatmap. Values smaller than this are set to the min.
norm_method Determines how to transform expression values prior to rendering
trend_formula A formula string specifying the model used in fitting the spline curve for each gene/feature.
return_heatmap Whether to return the heatmap object to the user.
cores Number of cores to use when smoothing the expression curves shown in the heatmap.
... Additional arguments passed to buildBranchCellDataSet
plot_genes_branched_pseudotime

Plot the branch genes in pseudotime with separate branch curves.

Description

This plotting function is used to make the branching plots for a branch dependent gene goes through the progenitor state and bifurcating into two distinct branches (Similar to the pitch-fork bifurcation in dynamic systems). In order to make the bifurcation plot, we first duplicated the progenitor states and by default stretch each branch into maturation level 0-100. Then we fit two nature spline curves for each branches using VGAM package.

Usage

plot_genes_branched_pseudotime(cds, branch_states = NULL, branch_point = 1, branch_labels = NULL, method = "fitting", min_expr = NULL, cell_size = 0.75, nrow = NULL, ncol = 1, panel_order = NULL, color_by = "State", expression_curve_linetype_by = "Branch", trend_formula = "~ sm.ns(Pseudotime, df=3) * Branch", reducedModelFormulaStr = NULL, label_by_short_name = TRUE, relative_expr = TRUE, ...)

Arguments

cds CellDataSet for the experiment
branch_states The states for two branching branches
branch_point The ID of the branch point to analyze. Can only be used when reduceDimension is called with method = "DDRTree".
branch_labels The names for each branching branch
method The method to draw the curve for the gene expression branching pattern, either loess (‘loess’) or VGLM fitting (‘fitting’)
min_expr The minimum (untransformed) expression level to use in plotted the genes.
cell_size The size (in points) of each cell used in the plot
nrow Number of columns used to layout the faceted cluster panels
ncol Number of columns used to layout the faceted cluster panels
panel_order The a character vector of gene short names (or IDs, if that’s what you’re using), specifying order in which genes should be layed out (left-to-right, top-to-bottom)
color_by The cell attribute (e.g. the column of pData(cds)) to be used to color each cell
expression_curve_linetype_by The cell attribute (e.g. the column of pData(cds)) to be used for the linetype of each branch curve
plot_genes_in_pseudotime

Plots expression for one or more genes as a function of pseudotime

Description

Plots expression for one or more genes as a function of pseudotime

Usage

plot_genes_in_pseudotime(cds_subset, min_expr = NULL, cell_size = 0.75, 
nrow = NULL, ncol = 1, panel_order = NULL, color_by = "State", 
trend_formula = "~ sm.ns(Pseudotime, df=3)", label_by_short_name = TRUE, 
relative_expr = TRUE, vertical_jitter = NULL, horizontal_jitter = NULL)

Arguments

cds_subset CellDataSet for the experiment
min_expr the minimum (untransformed) expression level to use in plotted the genes.
cell_size the size (in points) of each cell used in the plot
nrow the number of rows used when laying out the panels for each gene’s expression
ncol the number of columns used when laying out the panels for each gene’s expression
panel_order the order in which genes should be layed out (left-to-right, top-to-bottom)
color_by the cell attribute (e.g. the column of pData(cds)) to be used to color each cell
trend_formula the model formula to be used for fitting the expression trend over pseudotime
label_by_short_name label figure panels by gene_short_name (TRUE) or feature id (FALSE)
relative_expr Whether to transform expression into relative values
vertical_jitter A value passed to ggplot to jitter the points in the vertical dimension. Prevents overplotting, and is particularly helpful for rounded transcript count data.
horizontal_jitter A value passed to ggplot to jitter the points in the horizontal dimension. Prevents overplotting, and is particularly helpful for rounded transcript count data.
### Plots expression for one or more genes as a jittered, grouped points

**Description**

Plots expression for one or more genes as a jittered, grouped points

**Usage**

```r
plot_genes_jitter(cds_subset, grouping = "State", min_expr = NULL,
                 cell_size = 0.75, nrow = NULL, ncol = 1, panel_order = NULL,
                 color_by = NULL, plot_trend = FALSE, label_by_short_name = TRUE,
                 relative_expr = TRUE)
```

