Package 'immunoClust'

November 17, 2026

Type Package

Title immunoClust - Automated Pipeline for Population Detection in Flow Cytometry

Version 1.45.1

Date 2026-07-02

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Depends R(>= 4.2), flowCore

Imports methods, stats, graphics, grid, lattice, grDevices

Suggests BiocStyle, utils, testthat

Description immunoClust is a model based clustering approach for Flow Cytometry samples. The cell-events of single Flow Cytometry samples are modelled by a mixture of multinominal normal- or t-distributions. The cell-event clusters of several samples are modelled by a mixture of multinominal normal-distributions aiming stable co-clusters across these samples.

Collate generics.R class.immunoClust.R plot.immunoClust.R splom.immunoClust.R methods.immunoClust.R class.immunoMeta.R plot.immunoMeta.R methods.immunoMeta.R data.R process.R cell.clustering.R meta.clustering.R meta.annotation.R meta.SON.R meta.export.R clust.util.R transform.R

biocViews Clustering, FlowCytometry, SingleCell, CellBasedAssays, ImmunoOncology

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

git_branch devel

git_last_commit f1d31c0

git_last_commit_date 2026-07-24

Repository Bioconductor 3.24

Date/Publication 2026-11-16

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`immunoClust-package` *immunoClust - Automated Pipeline for Population Detection in Flow Cytometry*

Description

Model based clustering and meta-custering routines for Flow Cytometry (FC) data.

The immunoClust-pipeline consits of two major procedures:

`cell.process`	Clustering of cell-events
`meta.process`	Meta-clustering of cell-clusters

Cell-events clustering is performed for each FC data sample separately. After this all cell-clustering results are collected in a vector and meta-clustering is performed to obtain the across samples populations.

Author(s)

Till Sörensen <till-antoni.soerensen@charited.de>

References

Sörensen, T., Baumgart, S., Durek, P., Grützkau, A. and Häupl, T. immunoClust - an automated analysis pipeline for the identification of immunophenotypic signatures in high-dimensional cytometric datasets. *Cytometry A* (accepted).

`bhattacharyya` *Bhattacharyya Distance, Coefficient and Probability*

Description

Calculates the Bhattacharyya Distance, Coefficient and Probability

Usage

```
bhattacharyya.prob(gM,gS, cM,cS, alpha=1)

bhattacharyya.dist(gM, gS, cM, cS)

bhattacharyya.coeff(gM,gS, cM,cS, alpha=1)
```

Arguments

`gM`, `cM`	`P`-dimensional vector of cluster means
`gS`, `cS`	`PxP`-dimensinal matrix of clusters co-variances
`alpha`	A value between 0 and 1 used to balance the bhattacharrya probabilities, coefficients calculated with either the full covariance matrices or using only the diagonal elements of it.

Details

Calculates the bhattacharyya probabilty, distance or coefficient of the clusters, i.e. Gaussian distributions. Distance and Coefficient are symetric for both clusters, whereas the probabity is not.

Value

The Bhattacharyya probability, distance or coefficient

Author(s)

Till Sörensen `<till-antoni.soerensen@charite.de>`

Examples

```
data(dat.meta)

prob <- bhattacharyya.prob(prop(dat.meta,"M",c()), prop(dat.meta,"S"),
    mu(dat.meta,1), sigma(dat.meta,1))
dist <- bhattacharyya.dist(prop(dat.meta,"M",c()), prop(dat.meta,"S"),
    mu(dat.meta,1), sigma(dat.meta,1))
coeff <- bhattacharyya.coeff(prop(dat.meta,"M",c()), prop(dat.meta,"S"),
    mu(dat.meta,1), sigma(dat.meta,1))
```

`cell.ClustData` *Model Based Clustering of Data for a pre-defined Number of Clusters*

Description

Performs EM-iteration on cell events, where an initial event cluster membership is obtained by hierarchical clustering on a sample subset given a number of clusters.

Usage

```
cell.ClustData(data, K, parameters=NULL, expName="immunoClust Experiment",
               sample.number=1500, sample.standardize=TRUE,
               B=50, tol=1e-5, modelName="mvt")
```

Arguments

`data`	A numeric matrix, data frame of observations, or object of class flowFrame. Rows correspond to observations and columns correspond to measured parameters.
`K`	Given number of clusters for the final model.
`parameters`	A character vector specifying the parameters (columns) to be included in clustering. When it is left unspecified, all the parameters will be used.
`expName`	The name of the clustering experiment.
`sample.number`	The maximum number of samples used for initial hierarchical clustering.
`sample.standardize`	A numeric indicating whether the samples for hierarchical clustering are standardized (mean=0, SD=1).
`B`	The maximum number of EM-iterations.
`tol`	The tolerance used to assess the convergence of the EM-algorithm.
`modelName`	Used mixture model; either `"mvt"` for a t-mixture model or `"mvn"` for a Gaussian Mixture model.

Details

Although this function provides the possiblity to cluster an abitrary set of observed data into a fixed number of clusters, this function is used in the immunoClust-pipeline only for the calculation of the initial model with one cluster.

Value

The fitted model cluster information in an object of class immunoClust.

Author(s)

Till Sörensen <till-antoni.soerensen@charite.de>

References

Sörensen, T., Baumgart, S., Durek, P., Grützkau, A. and Häupl, T. immunoClust - an automated analysis pipeline for the identification of immunophenotypic signatures in high-dimensional cytometric datasets. *Cytometry A* (accepted).

See Also

immunoClust-object, cell.hclust

Examples

```
data(dat.fcs)
res <- cell.ClustData(dat.fcs, parameters=c("FSC-A", "SSC-A"), 5)
summary(res)
```

---

cell.EM *immunoClust EMt-iteration on Cell-events given initial Model Parameters*

Description

Performs EMt-iteration on cell event observations giving initial model parameters and returns the fitted clusters information in an object of class immunoClust.

Usage

```
cell.EMt(data,  K, w, m, s, parameters=NULL,
    expName="immunoClust Experiment",
    B=50, tol=1e-5, bias=0.5, modelName="mvt")

cell.EMstep(data,  K, w, m, s, parameters=NULL,
    expName="immunoClust EMstep",
    B=1, tol=1e-5, modelName="mvt")

cell.Estep(data, K, w, m, s, parameters=NULL,
    expName="immunoClust Estep", scale_Z=TRUE, modelName="mvt")
```

Arguments

data	A numeric matrix, data frame of observations, or object of class flowFrame.
parameters	A character vector specifying the parameters (columns) to be included in clustering. When it is left unspecified, all the parameters will be used.
expName	The name of the clustering experiment.

K	The number of clusters.
w	The K-dimensional vector of the mixture proportions.
m	The KxP-dimensional matrix of the K estimated cluster means.
s	The $KxPxP$-dimensional matrix of the K estimated cluster covariance matrices.
B	The maximum number of EMt-iterations.
tol	The tolerance used to assess the convergence of the EMt-algorithms.
bias	The ICL-bias used in the EMt-algorithm.
scale_Z	Scale the returned a-posteriori probabilities to one for each observed event.
modelName	Used mixture model; either "mvt" or "mvn" for a t- or Gaussian mixture model respectively.

Details

Whereas cell.EMt performs a complete EMt-iteration, cell.Estep only calculates the a-posteriori probabilities and the Maximum-A-Posteriori estimators of cluster membership for all events. For an EM-iteration use cell.EMstep.

Value

The fitted clusters information in an object of class immunoClust.

Author(s)

Till Sörensen <till-antoni.soerensen@charite.de>

References

Sörensen, T., Baumgart, S., Durek, P., Grützkau, A. and Häupl, T. immunoClust - an automated analysis pipeline for the identification of immunophenotypic signatures in high-dimensional cytometric datasets. *Cytometry A* (accepted).

See Also

cell.MEstep, cell.FitModel

Examples

```
data(dat.fcs)
data(dat.exp)
## cell.clustering result for dat.fcs
r <- dat.exp[[1]]
summary(r)
## apply model parameter to all (unfiltered) events
dat.trans <- trans.ApplyToData(r, dat.fcs)
r2 <- cell.EMt(dat.trans, K=ncls(r), w=weights(r),m=mu(r),s=sigma(r),
    parameters=parameters(r))
summary(r2)
```

`cell.FitModel` *immunoClust EMt-iteration on Cell-events given initial Model Parameters*

Description

The function fits initial model parameters to specific observed cell event data. The function returns the cluster information of the fitted model in an object of class `immunoClust`.

Usage

```
cell.FitModel(x, data, B=50, tol=1e-5, bias=0.5, modelName="mvt" )

cell.Classify(x, data, modelName="mvt" )
```

Arguments

`x`	An immunoClust object with the initial model parameter ($parameters$, K, w, mu, $sigma$).
`data`	A numeric matrix, data frame of observations, or object of class flowFrame.
`B`	The maximum number of EMt-iterations.
`tol`	The tolerance used to assess the convergence of the EMt-algorithms.
`bias`	The ICL-bias used in the EMt-algorithm.
`modelName`	Used mixture model; either `"mvt"` or `"mvn"` for a t- or Gaussian mixture model respectively.