**Arguments**

- `cds_subset`: CellDataSet for the experiment
- `grouping`: the cell attribute (e.g. the column of pData(cds)) to group cells by on the horizontal axis
- `min_expr`: the minimum (untransformed) expression level to use in plotted the genes.
- `cell_size`: the size (in points) of each cell used in the plot
- `nrow`: the number of rows used when laying out the panels for each gene’s expression
- `ncol`: the number of columns used when laying out the panels for each gene’s expression
- `panel_order`: the order in which genes should be layed out (left-to-right, top-to-bottom)
- `color_by`: the cell attribute (e.g. the column of pData(cds)) to be used to color each cell
- `plot_trend`: whether to plot a trendline tracking the average expression across the horizontal axis.
- `label_by_short_name`: label figure panels by gene_short_name (TRUE) or feature id (FALSE)
- `relative_expr`: Whether to transform expression into relative values

**Value**

a ggplot2 plot object
plot_genes_positive_cells

Plots the number of cells expressing one or more genes as a barplot

Description

Plots the number of cells expressing one or more genes as a barplot

Usage

plot_genes_positive_cells(cds_subset, grouping = "State", min_expr = 0.1, nrow = NULL, ncol = 1, panel_order = NULL, plot_as_fraction = TRUE, label_by_short_name = TRUE, relative_expr = TRUE, plot_limits = c(0, 100))

Arguments

cds_subset: CellDataSet for the experiment
grouping: the cell attribute (e.g. the column of pData(cds)) to group cells by on the horizontal axis
min_expr: the minimum (untransformed) expression level to use in plotted the genes.
nrow: the number of rows used when laying out the panels for each gene’s expression
ncol: the number of columns used when laying out the panels for each gene’s expression
panel_order: the order in which genes should be layed out (left-to-right, top-to-bottom)
plot_as_fraction: whether to show the percent instead of the number of cells expressing each gene
label_by_short_name: label figure panels by gene_short_name (TRUE) or feature id (FALSE)
relative_expr: Whether to transform expression into relative values
plot_limits: A pair of number specifying the limits of the y axis. If NULL, scale to the range of the data.

Value

a ggplot2 plot object
Examples

```r
## Not run:
data(HSMM)
MYOG_ID1 <- HSMM[row.names(subset(fData(HSMM), gene_short_name %in% c("MYOG", "ID1"))),]
plot_genes_positive_cells(MYOG_ID1, grouping="Media", ncol=2)
## End(Not run)
```

Description

Each gray point in the plot is a gene. The black dots are those that were included in the last call to
setOrderingFilter. The red curve shows the mean-variance model learning by estimateDispersions().

Usage

```r
plot_ordering_genes(cds)
```

Arguments

cds The CellDataSet to be used for the plot.

Description

Plots a pseudotime-ordered, row-centered heatmap

Usage

```r
plot_pseudotime_heatmap(cds_subset, cluster_rows = TRUE, 
hclust_method = "ward.D2", num_clusters = 6, hmcols = NULL, 
add_annotation_row = NULL, add_annotation_col = NULL, 
show_rownames = FALSE, use_gene_short_name = TRUE, 
norm_method = c("vstExprs", "log"), scale_max = 3, scale_min = -3, 
trend_formula = "~sm.ns(Pseudotime, df=3)", return_heatmap = FALSE, 
cores = 1)
```
Arguments

- **cds_subset**: CellDataSet for the experiment (normally only the branching genes detected with branchTest)
- **cluster_rows**: Whether to cluster the rows of the heatmap.
- **hclust_method**: The method used by pheatmap to perform hierarchical clustering of the rows.
- **num_clusters**: Number of clusters for the heatmap of branch genes
- **hmcols**: The color scheme for drawing the heatmap.
- **add_annotation_row**: Additional annotations to show for each row in the heatmap. Must be a dataframe with one row for each row in the fData table of cds_subset, with matching IDs.
- **add_annotation_col**: Additional annotations to show for each column in the heatmap. Must be a dataframe with one row for each cell in the pData table of cds_subset, with matching IDs.
- **show_rownames**: Whether to show the names for each row in the table.
- **use_gene_short_name**: Whether to use the short names for each row. If FALSE, uses row IDs from the fData table.
- **norm_method**: Determines how to transform expression values prior to rendering
- **scale_max**: The maximum value (in standard deviations) to show in the heatmap. Values larger than this are set to the max.
- **scale_min**: The minimum value (in standard deviations) to show in the heatmap. Values smaller than this are set to the min.
- **trend_formula**: A formula string specifying the model used in fitting the spline curve for each gene/feature.
- **return_heatmap**: Whether to return the pheatmap object to the user.
- **cores**: Number of cores to use when smoothing the expression curves shown in the heatmap.