Details

These functions are wrapper of the functions `cell.EM` and `cell.Estimation`, when model cluster parameters are combined in an object of class `immunoClust` and are used in the iterative cell event clustering process `cell.process` of *immuno*Clust and are not intended to be called directly.

Value

The fitted model cluster information in an object of class `immunoClust`.

Author(s)

Till Sörensen <till-antoni.soerensen@charite.de>

References

Sörensen, T., Baumgart, S., Durek, P., Grützkau, A. and Häupl, T. immunoClust - an automated analysis pipeline for the identification of immunophenotypic signatures in high-dimensional cytometric datasets. *Cytometry A* (accepted).

See Also

`cell.process`, `cell.EMt`, `cell.Estep`

Examples

```
data(dat.fcs)
data(dat.exp)
r1 <- dat.exp[[1]]
dat.trans <- trans.ApplyToData(r1, dat.fcs)
r2 <- cell.FitModel(r1, dat.trans)
```

`cell.hclust` *Hierarchical Model Based Clustering of Cell-events in the immunoClust-pipeline*

Description

Performs model based agglomerative clustering on cell event observations with weights. It is used in the interative cell event clustering approach of *immuno*Clust to obtain an initial cluster membership for the EM(t)-iteration.

Usage

```
cell.hclust(data, weights=NULL)
```

Arguments

`data`	The numeric $N \times P$-dimensional data matrix to cluster. Each row contains a P-dimensional overservation vector.
`weights`	The N-dimensional vector of optional weights to be applied for the overservations.

Details

This function is used internally in `cell.TestSubCluster` procedure of **immunoClust**.

Value

A numeric $(N-1) \times 2$-dimensional matrix which gives the minimum index for observations in each of the two clusters merged at the *i*th step in each row.

Author(s)

Till Sörensen <till-antoni.soerensen@charite.de>

References

Sörensen, T., Baumgart, S., Durek, P., Grützkau, A. and Häupl, T. immunoClust - an automated analysis pipeline for the identification of immunophenotypic signatures in high-dimensional cytometric datasets. *Cytometry A* (accepted).

See Also

`cell.TestSubCluster`, `cell.process`

Examples

```
data(dat.fcs)
inc <- sample(1:nrow(dat.fcs), 50)
result <- cell.hclust(exprs(dat.fcs)[inc,])
```

`cell.ME` *immunoClust EM-iteration on Cell-events given initial Cluster Membership Assignment*

Description

Performs an EM-iteration on cell event observations given an initial cluster membership for the cell events and returns the fitted cluster information in an object of class `immunoClust`.

Usage

```
cell.MEstep(data, label, parameters=NULL,
    expName="immunoClust Experiment",
    B=1, tol=1e-5, modelName="mvt")

cell.Mstep(data, label, parameters=NULL,
    expName="immunoClust Mstep", modelName="mvt")
```

Arguments

`data`	A numeric matrix, data frame of observations, or object of class flowFrame.
`parameters`	A character vector specifying the parameters (columns) to be included in clustering. When it is left unspecified, all the parameters will be used.
`expName`	The name of the clustering experiment.
`label`	The N-dimensional vector containing the initial cluster membership. A label-number of 0 for an event indicates that this event is not initially assigned to a cluster.
`B`	The maximum number of EMt-iterations.
`tol`	The tolerance used to assess the convergence of the EMt-algorithms.
`modelName`	Used mixture model; either `"mvt"` or `"mvn"` for a t- or Gaussian mixture model respectively.

Details

`cell.ME` and `cell.MEstep` do the same call. In `cell.MEstep` the calling options are a bit better structured and `cell.ME` becomes deprecated in future.

Value

The fitted clusters information in an object of class `immunoClust`.

Author(s)

Till Sörensen <till-antoni.soerensen@charite.de>

References

Sörensen, T., Baumgart, S., Durek, P., Grützkau, A. and Häupl, T. immunoClust - an automated analysis pipeline for the identification of immunophenotypic signatures in high-dimensional cytometric datasets. *Cytometry A* (accepted).

See Also

cell.EMt

Examples

```
data(dat.fcs)
data(dat.exp)
## cell.clustering result for dat.fcs
r1 <- dat.exp[[1]]
summary(r1)
## apply model parameter to all (unfiltered) events
dat.trans <- trans.ApplyToData(r1, dat.fcs)
r2 <- cell.MEstep(dat.trans, label(r1), parameters=parameters(r1) )
summary(r2)
```

---

cell.process *Clustering of Cell-events in the immunoClust-pipeline*

Description

This function performs iterative model based clustering on cell-event data. It takes the observed cell-event data as major input and returns an object of class `immunoClust`, which contains the fitted mixture model parameter and cluster membership information. The additional arguments control the routines for data preprocessing, major loop and EMt-iteration, the model refinement routine and transformation estimation.

Usage

```
cell.process(fcs, parameters=NULL,
    apply.compensation=FALSE, classify.all=FALSE,
    N=NULL, min.count=10, max.count=10, min=NULL, max=NULL,
    I.buildup=6, I.final=4, I.trans=I.buildup,
    modelName="mvt", tol=1e-5, bias=0.3,
    sub.tol= 1e-4, sub.bias=bias, sub.thres=bias, sub.samples=1500,
    sub.extract=0.8, sub.weights=1, sub.standardize=TRUE,
    trans.estimate=TRUE, trans.minclust=10,
    trans.a=0.01, trans.b=0.0, trans.parameters=NULL)

cell.MajorIterationLoop(dat, x=NULL, parameters=NULL,
    I.buildup=6, I.final=4,
    modelName="mvt", tol=1e-5, bias=0.3,
    sub.bias=bias, sub.thres=0.0, sub.tol=1e-4, sub.samples=1500,
    sub.extract=0.8, sub.weights=1, sub.EM="MEt", sub.standardize=TRUE)

cell.MajorIterationTrans(fcs, x=NULL, parameters=NULL,
    I.buildup=6, I.final=4, I.trans=I.buildup,
```

```
    modelName="mvt", tol=1e-5, bias=0.3,
    sub.bias=bias, sub.thres=0.0, sub.tol=1e-4, sub.samples=1500,
    sub.extract=0.8, sub.weights=1, sub.EM="MEt", sub.standardize=TRUE,
    trans.minclust=5, trans.a=0.01, trans.decade=-1, trans.scale=1.0,
    trans.proc="vsHtransAw")

cell.InitialModel(dat, parameters=NULL, trans.a = 0.01, trans.b = 0.0,
    trans.decade=-1, trans.scale=1.0)

cell.classifyAll(fcs, x, apply.compensation=FALSE)
```

Arguments

fcs	An object of class flowFrame. Rows correspond to observations and columns correspond to measured parameters.
dat	A numeric matrix, data frame of observations, or object of class flowFrame. Rows correspond to observations and columns correspond to measured parameters.
x	An object of class immunoClust. Used as inital model int the major iteration loop. When left unspecified the simplest model containing 1 cluster is used as initial model.

Arguments for data pre and post processing:

parameters	A character vector specifying the parameters (columns) to be included in clustering. When it is left unspecified, all the parameters will be used.
apply.compensation	A numeric indicator whether the compensation matrix in the flowFrame should be applied.
classify.all	A numeric indicator whether the removed over- and underexposed observations should also be classified after the clustering process.
N	Maximum number of observations used for clustering. When unspecified or higher than the number of observations (i.e. rows) in dat, all observations are used for clustering, otherwise only the first N observations.
min.count	An integer specifying the threshold count for filtering data points from below. The default is 10, meaning that if 10 or more data points are smaller than or equal to min, they will be excluded from the analysis. If min is NULL, then the minimum value of each parameter will be used. To suppress filtering, it is set to -1.
max.count	An integer specifying the threshold count for filtering data points from above. Interpretation is similar to that of min.count.
min	The lower limit set for data filtering. Note that it is a vector of length equal to the number of parameters (columns), implying that a different value can be set for each parameter.
max	The upper limit set for data filtering. Interpretation is similar to that of min.

Arguments for the major loop and EMt-iteration:

I.buildup	The number of major iterations, where the number of used observations is doubled successively.
I.final	The number of major iterations with all observations.

`I.trans` The number of iterations where transformation estimation is applied.

`modelName` Used mixture model; either `"mvt"` for a t-mixture model or `"mvn"` for a Gaussian Mixture model. With `"mvt2"` an implementation variant for `"mvt"` is given, which is more reliable for samples with cutted values at the lower or upper edges of the parameter space (e.g. for CyTOF all values below a detection limit are set to zero which leads to wrong co-variance estimators and poor clustering results).

`tol` The tolerance used to assess the convergence of the major EM(t)-algorithms of all observations.

`bias` The ICL-bias used in the major EMt-algorithms of all observations.

Arguments for model refinement (sub-clustering):

`sub.tol` The tolerance used to assess the convergence of the EM-algorithms in the sub-clustering.

`sub.bias` The ICL-bias used in the sub-clustering EMt-algorithms, in general the same as the ICL-bias.

`sub.thres` Defines the threshold, below which an ICL-increase is meaningless. The threshold is given as the multiple (or fraction) of the costs for a single cluster.

`sub.samples` The number of samples used for initial hierarchical clustering.