Value

A list of heatmap_matrix (expression matrix for the branch commitment), ph (pheatmap heatmap object), annotation_row (annotation data.frame for the row), annotation_col (annotation data.frame for the column).

plot_spanning_tree

Plots the minimum spanning tree on cells. This function is deprecated.

Description

This function arranges all of the cells in the cds in a tree and predicts their location based on their pseudotime value

Usage

```
plot_spanning_tree(cds, x = 1, y = 2, color_by = "State",
show_tree = TRUE, show_backbone = TRUE, backbone_color = "black",
markers = NULL, show_cell_names = FALSE, cell_size = 1.5,
cell_link_size = 0.75, cell_name_size = 2, show_branch_points = TRUE)
```
pq_helper

Recursively builds and returns a PQ tree for the MST

Description
Recursively builds and returns a PQ tree for the MST

Usage

pq_helper(mst, use_weights = TRUE, root_node = NULL)

Arguments

cds
CellDataSet for the experiment

x
the column of reducedDimS(cds) to plot on the horizontal axis

y
the column of reducedDimS(cds) to plot on the vertical axis

color_by
the cell attribute (e.g. the column of pData(cds)) to map to each cell’s color

show_tree
whether to show the links between cells connected in the minimum spanning tree

show_backbone
whether to show the diameter path of the MST used to order the cells

backbone_color
the color used to render the backbone.

markers
a gene name or gene id to use for setting the size of each cell in the plot

show_cell_names
draw the name of each cell in the plot

cell_size
The size of the point for each cell

cell_link_size
The size of the line segments connecting cells (when used with ICA) or the principal graph (when used with DDRTree)

cell_name_size
the size of cell name labels

show_branch_points
Whether to show icons for each branch point (only available when reduceDimension was called with DDRTree)

Value

a ggplot2 plot object

See Also

plot_cell_trajectory

Examples

## Not run:
data(HSMM)
plot_cell_trajectory(HSMM)
plot_cell_trajectory(HSMM, color_by="Pseudotime", show_backbone=FALSE)
plot_cell_trajectory(HSMM, markers="MYH3")
## End(Not run)
Arguments

mst The minimum spanning tree, as an igraph object.
use_weights Whether to use edge weights when finding the diameter path of the tree.
root_node The name of the root node to use for starting the path finding.

reducedDimA Get the weights needed to lift cells back to high dimensional expression space.

Description

Retrieves the weights that transform the cells’ coordinates in the reduced dimension space back to the full (whitened) space.

Usage

reducedDimA(cds)

Arguments

cds A CellDataSet object.

Value

A matrix that when multiplied by a reduced-dimension set of coordinates for the CellDataSet, recovers a matrix in the full (whitened) space.

Examples

## Not run:
A <- reducedDimA(HSMM)
## End(Not run)

reducedDimA<- Get the weights needed to lift cells back to high dimensional expression space.

Description

Sets the weights transform the cells’ coordinates in the reduced dimension space back to the full (whitened) space.

Usage

reducedDimA(cds) <- value
reducedDimK

Arguments

    cds    A CellDataSet object.
    value  A whitened expression data matrix

Value

    An updated CellDataSet object

Examples

    ## Not run:
    cds <- reducedDimA(A)
    ## End(Not run)

reducedDimK  Retrieves the the whitening matrix during independent component analysis.

Description

    Retrieves the the whitening matrix during independent component analysis.

Usage

    reducedDimK(cds)

Arguments

    cds    A CellDataSet object.

Value

    A matrix, where each row is a set of whitened expression values for a feature and columns are cells.

Examples

    ## Not run:
    K <- reducedDimW(HSMM)
    ## End(Not run)
reducedDimK <-  

Sets the whitening matrix during independent component analysis.

Description

Sets the the whitening matrix during independent component analysis.

Usage

reducedDimK(cds) <- value

Arguments

cds  A CellDataSet object.
value  a numeric matrix

Value

A matrix, where each row is a set of whitened expression values for a feature and columns are cells.