`sub.extract` The threshold used for cluster data extraction.

`sub.weights` Power of weights applied to hierarchical clustering, where the used weights are the probabilities of cluster membership.

`sub.EM` Used EM-algorithm; either `"MEt"` for EMt-iteration or `"ME"` for EM-iteration without test step.

`sub.standardize`
A numeric indicating whether the samples for hierarchical clustering are standardized (mean=0, SD=1).

Arguments for transformation optimization:

`trans.estimate` A numeric indicator whether transformation estimation should be applied.

`trans.minclust` The minimum number of clusters required to start transformation estimation.

`trans.a` A numeric vector, giving the (initial) scaling a for the asinh-transformation $h(y) = asin(a \cdot y + b)$. A scaling factor of $a = 0$ indicates that a parameter is not transformed.

`trans.b` A numeric vector, giving the (initial) translation b for the asinh-transformation.

`trans.parameters`
A character vector, specifying the parameters (columns) to be applied for transformation. When it is left unspecified, the parameters to be transformed are obtained by the `PxDISPLAY` information of the flowFrame description parameters. All parameters with LOG display values are transformed.

`trans.decade` A numeric scale value for the theorectical maximum of transformed observation value. If below 0, no scaling of the trasnformed values is applied, which is the default in the *immuno*Clust-pipeline.

`trans.scale` A numeric scaling factor for the linear (i.e. not transformed) parameters. By default the linear parameters (normally the scatter parameters) are not scaled.

`trans.proc` An experimental switch for alternative procedures; should be "vsHtransAw".

Details

The `cell.process` function does data preprocessing and calls the major iteration loop either with or without integrated transformation optimization. When transformation optimization is applied the transformation parameters give the initial transformation otherwise they define the fixed transformation.

The major iteration loop with included transformation optimization relies on `flowFrames` structure from the `flowCore`-package for the storage of the observed data.

The `cell.InitialModel` builds up an initial `immunoClust-object` with one cluster and the given transformation parameters.

The `cell.classifyAll` calculates the cluster membership for the removed cell events. The assigment of the cluster membership is critical for over- and underexposed obsevervations and the interpretaion is problematic.

Value

The fitted model information in an object of class `immunoClust`.

Note

a) The data preprocessing arguments (`min.count`, `max.count`, `min` and `max`) for removing over- and underexposed observations are adopted from `flowCust-package` with the same meaning.

b) The `sub.thres` value is given in here in relation to the single cluster costs $\frac{1}{2} \cdot P \cdot (P+1) \cdot log(N)$. An absolute increase of the log-likelihood above is reported as reasonable from the literature. From our experience a higher value is required for this increase in FC data. For the ICL-bias and the sub.thres identical values were chosen. For the CyTOF dataset this value had been adjusted to 0.05 since the absolute increase of the log-likelihood became to high due to the high number of parameters.

c) The `sub.extract` value controls the smooth data extraction for a cluster. A higher value includes more events for a cluster in the sub-clustering routine.

d) The default value of `trans.a=0.01` for the initial transformation is optimized for Fluorescence Cytometry. For CyTOF data the initial scaling value was `trans.a=1.0`.

Author(s)

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References

Sörensen, T., Baumgart, S., Durek, P., Grützkau, A. and Häupl, T. immunoClust - an automated analysis pipeline for the identification of immunophenotypic signatures in high-dimensional cytometric datasets. *Cytometry A* (accepted).

See Also

`immunoClust-object`, `plot`, `splom`, `cell.FitModel`, `cell.SubClustering`, `trans.FitToData`

Examples

```
data(dat.fcs)
res <- cell.process(dat.fcs)
summary(res)
```

`cell.removed` *Brief Information of removed Cell-events by immunoClust Cell-event Clustering*

Description

Gives information about the amount of overexposed cell-event observetion in a FCS-file.

Usage

```
removed.above(fcs, parameters=NULL, N=NULL, max.count=10, max=NULL)
removed.below(fcs, parameters=NULL, N=NULL, min.count=10, min=NULL)
```

Arguments

`fcs`	An object of class flowFrame. Rows correspond to observations and columns correspond to measured parameters.
`parameters`	A character vector specifying the parameters (columns) to be included in clustering. When it is left unspecified, all the parameters will be used.
`N`	Maximum number of observations used for clustering. When unspecified or higher than the number of observations (i.e. rows) in dat, all observations are used for clustering, otherwise only the first `N` observations.
`max.count`	An integer specifying the threshold count for filtering data points from above. The default is 10, meaning that if 10 or more data points are larger than or equal to `max`, they will be excluded from the analysis. If `max` is `NULL`, then the maximum value of each parameter will be used. To suppress filtering, it is set to -1.
`max`	The upper limit set for data filtering. Note that it is a vector of length equal to the number of parameters (columns), implying that a different value can be set for each parameter.
`min.count`	analoguous to `max.count`.
`min`	analoguous to `min`.

Value

A table with two rows containing the number of events above `max` in each parameter and above in only this parameter. The two last columns give the sum and percentage of all events above `max` in any parameter.

Author(s)

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Examples

```
data(dat.fcs)
removed.above(dat.fcs)
```

`cell.SubClustering` *immunoClust Model Refinement Step in iterative Cell-events Clustering*

Description

These function tests each cell-cluster of a model for refining it into more sub-clusters and returns the refined model parameter in an object of class `immunoClust`.

Usage

```
cell.SubClustering( x, dat, B=50, tol=1e-5, thres=0.1, bias=0.5,
                    sample.weights=1, sample.EM="MEt",
                    sample.number=1500, sample.standardize=TRUE,
                    extract.thres=0.8, modelName="mvt")

cell.TestSubCluster(x, y, t, cluster, J=8, B=500, tol=1e-5, bias=0.5,
                    sample.EM="MEt", sample.df=5, sample.number=1500,
                    sample.standardize=TRUE, modelName="mvt")
```

Arguments

`x`	An immunoClust object with the initial model parameter (K, w, mu, $sigma$).
`dat`	A numeric matrix, data frame of observations, or object of class flowFrame.
`B`	The maximum number of EM(t)-iterations in Sub-Clustering.
`tol`	The tolerance used to assess the convergence of the EM(t)-algorithms in Sub-Clustering.
`thres`	Defines the threshold, below which an ICL-increase is meaningless. The threshold is given as the multiple (or fraction) of the costs for a single cluster.
`bias`	The ICL-bias used in the EMt-algorithm.
`sample.weights`	Power of weights applied to hierarchical clustering, where the used weights are the probabilities of cluster membership.
`sample.EM`	Used EM-algorithm; either `"MEt"` for EMt-iteration or `"ME"` for EM-iteration without test step.
`sample.number`	The number of samples used for initial hierarchical clustering.
`sample.standardize`	A numeric indicating whether the samples for hierarchical clustering are standardized (mean=0, SD=1).
`extract.thres`	The threshold used for cluster data extraction.
`modelName`	Used mixture model; either `mvt` for a t-mixture model or `mvn` for a Gaussian Mixture model.
`y`	A numeric matrix of the observations beloning to the particular cluster.
`t`	A numeric vector with the probability weights for the observations belonining to the particular cluster.
`cluster`	An integer index of the particular cluster
`J`	The number of sub-models to be builded and tested for a particular cluster.
`sample.df`	Degree of freedom for the t-distibutions in a t-mixture model. Has to be 5 in immunoClust.

Details

These function are used internally by the cell-clustering procedures of `cell.process` in *immuno*Clust and are not intended to be used directly.

Value

The cluster parameters of the refined model in an object of class `immunoClust`.

Author(s)

Till Sörensen <till-antoni.soerensen@charite.de>

References

Sörensen, T., Baumgart, S., Durek, P., Grützkau, A. and Häupl, T. immunoClust - an automated analysis pipeline for the identification of immunophenotypic signatures in high-dimensional cytometric datasets. *Cytometry A* (accepted).

See Also

`cell.process`, `cell.hclust`

Examples

```
data(dat.fcs)
data(dat.exp)
dat.trans <- trans.ApplyToData(dat.exp[[1]], dat.fcs)
#need to re-calculate the cluster membership probabilities
# not stored in dat.exp
r1 <- cell.Classify(dat.exp[[1]], dat.trans)
summary(r1)
r2 <- cell.SubClustering(r1, dat.trans)
summary(r2)
```

---

dat.exp *immunoClust Meta-clustering Sample*

Description

A `vector` of `immunoClust-objects` with `cell.process` clustering results of five samples.

Usage

```
data("dat.exp")
```

Details

Cell-event clustering was performed on reduced (10.000 events) sample data of the dataset of *immuno*Clust, MACS-depleted populations datasets 2010. URL http://flowrepository.org/id/FR-FCM-ZZWB.

Value

A vector of 5 immnoClust-objects for the cell clustering results of 5 FC samples.

`[[1]]` CD19 MACS-depleted cells

`[[2]]` CD15 MACS-depleted cells

`[[3]]` CD14 MACS-depleted cells

`[[4]]` CD4 MACS-depleted cells

`[[5]]` CD3 MACS-depleted cells

Source

http://flowrepository.org/id/FR-FCM-ZZWB

Examples

```
data(dat.exp)

## process meta clustering
meta <- meta.process(dat.exp, meta.bias=0.6)

## extract event counts in the 5 samples for all meta clusters
res <- meta.numEvents(meta)
```

---

dat.fcs *immunoClust Cell-clustering Sample*

Description

`flowFrame` data sample with 10.000 events in 7 parameters.

Usage

```
data(dat.fcs)
```

Details

This FCS sample is a reduced (10.000 events) dataset in flowFrame format of the first sample in the dataset of immunoClust, MACS-depleted populations datasets 2010. URL http://flowrepository.org/id/FR-FCM-ZZWB.

Value

A `flowCore` `flowFrame` with 10.000 observations on the following 7 parameters.

`FCS-A` Forward scatter

`SSC-A` Sideward scatter

`FITC-A` CD14

`PE-A` CD19

`APC-A` CD15

`APC-Cy7-A` CD4

`Pacific Blue-A` CD3

Source

http://flowrepository.org/id/FR-FCM-ZZWB

Examples

```
data(dat.fcs)
show(dat.fcs)
## Not run:
## process cell clustering
dat.res <- cell.process(dat.fcs)

## apply asinh-transformation
dat.fcs.transformed <- trans.ApplyToData(dat.res, dat.fcs)

## plot results
splom(dat.res, dat.fcs.transformed,N=1000)

## End(Not run)
```

---

dat.meta *immunoClust Meta-clustering Results Sample*

Description

The Meta-clustering result of the `dat.exp` data set.

Usage

```
data("dat.meta")
```

Details

The Meta-clustering was performed with an ICL-bias of 0.4.

Value

A list-object containing the meta-clusering result. A detailed description is documented in the value section for the `meta.process` function.

Source

http://flowrepository.org/id/FR-FCM-ZZWB

Examples

```
data(dat.meta)

## extract event counts in the 5 samples for all meta clusters
res <- meta.numEvents(dat.meta)
```

generics.immunoclust *Generic function definitions in immunoClust*

Description

Collection of generic function definitions used in immunoClust either for an `immunoClust` or an `immunoMeta` object.

Usage

```
nsam(object, ...)

sam_ncls(object, ...)

sam_names(object, ...)

sam_clsWeights(object, ...)

sam_clsEvents(object, ...)

sam_clsMu(object, ...)

sam_clsSigma(object, ...)

nobs(object, ...)

npar(object, ...)

ICL_bias(object, ...)

ncls(object, ...)

weights(object, ...)

mu(object, ...)

sigma(object, ...)

label(object, ...)

aposteriori(object, ...)

subset(x, ...)

parameters(object, ...)


transformParams(object, ...)

clusterCoeff(object, ...)
```

```
clusterDist(object, ...)

clusterProb(object, ...)
```

Arguments

object, x	an object to apply the function.
...	addionional options to be passed to methods

Value

The appropriate value for the specific cal (see dection Details).

Details

nsam returns the number of samples co-clustered in the object.

sam_names returns the names of co-clustered samples.

sam_ncls returns the number of clusters for each co-clustered samples.

sam_clsWeights returns the cluster weights of all samples cell-clusters.

sam_clsEvents returns the cluster event numbers of all samples cell-clusters.

sam_clsMu returns the cluster means of all samples cell-clusters.

sam_clsSigma returns the cluster co-variance matrices of all samples cell-clusters.

nobs already generic in `stats`. Here, returns the number of clustered objects either cell-events or cell-clusters in cell event or meta clustering.

npar returns the number of parameters used for clustering.

ICL_bias return the relaxing ICL_bias used for clustering.

ncls returns the number of clusters, either cell-event cluster or meta-cluster.

weights already generic in `stats`. Here, returns the weights of the mixture models for the cell-event or meta-clustering.

mu returns the cluster means.

sigma already generic in `stats`. Here, returns the co-variance matrices of the clusters.

label returns the cluster label, i.e. the assignment of the clustered objects to the clusters.

aposteriori returns the a posteriori probabilities of cluster membership for the clustered objects.

events returns the number of cell-events for the clusters.

subset alreay generic in `stats`. Here, returns an object with mixture model on a subset of parameters.

parameters already generic in `flowCore`. Here, lists the parameters used for clustering.

parameters<- Modifies the list of parameters used for clustering.

transformParam return an object with transformed mixture model parameters.

clusterCoeff returns the bhattacharrya coefficient of meta clusters for a meta level.

clusterDist returns the bhattacharrya distance of meta clusters for a meta level.

clusterProb returns the bhattacharrya probability of meta clusters for a meta level.

Author(s)

Till Sörensen <till-antoni.soerensen@charite.de>

See Also

immunoClust, immunoMeta

---

immunoClust-object *immunoClust-Object*

Description

The immunoClust object contains the clustering results in the *immuno*Clust-pipeline as obtained by cell.process or meta.process.

Usage

```
## S4 method for signature 'immunoClust'
summary(object)
## S4 method for signature 'immunoClust'
show(object)
```

Arguments

object	An object of class immunoClust as returned by the cell.process or meta.process functions of the *immuno*Clust-pipeline.

Value

An object of class immunoClust has the following slots:

expName	The name of the clustering experiment.
fcsName	The path of the clustered FCS-file.
parameters	The parameters used for clustering.
removed.below	Number of observations removed from below.
removed.above	Number of observations removed from above.
trans.a	The P-dimensional vector of the scaling factors for the asinh-transformation of each used parameter. A
trans.b	The P-dimensional vector of the translations for the asinh-transformation of each used parameter.
trans.decade	experimental; should be -1.
trans.scale	experimental; should be 1.0.
K	The number of clusters.
N	The number of observations.
P	The number of used parameters.
w	The K-dimensional vector of the mixture proportions.
mu	The KxP-dimensional matrix of the K estimated cluster means.
sigma	The $KxPxP$-dimensional matrix of the K estimated cluster covariance matrices.
z	The KxN-dimensional matrix containing the a-posteriori probabilities of cluster membership.
label	The N-dimensional vector containing the maximum a posteriori estimator for cluster membership.
logLike	A vector of length 3 containing the BIC, ICL and the classification likelihood without penalty of the fit
BIC	The Bayesian Information Criterion for the fitted mixture model.
ICL	The Integrate Classification Likelihood for the fitted model.
history	experimental; unused so far.
state	experimental; unused so far.

Author(s)

Till Sörensen <till-antoni.soerensen@charite.de>

References

Sörensen, T., Baumgart, S., Durek, P., Grützkau, A. and Häupl, T. immunoClust - an automated analysis pipeline for the identification of immunophenotypic signatures in high-dimensional cytometric datasets. *Cytometry A* (accepted).

See Also

`cell.process`, `meta.process`

Examples

```
data(dat.exp)
summary(dat.exp[[1]])
```

`immunoMeta-class` *'immunoMeta': a class for storing meta-clustering results*

Description

The `immunoMeta` object contains the clustering results in the *immuno*Clust-pipeline obtained by `meta.process`. Additionally, it offers methods to structure the meta-clusters and build up a hierarchical annotation tree.

Usage

```
immunoMeta(res,dat,gating)

## S3 method for class 'immunoMeta'
summary(object, ...)
## S3 method for class 'immunoMeta'
show(object)
```

Arguments

`res`	An `immunoClust` object as a result of the meta-clustering.
`dat`	The data on which the meta-clustering was performed.
`gating`	a hierarchial structure annotation of the meta-clusters.
`object`	An object of class `immunoMeta` as returned by the `meta.process` functions of the *immuno*Clust-pipeline.
`...`	additinal options for underlying methods.

Value

An object of class `immunoMeta` has the following slots:

`dat.clusters`	A `dat` list-object of the cell event clusters used for meta-clustering.
`res.clusters`	The `immunoClust-object` of the fitted meta-clustering mixture model.
`dat.scatter`	A `dat` list-object of the scatter parameters for the cell event clusters used for scatter clustering.
`res.scatter`	The `immunoClust-object` of the fitted scatter-clustering mixture model.
`gating`	A list-object containing the hierarchical annotation-tree.

The components of the `dat` list-objects are:

`P`	The number of parameters for the cell event clusters.
`N`	The number of cell-clustering experiments.
`K`	The N-dimensional vector with the numbers of cell event clusters in each experiment. The total number of c
`W`	The $totK$-dimensional vector with the mixture proportions of all clusters.
`M`	The $totKxP$-dimensional matrix of all cluster means.
`S`	The $totKxPxP$-dimensional matrix of all cluster covariance matrices.
`expNames`	The N-dimensional character vector with the cell-clustering experiment names.
`expEvents`	The N-dimensional vector with the numbers of events in each cell-clustering experiment.
`clsEvents`	The $totK$-dimensional vector with the number of events in each cluster.
`desc`	The P-dimensional character vector with the parameter description.

Author(s)

Till Sörensen <till-antoni.soerensen@charite.de>

See Also

`meta.process`

Examples

```
data(dat.meta)
summary(dat.meta)
```

`meta.clustering` *Clustering of Cell-clusters in the immunoClust-pipeline*

Description

This function provides a direct access to the meta-clustering procedure. The method described and discussed in this manuscript is the EMt-classification (EM-method=20) with the number of events for each cluster as weights. It returns the fitted mixture model parameter in an object of class immunoClust.