Examples

## Not run:
cds <- reducedDimK(K)
## End(Not run)

reducedDimS  

Retrieves the coordinates of each cell in the reduced-dimensionality space generated by calls to reduceDimension.

Description

Reducing the dimensionality of the expression data is a core step in the Monocle workflow. After you call reduceDimension(), this function will return the new coordinates of your cells in the reduced space.

Usage

reducedDimS(cds)

Arguments

cds  A CellDataSet object.

Value

A matrix, where rows are cell coordinates and columns correspond to dimensions of the reduced space.
Examples

## Not run:
S <- reducedDimS(HSMM)
## End(Not run)

reducedDimS<-  
Set embedding coordinates of each cell in a CellDataSet.

Description

This function sets the coordinates of each cell in a new (reduced-dimensionality) space. Not intended to be called directly.

Usage

reducedDimS(cds) <- value

Arguments

cds A CellDataSet object.
value A matrix of coordinates specifying each cell’s position in the reduced-dimensionality space.

Value

An update CellDataSet object

Examples

## Not run:
cds <- reducedDimS(S)
## End(Not run)

reducedDimW
Get the whitened expression values for a CellDataSet.

Description

Retrieves the expression values for each cell (as a matrix) after whitening during dimensionality reduction.

Usage

reducedDimW(cds)

Arguments

cds A CellDataSet object.
setReducedDimW<-

A matrix, where each row is a set of whitened expression values for a feature and columns are cells.

Examples

```r
## Not run:
W <- reducedDimW(HSMM)
## End(Not run)
```

Description

Sets the whitened expression values for each cell prior to independent component analysis. Not intended to be called directly.

Usage

```r
reducedDimW(cds) <- value
```

Arguments

- `cds` A CellDataSet object.
- `value` A whitened expression data matrix

Value

An updated CellDataSet object

Examples

```r
## Not run:
# ' cds <- reducedDimA(A)
## End(Not run)
```
compute a projection of a CellDataSet object into a lower dimensional space

Description

Monocle aims to learn how cells transition through a biological program of gene expression changes in an experiment. Each cell can be viewed as a point in a high-dimensional space, where each dimension describes the expression of a different gene in the genome. Identifying the program of gene expression changes is equivalent to learning a trajectory that the cells follow through this space. However, the more dimensions there are in the analysis, the harder the trajectory is to learn. Fortunately, many genes typically co-vary with one another, and so the dimensionality of the data can be reduced with a wide variety of different algorithms. Monocle provides two different algorithms for dimensionality reduction via reduceDimension. Both take a CellDataSet object and a number of dimensions allowed for the reduced space. You can also provide a model formula indicating some variables (e.g. batch ID or other technical factors) to "subtract" from the data so it doesn’t contribute to the trajectory.

Usage

reduceDimension(cds, max_components = 2, reduction_method = c("DDRTree", "ICA"), norm_method = c("vstExprs", "log", "none"), residualModelFormulaStr = NULL, pseudo_expr = NULL, verbose = FALSE, ...)

Arguments

cds the CellDataSet upon which to perform this operation
max_components the dimensionality of the reduced space
reduction_method A character string specifying the algorithm to use for dimensionality reduction.
norm_method Determines how to transform expression values prior to reducing dimensionality
residualModelFormulaStr A model formula specifying the effects to subtract from the data before cluster-
ing.
pseudo_expr amount to increase expression values before dimensionality reduction
verbose Whether to emit verbose output during dimensionality reduction
...
additional arguments to pass to the dimensionality reduction function

Details

You can choose two different reduction algorithms: Independent Component Analysis (ICA) and Discriminative Dimensionality Reduction with Trees (DDRTree). The choice impacts numerous downstream analysis steps, including orderCells. Choosing ICA will execute the ordering procedure described in Trapnell and Cacchiarelli et al., which was implemented in Monocle version 1. DDRTree is a more recent manifold learning algorithm developed by Qi Mao and colleagues. It is substantially more powerful, accurate, and robust for single-cell trajectory analysis than ICA, and is now the default method.
Often, experiments include cells from different batches or treatments. You can reduce the effects of these treatments by transforming the data with a linear model prior to dimensionality reduction. To do so, provide a model formula through `residualModelFormulaStr`.