Usage

```
meta.Clustering(P, N, K, W, M, S, label=NULL, I.iter=10, B=500, tol=1e-5,
                bias=0.25, sub.thres = bias, alpha=0.5, EM.method=20,
                HC.samples=2000, norm.method=0, norm.blur=2, norm.minG=10,
                verbose=FALSE)
```

Arguments

P	The number of observed parameters for the cell event clusters.
N	The number of cell-clustering experiments.
K	The N-dimensional vector with the numbers of cell event clusters in each experiment. The total number of clusters is $totK = sum_{i=1}^{K} K_i$.
W	The $totK$-dimensional vector with weights of all clusters.
M	The $totKxP$-dimensional matrix of all cluster means.
S	The $totKxPxP$-dimensional matrix of all cluster covariance matrices.
label	Optional initial cluster assignment. If label equla NULL all clusters are assigned in one cluster in the initial clustering step.
I.iter	The maximum number of major iteration steps.
B	The $totKxPxP$-dimensional matrix of all cluster covariance matrices.
tol	The tolerance used to assess the convergence of the EM(t)-algorithms.
bias	The ICL-bias used in the EMt-iteration of the meta-clustering.
sub.thres	Defines the threshold, below which an ICL-increase is meaningless. The threshold is given as the multiple (or fraction) of the costs for a single cluster.
alpha	A value between 0 and 1 used to balance the bhattacharrya probabilities calculated with either the full covariance matrices or using only the diagonal elements of it. When working with uncompensated FC data very high correlations between parameters may be observed due to spill over. This leads to a very low bhattacharrya probability for two clusters even if they are located nearby. Using a mixture of the probabilities calculated with the complete covariance matrices and the variance information of each parameter avoids this problem. With a value of alpha=1, only the probabilities with complete covariance matrices are applied. A reasonable value for alpha is 0.5.
EM.method	0 = KL-minimization not weighted 1 = BC-maximization not weighted 10 = BC-maximization weighted 2 = EMt-classification not weighted 20 = EMt-classification weighted
HC.samples	The number of samples used for initial hierarchical clustering.
norm.method	Normalization function; see meta.Normalize for details.
norm.blur	For the normalization step the a-posteriori probabilites of the cell-clusters belonging to a meta.clusters a used. In order to capture narrow cell-clusters reasonable the co-variance of the cell-clusters is blured for the a-posteriori probabilities in the normalization step.
norm.minG	Minimum number of obtained meta-clusters required to process the normalization step in the major iteration loop.
verbose	detailed messages during process

Details

This function is used internally by the meta-clustering procedure meta.process in *immuno*Clust.

Value

The fitted model information in an object of class immunoClust.

Author(s)

Till Sörensen <till-antoni.soerensen@charite.de>

References

Sörensen, T., Baumgart, S., Durek, P., Grützkau, A. and Häupl, T. immunoClust - an automated analysis pipeline for the identification of immunophenotypic signatures in high-dimensional cytometric datasets. *Cytometry A* (accepted).

See Also

immunoClust-object, meta.SubClustering, meta.process

Examples

```
data(dat.exp)
d <- meta.exprs(dat.exp)
res <- meta.Clustering(d$P, d$N, d$K, d$clsEvents, d$M, d$S)
```

---

meta.export *immunoClust Meta-clustering Results Export*

Description

Thess functions collect the output of the meta.process and extracts the event numbers, relative frequencies or mean fluorescence intensities for each meta-cluster and cell-clustering experiment in a numeric table.

Usage

```
meta.numEvents(meta, out.all=TRUE, out.removed=FALSE, out.unclassified=TRUE)
meta.relEvents(meta, out.all=TRUE, out.removed=FALSE, out.unclassified=TRUE)
meta.relParent(meta, out.all=TRUE, out.removed=FALSE, out.unclassified=TRUE)

meta.parMFI(meta, par, out.all=TRUE, out.unclassified = TRUE)

meta.numClusters(meta, out.all=TRUE)

meta.freqTable(meta)
```

Arguments

meta	The list-object returned by the function meta.process.
par	An integer index to the specific parameter.
out.all	A numeric indicator whether the event numbers of all hierarchical gating levels are obtained or only the meta-clusters themselves.
out.removed	A numeric indcator whether the number of removed events, which are not used for clustering are exported.
out.unclassified	A numeric indicator whether the event numbers of the hierarchical gating levels or all meta-clusters are exported.

Value

A numberic matrix with

numEvents the number of cell events

relEvents relative frequencies, i.e. the number of cell events per total meeasured events

relParent relative frequencies according to parent relationship in the annotated hierarchy.

parMFI mean fluorecence intensities in one parameter, i.e. the meta-cluster centers in asinh-tranformed scale

numClusters the number of cell clusters

freqTable relative frequencies with respect to all gating hierarchie levels

in each meta-cluster (and gating hierarchy level) for each cell-clustering experiment.

Author(s)

Till Sörensen <till-antoni.soerensen@charite.de>

References

Sörensen, T., Baumgart, S., Durek, P., Grützkau, A. and Häupl, T. immunoClust - an automated analysis pipeline for the identification of immunophenotypic signatures in high-dimensional cytometric datasets. *Cytometry A* (submitted).

See Also

meta.process

Examples

```
data(dat.exp)
meta <- meta.process(dat.exp)
tbl <- meta.numEvents(meta)
```

---

meta.exprs *Collecting Data of an immunoClust vector*

Description

The function takes a vector of `immunoClust`-object obtained by the `cell.process` function and extracts ths information into a `list` object.

Usage

```
meta.exprs(exp, sub=c())
```

Arguments

exp	The vector of `immunoClust` object with the cell clustering results.
sub	A integer array indicating the parameter subset to be collected.

Value

A `list` object with the following slots:

`P`	The number of observed parameters for the cell event clusters.
`N`	The number of cell-clustering samples.
`K`	The N-dimensional vector with the numbers of cell event clusters in each experiment. The total number of clusters is $totK = sum_{i=1}^{N} K_i$.
`W`	The $totK$-dimensional vector with weights of all clusters.
`M`	The $totKxP$-dimensional matrix of all cluster means.
`S`	The $totKxPxP$-dimensional matrix of all cluster covariance matrices.
`expNames`	The N-dimensional vector with the experiment names of the cell clustering samples.
`expEvents`	The N-dimensional vector for the total number of events of the cell clustering samples.
`clsEvents`	The $totK$-dimensional vector for the event number of all clusters.
`desc`	The P-dimensional vector for the parameter description.

Author(s)

Till Sörensen `<till-antoni.soerensen@charite.de>`

References

Sörensen, T., Baumgart, S., Durek, P., Grützkau, A. and Häupl, T. immunoClust - an automated analysis pipeline for the identification of immunophenotypic signatures in high-dimensional cytometric datasets. *Cytometry A* (accepted).

See Also

`immunoClust`.

Examples

```
data(dat.exp)
d <- meta.exprs(dat.exp, sub=c(1,2))
```

`meta.hclust` *Hierarchical Meta-clustering of Cell-clusters in the immunoClust-pipeline*

Description

Performs agglomerative clustering on cell-clusters. It is used in the interative meta-clustering approach of *immuno*Clust to obtain an initial meta-cluster membership for the EM(t)-iteration.

Usage

```
meta.hclust(P, N, W, M, S)
```

Arguments

P	The number of parameters.
N	The number of clusters.
W	The N-dimensional vector with cluster weights, i.e. numbers of events in a cluster.
M	The $N \times P$-dimensional vector with cluster means.
S	The $N \times P \times P$-dimensional vector with cluster covariance matrices.

Details

This function is used internally in `meta.TestSubCluster` of **immunoClust**.

Value

A numeric $(N-1) \times 2$-dimensional matrix which gives the minimum index for observations in each of the two clusters merged at the *i*th step in each row.

Note

The merging distances need not to be monotonic increasing.

Author(s)

Till Sörensen <till-antoni.soerensen@charite.de>

References

Sörensen, T., Baumgart, S., Durek, P., Grützkau, A. and Häupl, T. immunoClust - an automated analysis pipeline for the identification of immunophenotypic signatures in high-dimensional cytometric datasets. *Cytometry A* (accepted).

See Also

`meta.TestSubCluster`, `meta.process`

Examples

```
data(dat.exp)
r <- dat.exp[[1]]
#hcPairs <- meta.hclust(r@P, r@K, r@w, r@mu, t(apply(r@sigma,1,c)))
hcPairs <- meta.hclust(npar(r), ncls(r), weights(r),
    mu(r), t(apply(sigma(r),1,c)))
```

`meta.ME` *immunoClust EM(t)-iteration on Cell-clusters*

Description

Performs an EM(t)-iteration on cell-clusters given an initial meta-cluster membership for the cell-clusters and returns the fitted meta-clusters information in an object of class `immunoClust`.

Usage

```
meta.ME(P, N, K, W, M, S, label, B=100, tol=1e-5, method=20, bias=0.25,
    alpha=0.5, min.class=0)

meta.Mstep(P, N, K, W, M, S, label, alpha=0.5)
```

Arguments

`P`	The number of observed parameters for the cell event clusters.
`N`	The number of cell-clustering experiments.
`K`	The N-dimensional vector with the numbers of cell event clusters in each experiment. The total number of clusters is $totK = sum_{i=1}^{K} K_i$.
`W`	The $totK$-dimensional vector with weights, i.e. number of events, of all clusters.
`M`	The $totKxP$-dimensional matrix of all cluster means.
`S`	The $totKxPxP$-dimensional matrix of all cluster covariance matrices.
`label`	The $totK$-dimension integer vector with the initial cell-cluster to meta-cluster membership.
`B`	The $totKxPxP$-dimensional matrix of all cluster covariance matrices.
`tol`	The tolerance used to assess the convergence of the EM(t)-algorithms.
`method`	0 = KL-minimization not weighted 1 = BC-maximization not weighted 10 = BC-maximization weighted 2 = EMt-classification not weighted 20 = EMt-classification weighted
`bias`	The ICL-bias used in the EMt-iteration of the meta-clustering.
`alpha`	A value between 0 and 1 used to balance the bhattacharrya probabilities calculated with either the full covariance matrices or using only the diagonal elements of it.
`min.class`	The minimum number of clusters for the final model.

Details

This function is used internally by the meta-clustering procedures `meta.process` and `meta.Clustering` in *immuno*Clust.

While `meta.ME` performs a complete EM-iteration with ICL testing to maintain the clusters, `meta.Mstep` performs a single maximisation step.

Value

The fitted meta-clusters information in an object of class immunoClust.

Author(s)

Till Sörensen <till-antoni.soerensen@charite.de>

References

Sörensen, T., Baumgart, S., Durek, P., Grützkau, A. and Häupl, T. immunoClust - an automated analysis pipeline for the identification of immunophenotypic signatures in high-dimensional cytometric datasets. *Cytometry A* (accepted).

See Also

meta.process, meta.Clustering

Examples

```
data(dat.exp)
d <- meta.exprs(dat.exp)
r <- meta.ME(d$P, d$N, d$K, d$clsEvents, d$M, d$S, label=rep(1,sum(d$K)))
```

---

meta.normalize *immunoClust normalization step with the meta.clustering process*

Description

Performs a normalization via linear regression of the cell-cluster samples to the meta-clustering model.

Usage

```
meta.Normalize(P, N, K, W, M, S, G, Z, method=3)
```

Arguments

P	The number of observed parameters for the cell event clusters.
N	The number of cell-clustering experiments.
K	The N-dimensional vector with the numbers of cell event clusters in each experiment. The total number of clusters is $totK = sum_{i=1}^{K} K_i$.
W	The $totK$-dimensional vector with weights, i.e. number of events, of all clusters.
M	The $totKxP$-dimensional matrix of all cluster means.
S	The $totKxPxP$-dimensional matrix of all cluster covariance matrices.
G	The number of meta-clusters.
Z	The $totKxG$-dimensional matrix with the a-posteriori probabilities for a cell-cluster belonging to a meta-cluster.

`method` Alternative methods used for the normalization routine. Let Y denote the consensus meta-model build from all cell-event clusters of all experiments using the a-posteriori Z and X the cell-event clusters in each experiment.

0 = no normalization

1 = $Y = a \times X$

2 = $Y = a \times X + b$

3 = $X = a \times Y$

4 = $X = a \times Y + b$

Details

The regression used the cell-cluster and meta-cluster means weighted by the probabilities for a cell-cluster belonging to the meta-cluster. It builds a consensus meta-model from all cell-clusters using the a-posteriori probabilities Z.

Value

Returns the normalized cell-clusters means and co-variance matrices in a list-object with the following slots:

P The number of observed parameters for the cell event clusters.

N The number of cell-clustering experiments.

K The N-dimensional vector with the numbers of cell event clusters in each experiment. The total number of clusters is $totK = sum_{i=1}^{K} K_i$.

W The $totK$-dimensional vector with weights, i.e. number of events, of all clusters.

M The $totKxP$-dimensional matrix of all cluster means.

S The $totKxPxP$-dimensional matrix of all cluster covariance matrices.

Author(s)

Till Sörensen <till-antoni.soerensen@charite.de>

See Also

meta.process, meta.Clustering

Examples

```
data(dat.meta)
#dat <- dat.meta$dat.clusters
res <- dat.meta$res.clusters
dat.norm <- meta.Normalize(npar(dat.meta), nsam(dat.meta),
    sam_ncls(dat.meta), sam_clsEvents(dat.meta), sam_clsMu(dat.meta),
    sam_clsSigma(dat.meta), ncls(res), aposteriori(res))
```

meta.process *Meta-clustering of Cell-clusters in the immunoClust-pipeline*

Description

This function performs iterative model based clustering on the clusters obtained by cell.process of several samples. Its input is a vector of the immunoClust-objects of the samples.

Usage

```
meta.process(exp, dat.subset=c(), meta.iter=10, tol=1e-05, meta.bias=0.2,
             meta.alpha=.5, norm.method=0, norm.blur=2, norm.minG=10)
```

Arguments

exp	A vector of list objects, each list contains the cell-clustering result of a sample in the res field. Addition fields are name and fsc containing the cell-sample name and fcs-filename, which are used for data output and plot routines.
dat.subset	A numeric vector defining the used observed parameters for the meta-clustering. If unset, all parameters in the cell-clustering results are used.
meta.iter	The number of major iterations.
tol	The tolerance used to assess the convergence of the EM(t)-algorithms.
meta.bias	The ICL-bias used in the EMt-iteration of the meta-clustering.
meta.alpha	A value between 0 and 1 used to balance the bhattacharrya probabilities calculated with either the full covariance matrices or using only the diagonal elements of it. When working with uncompensated FC data, very high correlations between parameters may be observed due to spill over. This leads to a very low bhattacharrya probability for two clusters even if they are located nearby. Using a mixture of the probabilities calculated with the complete covariance matrices and the variance information of each parameter avoids this problem. With a value of alpha=1, only the probabilities with complete covariance matrices are applied. A reasonable value for alpha is 0.5.
norm.method	A numeric selector for the normalization step to be performed during the major iteration.
norm.blur	The bluring constant by which the cell-clusters co-variance matrices are increased within the normalization step.
norm.minG	Minimum number of meta-clusters required before processing the normalization step.

Value

The function returns a immunoMeta with the following components:

dat.clusters	A dat list-object of the cell event clusters used for meta-clustering.
res.clusters	The immunoClust-object of the fitted meta-clustering mixture model.
dat.scatter	A dat list-object of the scatter parameters for the cell event clusters used for scatter clustering.
res.scatter	The immunoClust-object of the fitted scatter-clustering mixture model.
gating	A list-object containing the hierarchical gating-tree.

Author(s)

Till Sörensen <till-antoni.soerensen@charite.de>

References

Sörensen, T., Baumgart, S., Durek, P., Grützkau, A. and Häupl, T. immunoClust - an automated analysis pipeline for the identification of immunophenotypic signatures in high-dimensional cytometric datasets. *Cytometry A* (accepted).

See Also

immunoMeta-object, immunoClust-object, meta.Clustering, meta.export, cell.process

Examples

```
data(dat.exp)
meta <- meta.process(dat.exp)
summary(meta)
tbl <- meta.numEvents(meta)
```

---

meta.regnorm *immunoClust normalization procedure*

Description

Performs a normalization via linear regression of the sample clusters in x to the clusters in y.

Usage

```
meta.RegNorm(y, x, method=1, alpha=0.5)
```

Arguments

y	immunoClust-object with the destination clusters.
x	immunoClust-object with the cluster to normalize.
method	Alternative methods used for the normalization routine. 1 = $X = a \times Y$ 2 = $X = a \times Y + b$
alpha	A value between 0 and 1 used to balance the bhattacharrya probabilities calculated with either the full covariance matrices or using only the diagonal elements of it.

Value

Returns the normalized cell-clusters means and co-variance matrices in a list-object with the following slots:

P The number of observed parameters for the cell event clusters.

N The number of cell-clustering experiments.

K The N-dimensional vector with the numbers of cell event clusters in each experiment. The total number of clusters is $totK = sum_{i=1}^{K} K_i$.

M The $totKxP$-dimensional matrix of all cluster means.

S The $totKxPxP$-dimensional matrix of all cluster covariance matrices.

Author(s)

Till Sörensen <till-antoni.soerensen@charite.de>

Examples

```
data(dat.meta)
data(dat.exp)
dat.norm <- meta.RegNorm(dat.meta$res.clusters, dat.exp[[1]])
```

---

meta.SON.clustering *meta clustering process with internal SON normalisation*

Description

The meta.SON.clustering is an extension of the meta-clustering process co-clustering several samples cluster results. It integrates a SONormalization step between the meta-clustering iterations.