Prior to reducing the dimensionality of the data, it usually helps to normalize it so that highly expressed or highly variable genes don’t dominate the computation. `reduceDimension()` automatically transforms the data in one of several ways depending on the `expressionFamily` of the `CellDataSet` object. If the `expressionFamily` is `negbinomial` or `negbinomial.size`, the data are variance-stabilized. If the `expressionFamily` is `Tobit`, the data are adjusted by adding a pseudo-count (of 1 by default) and then log-transformed. If you don’t want any transformation at all, set `norm_method` to "none" and `pseudo_expr` to 0. This maybe useful for single-cell qPCR data, or data you’ve already transformed yourself in some way.

**Value**

an updated `CellDataSet` object

---

**relative2abs**

Transform relative expression values into absolute transcript counts.

**Description**

Transform a relative expression matrix to absolute transcript matrix based on the inferred linear regression parameters from most abundant isoform relative expression value. This function takes a relative expression matrix and a vector of estimated most abundant expression value from the isoform-level matrix and transform it into absolute transcript number. It is based on the observation that the recovery efficient of the single-cell RNA-seq is relative low and that most expressed isoforms of gene in a single cell therefore only sequenced one copy so that the most abundant isoform log10-FPKM (t^*) will corresponding to 1 copy transcript. It is also based on the fact that the spikein regression parameters k/b for each cell will fall on a line because of the intrinsic properties of spikein experiments. We also assume that if we perform the same spikein experiments as Treutlein et al. did, the regression parameters should also fall on a line in the same way. The function takes the the vector t^* and the detection limit as input, then it uses the t^* and the m/c value corresponding to the detection limit to calculate two parameters vectors k^* and b^* (corresponding to each cell) which correspond to the slope and intercept for the linear conversion function between log10 FPKM and log10 transcript counts. The function will then apply a linear transformation to convert the FPKM to estimated absolute transcript counts based on the the k^* and b^*. The default m/c values used in the algorithm are 3.652201, 2.263576, respectively.

**Usage**

```
relative2abs(relative_cds, t_estimate = estimate_t(exprs(relative_cds)), modelFormulaStr = "~1", ERCC_controls = NULL, ERCC_annotation = NULL, volume = 10, dilution = 40000, mixture_type = 1, detection_threshold = 800, expected_capture_rate = 0.25, verbose = FALSE, return_all = FALSE, cores = 1)
```

**Arguments**

- `relative_cds` the cds object of relative expression values for single cell RNA-seq with each row and column representing genes/isoforms and cells. Row and column names should be included
`relative2abs`  

- **t_estimate**: a vector for the estimated most abundant FPKM value of isoform for a single cell. Estimators based on gene-level relative expression can also give good approximation but estimators based on isoform FPKM will give better results in general.

- **modelFormulaStr**: a formula used to grouping cells for transcript counts recovery. Default is `"~ 1"`, which means to recover the transcript counts from all cells.

- **ERCC_controls**: the FPKM matrix for each ERCC spike-in transcript in the cells if user wants to perform the transformation based on their spike-in data. Note that the row and column names should match up with the ERCC_annotation and relative_exprs_matrix respectively.

- **ERCC_annotation**: the ERCC_annotation matrix from illumina USE GUIDE which will be used for calculating the ERCC transcript copy number for performing the transformation.

- **volume**: the approximate volume of the lysis chamber (nanoliters). Default is 10

- **dilution**: the dilution of the spikein transcript in the lysis reaction mix. Default is 40,000. The number of spike-in transcripts per single-cell lysis reaction was calculated from

- **mixture_type**: the type of spikein transcripts from the spikein mixture added in the experiments. By default, it is mixture 1. Note that m/c we inferred are also based on mixture 1.

- **detection_threshold**: the lowest concentration of spikein transcript considered for the regression. Default is 800 which will ensure (almost) all included spike transcripts expressed in all the cells. Also note that the value of c is based on this concentration.

- **expected_capture_rate**: the expected fraction of RNA molecules in the lysate that will be captured as cDNAs during reverse transcription.

- **verbose**: a logical flag to determine whether or not we should print all the optimization details.

- **return_all**: parameter for the intended return results. If setting TRUE, matrix of m, c, k^*, b^* as well as the transformed absolute cds will be returned in a list format.

- **cores**: number of cores to perform the recovery. The recovery algorithm is very efficient so multiple cores only needed when we have very huge number of cells or genes.