Usage

```
meta.SON.clustering(
meta,
cycles=6, alpha=0.5, scale.factor=2, scale.steps=0,
meta.iter=1, meta.bias=0.3, meta.thres=meta.bias, meta.tol=1e-5,
SON.cycles=1, SON.rlen=100, SON.deltas=c(1/SON.rlen,1/SON.rlen),
SON.blurring=c(2,0.1), batch.samples=nsam(meta)/2,
verbose=0
)
```

Arguments

meta	an immunoMeta-object for which the clustering should be refined.
cycles	number of major iteration steps.
alpha	The alpha value for calculation the bhattacharyya probabilities.
scale.factor	scale factor for the internal model scaling step.
scale.steps	scale steps for the internal model scaling step. 0 means no model scaling.
meta.iter	number of iterations for meta-clustering step
meta.bias	ICL bias for meta-clustering step

meta.thres	sub.thres for meta-clustering step
meta.tol	maximal tolerance for meta-clustering step
SON.cycles	number of cycles in SONormalization step
SON.rlen	runlength in SON normalization step
SON.deltas	deltas parameter in SONormalization step
SON.blurring	bluring parameter in SONormalisation step
batch.samples	minimal number of sample for meta.clusters used in the SONormalisation step
verbose	detailed messages during process

Details

For the refined meta.SON.clustering process a simple meta.process should be performed first. The resulting immunoMeta-object then serves as input data for the meta.SON.clustering.

Within the meta.SON.clustering between two meta.Clustering steps a SON normalization step is performed, which shifts the clusters of each sample towards the meta-clusters. The SON normalization for a sample consists of an optional first step to scale the model build by meta clusters best possible to the sample clusters. Afterwards, the meta clusters are moved to towards the sample clusters. This is done in a similar way to SOM clustering mapping. Finally, the sample clusters are retracted to the meta-clusters distribution. For this purpose the Bhattacharyya probabilities of sample and meta clusters are used.

Value

An immunoMeta-object for the co-clustering result.

Author(s)

Till Sörensen <till.soerensen@bioretis.com>

References

pre-print

See Also

meta.Clustering

Examples

```
data(dat.meta)
meta <- meta.SON.clustering(dat.meta, cycles=2)
```

`meta.SON.combineClustering` *Transfer the annotation of an immunoMeta-object to an immunoClust-object.*

Description

An immunoMeta-object is co-clustered with an immunoClust-object of the same parameter structure. Co-clustering includes SON normalization steps. The returned immnuoCLust-object contians the meta-clusters unchanged in order and numeration.

Usage

```
meta.SON.combineClustering(
meta, res, par=seq_len(npar(meta)),
map.cluster=seq_len(ncls(meta)),
use.cluster=seq_len(ncls(res)),
meta.alpha=0.5, meta.bias=0.1, meta.iter=100, meta.tol=1e-5,
SON.method=1, SON.cycles=4, SON.rlen=10,
SON.deltas=c(1/SON.rlen,1/SON.rlen), SON.blurring=c(2,1),
traceG=c(), traceK=c())
```

Arguments

`meta`	The annotated immunoMeta-object.
`res`	An immunoClust-object as results from cell-event clustering for a sample
`par`	An integer array with the parameters to be used for SON mapping.
`map.cluster`	The model clusters to be used for SON mapping.
`use.cluster`	the sample clusters to be used for SON mapping.
`meta.alpha`	The alpha value in calculation the bhattacharyya probabilities.
`meta.bias`	The ICL bias for meta co-clustering step.
`meta.iter`	Maximal iterations in the meta co-clustering step.
`meta.tol`	Maximal tolerance for meta co-clustering step.
`SON.method`	Method selection for SON normalization step.
`SON.cycles`	Number cycles in the SON normalization step.
`SON.rlen`	runlength in the SON normalization step.
`SON.deltas`	delta parameter in the SON normalization step.
`SON.blurring`	blurring parameter in the SON normalization step.
`traceG`	An array of model cluster to trace in the process.
`traceK`	An array of sample cluster to trace in the process.

Details

The co-clustering consists of a normalization and meta-clustering step. A sample cluster is than labeled according to its corresponding meta cluster. The SON-normalization and meta-clustering steps are parameterised by the SON and meta arguments.

Value

An immunoClust-object from meta-clusters and combined observation from meta- and samples-cluster. The first G elements of the label coresponds to the meta-clusters, afterwards the labelling of the samples-clusters indicates the nearest meta-cluster for the sample-cluster.

Author(s)

Till Sörensen <till.soerensen@bioretis.com>

References

in progress

See Also

meta.Clustering

Examples

```
data(dat.exp)
data(dat.meta)
res <- meta.SON.combineClustering(dat.meta, dat.exp[[1]], SON.cycles=2)
```

---

meta.SubClustering *immunoClust Model Refinement Step in iterative Meta-clustering*

Description

These function tests each meta-cluster of a model for refining it into more sub-clusters and returns the refined cluster memberships in an integer array.s

Usage

```
meta.SubClustering(x, P, N, W, M, S, tol=1e-5, bias=0.25, thres=bias,
    alpha=1.0, EM.method=20, HC.samples=2000, verbose=FALSE)

meta.TestSubCluster(x, P, N, W, M, S, J=8, B=500, tol=1e-5, bias=0.5,
    alpha=1.0, EM.method=20, HC.samples=2000)
```

Arguments

x	An immunoClust object with the initial model parameter (K, $label$).
P	The number of parameters.
N	The number of clusters.
W	The N-dimensional vector with cluster weights, i.e. numbers of events in a cluster.
M	The NxP-dimensional vector with cluster means.
S	The $NxPxP$-dimensional vector with the cluster covariance matrices.
tol	The tolerance used to assess the convergence of the EM(t)-algorithms in Sub-Clustering.

bias	he ICL-bias used in the EMt-algorithm.
thres	Defines the threshold, below which an ICL-increase is meaningless. The threshold is given as the multiple (or fraction) of the costs for a single cluster.
alpha	A value between 0 and 1 used to balance the bhattacharrya probabilities calculated with either the full covariance matrices or using only the diagonal elements of it.
J	The number of sub-models to be builded and tested for a particular cluster.
B	The maximum number of EM(t)-iterations in Sub-Clustering.
EM.method	0 = KL-minimization not weighted 1 = BC-maximization not weighted 10 = BC-maximization weighted 2 = EMt-classification not weighted 20 = EMt-classification weighted
HC.samples	The number of samples used for initial hierarchical clustering.
verbose	detailed messages during process

Details

These function are used internally by the meta-clustering procedures `meta.process` and `meta.Clustering` in *immuno*Clust and are not intended to be used directly.

Value

An integer array of length N containing the cell-clusters meta-cluster memberships of the refined model.

Author(s)

Till Sörensen <till-antoni.soerensen@charite.de>

References

Sörensen, T., Baumgart, S., Durek, P., Grützkau, A. and Häupl, T. immunoClust - an automated analysis pipeline for the identification of immunophenotypic signatures in high-dimensional cytometric datasets. *Cytometry A* (accepted).

See Also

`meta.process`, `meta.Clustering`, `meta.hclust`

Examples

```
data(dat.exp)
d <- meta.exprs(dat.exp)
#label <- rep(1,sum(d$K))
#label <- meta.SubClustering(d$P, sum(d$K), d$clsEvents, d$M, d$S, label=label)

r0 <- new("immunoClust", K=sum(d$K), label=rep(1,sum(d$K)))
label <- meta.SubClustering(r0, d$P, sum(d$K), d$clsEvents, d$M, d$S)

r1 <- meta.ME(d$P, d$N, d$K, d$clsEvents, d$M, d$S, label)
```

`methods.immunoClust` *Acessors and Methods for immunoClust Objects*

Description

Documentation of the accessors and methods for immunoClust-objects

Arguments

`object, immunoClust`	an object of class `immunoClust` as return by `cell.process`.
`cls`	cluster subset for retrieved slot values.
`par`	parameter subset for retrieved slot values.

Accessors

nobs the number of cell events clustered

Usage:

```
nobs(immunoClust)
```

ICL_bias the ICL bias applied in clustering

Usage:

```
ICL_bias(immunoClust)
```

ncls the number of clusters.

Usage:

```
ncls(immunoClust)
```

npar the number of parameters measured, cell-clustered

Usage:

```
npar(immunoClust)
```

parameters, parameters<- extracts or replaces the names of measured, cell-clustered parameters

Usage:

```
parameters(immunoClust)
parameters(immunoClust) <- value
```

label the clustering label, that is the assignment of the cell-events to the clusters.