**Value**

- an matrix of absolute count for isoforms or genes after the transformation.

**Examples**

```r
## Not run:
HSMM_relative_expr_matrix <- exprs(HSMM)
HSMM_abs_matrix <- relative2abs(HSMM_relative_expr_matrix,
  t_estimate = estimate_t(HSMM_relative_expr_matrix))
## End(Not run)
```
### residualMatrix

<table>
<thead>
<tr>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Generates a matrix of response values for a set of fitted models</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Usage</th>
</tr>
</thead>
<tbody>
<tr>
<td>residualMatrix(models, residual_type = &quot;response&quot;, cores = 1)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Arguments</th>
</tr>
</thead>
<tbody>
<tr>
<td>models: a list of models, e.g. as returned by fitModels()</td>
</tr>
<tr>
<td>residual_type: the response desired, as accepted by VGAM's predict function</td>
</tr>
<tr>
<td>cores: number of cores used for calculation</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>a matrix where each row is a vector of response values for a particular feature's model, and columns are cells.</td>
</tr>
</tbody>
</table>

### responseMatrix

<table>
<thead>
<tr>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Generates a matrix of response values for a set of fitted models</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Usage</th>
</tr>
</thead>
<tbody>
<tr>
<td>responseMatrix(models, newdata = NULL, response_type = &quot;response&quot;, cores = 1)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Arguments</th>
</tr>
</thead>
<tbody>
<tr>
<td>models: a list of models, e.g. as returned by fitModels()</td>
</tr>
<tr>
<td>newdata: a dataframe used to generate new data for interpolation of time points</td>
</tr>
<tr>
<td>response_type: the response desired, as accepted by VGAM's predict function</td>
</tr>
<tr>
<td>cores: number of cores used for calculation</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>a matrix where each row is a vector of response values for a particular feature's model, and columns are cells.</td>
</tr>
</tbody>
</table>
scale_pseudotime

Scale pseudotime to be in the range from 0 to 100

Description
This function transforms the pseudotime scale so that it ranges from 0 to 100. If there are multiple branches, each leaf is set to be 100, with branches stretched accordingly.

Usage
scale_pseudotime(cds, verbose = F)

Arguments
cds the CellDataSet upon which to perform this operation
verbose Whether to emit verbose output

Value
an updated CellDataSet object which an

selectNegentropyGenes Filter genes with extremely high or low negentropy

Description
Filter genes with extremely high or low negentropy

Usage
selectNegentropyGenes(cds, lower_negentropy_bound = "0%", upper_negentropy_bound = "99%", expression_lower_thresh = 0.1, expression_upper_thresh = Inf)

Arguments
cds a CellDataSet object upon which to perform this operation
lower_negentropy_bound the centile below which to exclude to genes
upper_negentropy_bound the centile above which to exclude to genes
expression_lower_thresh the expression level below which to exclude genes used to determine negentropy
expression_upper_thresh the expression level above which to exclude genes used to determine negentropy

Value
a vector of gene names
**Examples**

```r
## Not run:
reasonableNegentropy <- selectNegentropyGenes(HSMM, "07\%", "95\%", 1, 100)

## End(Not run)
```

**Description**

This is a handy wrapper function around dplyr’s `top_n` function to extract the most specific genes for each cell type. Convenient, for example, for selecting a balanced set of genes to be used in semi-supervised clustering or ordering.

**Usage**

```r
selectTopMarkers(marker_specificities, num_markers = 10)
```

**Arguments**

- **marker_specificities**
  The dataframe of specificity results produced by `calculateMarkerSpecificity()`
- **num_markers**
  The number of markers that will be shown for each cell type

**Value**

A data frame of specificity results

---

**setOrderingFilter**

Sets the features (e.g. genes) to be used for ordering cells in pseudotime.

**Description**

Sets the features (e.g. genes) to be used for ordering cells in pseudotime.

**Usage**

```r
setOrderingFilter(cds, ordering_genes)
```

**Arguments**

- **cds**
  the CellDataSet upon which to perform this operation
- **ordering_genes**
  a vector of feature ids (from the CellDataSet’s featureData) used for ordering cells

**Value**

an updated CellDataSet object
spike_df

Spike-in transcripts data.

Description

A dataset containing the information for the 92 ERCC spikein transcripts (This dataset is based on the data from the Nature paper from Stephen Quake group)

Usage

spike_df

Format

A data frame with 92 rows and 9 variables:

- **ERCC_ID**  ID for ERCC transcripts
- **subgroup**  Subgroup for ERCC transcript
- **conc_attomoles_ul_Mix1**  Concentration of Mix 1 (attomoles / ul)
- **conc_attomoles_ul_Mix2**  Concentration of Mix 2 (attomoles / ul)
- **exp_fch_ratio**  expected fold change between mix 1 over mix 2
- **numMolecules**  number of molecules calculated from concentration and volume
- **rounded_numMolecules**  number in rounded digit of molecules calculated from concentration and volume

vstExprs

Return a variance-stabilized matrix of expression values

Description

This function was taken from the DESeq package (Anders and Huber) and modified to suit Monocle’s needs

Usage

vstExprs(cds, dispModelName = "blind", expr_matrix = NULL, round_vals = TRUE)

Arguments

- **cds**  A CellDataSet to use for variance stabilization.
- **dispModelName**  The name of the dispersion function to use for VST.
- **expr_matrix**  An matrix of values to transform. Must be normalized (e.g. by size factors) already. This function doesn’t do this for you.
- **round_vals**  Whether to round expression values to the nearest integer before applying the transformation.
Index

*Topic datasets
  - spike_df, 53

addCellType (newCellTypeHierarchy), 27

BEAM, 3, 4, 5
branchTest, 4
buildBranchCellDataSet, 5

calABCs, 6
calculateMarkerSpecificity, 52
calculateMarkerSpecificity (newCellTypeHierarchy), 27
calibrate_per_cell_total_proposal, 7
calIBRs, 7
CellDataSet, 8
CellDataSet, ANY, ANY-method (CellDataSet-methods), 9
CellDataSet-class (CellDataSet), 8
CellDataSet-methods, 9
cellPairwiseDistances, 10
cellPairwiseDistances<-, 11
CellType, 11
CellType-class (CellType), 11
CellTypeHierarchy, 12
CellTypeHierarchy-class (CellTypeHierarchy), 12
classifyCells (newCellTypeHierarchy), 27
classifyCells, 12, 28
clusterCells, 13

DDRTree, 30, 47
detectBifurcationPoint, 14
detectGenes, 15
diff_test_helper, 17
differentialGeneTest, 16
dispersionTable, 17

estimate_t, 19
estimateDispersion, CellDataSet-method (CellDataSet-methods), 9
estimateDispersionForCellDataSet, 18
estimateSizeFactors, CellDataSet-method (CellDataSet-methods), 9

estimateSizeFactorsForMatrix, 18
extract_good_branched_ordering, 20

fit_model_helper, 21
fitModel, 20
genSmoothCurveResiduals, 21
genSmoothCurves, 22
get_classic_muscle_markers, 23

load_HSMM, 23
load_HSMM, markers, 23
load_lung, 23

markerDiffTable, 24
mcesApply, 24
minSpanningTree, 25
minSpanningTree<-, 26

newCellDataSet, 26
newCellTypeHierarchy, 27

order_p_node, 30
orderCells, 29, 47

plot_cell_trajectory, 31
plot_clusters, 32
plot_coexpression_matrix, 33
plot_genes_branched_heatmap, 33
plot_genes_branched_pseudotime, 35
plot_genes_in_pseudotime, 36
plot_genes_jitter, 37
plot_genes_positive_cells, 38
plot_ordering_genes, 39
plot_pseudotime_heatmap, 39
plotSpanningTree, 40
pq_helper, 41

reducedDimA, 42
reducedDimA<-, 42
reducedDimK, 43
reducedDimK<-, 44
reducedDimS, 44
reducedDimS<-, 45
reducedDimW, 45
INDEX

reducedDimW<-, 46
reduceDimension, 6, 12, 30, 47
relative2abs, 48
residualMatrix, 50
responseMatrix, 50

scale_pseudotime, 51
selectNegentropyGenes, 51
selectTopMarkers, 52
setOrderingFilter, 52
sizeFactors, CellDataSet-method
  (CellDataSet-methods), 9
sizeFactors<-, CellDataSet, numeric-method
  (CellDataSet-methods), 9
sparseMatrix, 28
spike_df, 53

vglm, 16
vstExprs, 53