Usage:

```
label(immunoClust)
```

weights the clustering weights for the cluster selection (all cluster by default)

Usage:

```
weights(immunoClust,cls=seq_len(ncls(immunoClust)))
```

mu the cluster mean values for the cluster and parameter selection (all cluster and all parameter by default)

Usage:

```
mu(immunoClust, cls=seq_len(ncls(immunoClust)), par=seq_len(npar(immunoClust)))
```

sigma the cluster co-variance values for the cluster and parameter selection (all cluster and all parameter by default)

Usage:

```
sigma(immunoClust, cls=seq_len(ncls(immunoClust)), par=seq_len(npar(immunoClust)))
```

aposteriori the a-posteriori probabilities of cluster membership for each event

Usage:

```
aposteriori(immunoClust)
```

events the cell-event numbers for the cluster selection (all cluster by default)

Usage:

```
events(immunoClust, ncls=seq_len(ncls(immunoClust)))
```

cells the cell-events indices in the FCS-file for the cluster selection (all cluster by default). if na.rm ist TRUE the removed events are obmitted and the indices fits to the a-posteriori matrix z in the immunoClust-object

Usage:

```
cells(immunoClust, ncls=seq_len(ncls(immunoClust)), na.rm=FALSE)
```

Methods

subset Builds the immunoClust-object for a parameter subset

Usage:

```
res <- subset(immunoClust, par)
```

transformParams Scales and translates the cluster means of the immunoClust-object in each parameter

Usage:

```
res <- transformParams(immunoClust, scale=c(), offset=c())
```

Author(s)

Till Sörensen <till-antoni.soerensen@charite.de>

See Also

immunoClust-object

Examples

```
###
data(dat.exp)
## cell.clustering result for dat.fcs
res <- dat.exp[[1]]
nobs(res)
ncls(res)
```

---

methods.immunoMeta *Acessors and Methods for immunoMeta Objects*

Description

Documentation of the accessors and methods for immunoMeta-objects

Arguments

object, immunoMeta	an object of class immunoMeta as return by meta.process.
cls	cluster subset for retrieved slot values.
par	parameter subset for retrieved slot values.
pos	Gives the position in the immunoMeta-hierarchy. pos is an array of indices which addresses the level of interest. Each level in the immunoMeta-hierarchy consists of a name (desc), meta-cluster subset (array of cluster indices) and a vector of sub-levels. pos is the sequence of indices into these sub-levels begining at root level.

Accessors

nsam the number of immunoClust-objects (samples) which are co-clustered.

Usage:

```
nsam(immunoMeta)
```

sam_names the sample names i.e. expName in theimmunoClust-objects (samples) which are co-clustered.

Usage:

```
sam_ncls(immunoMeta, for.samples=seq_len(nsam(meta))
```

sam_ncls the number of cell event clusters in theimmunoClust-objects (samples) which are co-clustered.

Usage:

```
sam_ncls(immunoMeta, for.samples=seq_len(nsam(meta))
```

sam_clsWeights the weigths of all cell event clusters which are collected for co-clustering.

Usage:

```
sam_clsWeights(immunoMeta)
```

sam_clsMu the means of all cell event clusters which are collected for co-clustering.

Usage:

```
sam_clsMu(immunoMeta)
```

sam_clsSigma the co-variance matrices of all cell event clusters which are collected for co-clustering.

Usage:

```
sam_clsSigma(immunoMeta)
```

sam_clsEvents the event numbers of all cell event clusters which are collected for co-clustering.

Usage:

```
sam_clsEvents(immunoMeta)
```

nobj the number of cell events clusters from sample cell-clustering which are co-clustered.

Usage:

```
nobj(immunoMeta)
```

ICL_bias the ICL bias applied in meta-clustering

Usage:

```
ICL_bias(immunoMeta)
```

ncls the number of meta-clusters.

Usage:

```
ncls(immunoMeta)
```

npar the number of parameters measured, cell-clustered and meta-clustered

Usage:

```
npar(immunoMeta)
```

parameters, parameters<- extracts or replaces the names of measured, cell-clustered and meta-clustered parameters

Usage:

```
parameters(immunoMeta)
parameters(immunoMeta) <- value
```

label the meta-clustering label, that is the assignment of the cell-clusters to the meta-clusters.

Usage:

```
label(immunoMeta, for.sample=NA)
```

If for.sample is specified, the label part for this sample only.

weights the meta-clustering weights for the cluster selection (all meta-cluster by default)

Usage:

```
weights(immunoMets,cls=seq_len(ncls(immunoMeta)))
```

mu the meta-cluster mean values for the cluster and parameter selection (all meta-cluster and all parameter by default)

Usage:

```
mu(immunoMeta, cls=seq_len(ncls(immunoMeta)), par=seq_len(npar(immunoMeta)))
```

sigma the meta-cluster co-variance values for the cluster and parameter selection (all meta-cluster and all parameter by default)

Usage:

```
sigma(immunoMeta, cls=seq_len(ncls(immunoMeta)), par=seq_len(npar(immunoMeta)))
```

aposteriori the a-posteriori probabilities of cluster membership for each cell-cluster

Usage:

```
aposteriori(immunoMeta)
```

events the cell-event numbers for each sample for the cluster selection (all meta-cluster by default)

Usage:

```
events(immunoMeta, ncls=seq_len(ncls(immunoMeta)), for.sample=NA)
```

If for.sample is specified, the cell-event numbers for this sample only.

prop, prop<- get or a property value in the hierarchy level given by `pos` and named `name`

Usage:

```
prop(immunoMeta, name, pos=c())
prop(immunoMeta, name, pos, for.level=TRUE, for.sublevels=FALSE) <- value
```

If the option `for.sublevels` is set, the property value will by setted deep for all sub-levels of the by `pos` specified level.

The `prop` interface is very basic and no checks for meaningfull properties and values are performed. It could be used for everything at any time. Nevertheless, there are some property keys which are used internally mainly to control the plot routine for the levels.

`desc` the name of this level.

`M` the mean of all clusters in this level

`S` the co-variance matrix of all clusters in this level

`pscales` a list of `npar` entries for the limits and ticks information. Normaly, only set on root-level and then used for all sub-levels. But could set and altered at any level.

`plot.subset` an array of parameter indices used as default for the plot of this level.

`plot.color` an index in the `palette` or other specified color used for plots of this level in its parent level.

`plot.childs` to be renamed in `plot.levels`.

`plot.parent` when set, additionally all cluster of the parent level are plotted in light gray.

desc, desc<- Get or set the `desc` property in the by `pos` specified level.

Usage:

```
desc(immunoMeta, pos)
desc(immunoMeta, pos) <- value
```

descFull Gives the full description path for the level given by `pos`, i.e. the concatinate `desc` values of this all parent levels.

Usage:

```
descFull(immunoMeta, pos)
```

level, level<- Get or replace the level object at specified `pos`,

Usage:

```
value <- level(immunoMeta, pos)
level(immunoMeta, pos ) <- value
```

findLevel Find the level `pos` value for a specific cluster `cls`

Usage:

```
pos <- findLevel(immunoMeta, cls)
```

clusters Retrieves the cluster subset for the level at `pos`.

Usage:

```
cls <- clusters(immunoMeta, pos)
```

classified Retrieves the cluster subset for the level at `pos` which are classified in sub-levels.

Usage:

```
cls <- classified(immunoMeta, pos)
```

unclassified Retrieves the cluster subset for the level at `pos` which are not classified in sub-levels.

Usage:

```
cls <- unclassified(immunoMeta, pos)
```

Manipulators

addLevel<- Adds a level at a specified hierarchy position `pos`. A level consists of a name (`desc`) and a cluster subset `cls`.

Usage:

```
addLevel(immunoMeta, pos, desc="new level") <- cls
```

move<- Moves a cluster subset to a specific immunoMeta level. Clusters in `cls` are added to parent levels if nessesary and removed from other levels.

Usage:

```
move(immunoMeta, pos) <- cls
```

remove<- removes a cluster subset from a specific immunoMeta level.

Usage:

```
remove(immunoMeta, pos) <- cls
```

parent<- sets the parent for this level, or this level as parent for all its sub-levels

Usage:

```
parent(immunoMeta, pos) <- c()
parent(immunoMeta, pos) <- level
```

transfer<- Overtakes the annotation of an immunoMeta-object to this immunoMeta-object

Usage:

```
transfer(immunoMeta) <- annotatedMeta
```

Methods

finalize After manipulations of a `immunoMeta`-object `finalize` restructure all levels and returns the finalized object, where the parent relations are solved and the mean and co-variances of all levels are build.

Usage:

```
immunoMeta <- finalize(immunoMeta)
```

subset Builds the `immunoMeta`-object for a cluster and/or parameter subset

Usage:

```
subsetMeta <- subset(immunoMeta, cls=seq_len(ncls(meta)), par=seq_len(npar(meta)))
```

transformParams Scales and translates the cluster means of the `immunoMeta`-object in each parameter

Usage:

```
transformedMeta <- transformParams(immunoMeta, scale=c(), offset=c())
```

clusterCoeff Calculates the bhattacharya coefficients of clusters `cls` for a level `lvl` in the `immunoMeta`-object

Usage:

```
ret <- clustersCoeff(immunoMeta, cls, lvl, par=seq_len(npar(immunoMeta))
```

clusterDist Calculates the bhattacharya distances of clusters `cls` for a level `lvl` in the `immunoMeta`-object

Usage:

```
ret <- clustersDist(immunoMeta, cls, lvl, par=seq_len(npar(immunoMeta))
```

clusterProb Calculates the bhattacharya probabilities of clusters `cls` for a level `lvl` in the `immunoMeta`-object

Usage:

```
ret <- clustersProb(immunoMeta, cls, lvl, par=seq_len(npar(immunoMeta))
```

Author(s)

Till Sörensen <till-antoni.soerensen@charite.de>

See Also

immunoMeta-object

Examples

```
###
data(dat.meta)
npar(dat.meta)
ncls(dat.meta)
cls <- clusters(dat.meta,c(1))
move(dat.meta,c(2)) <- cls
```

plot.immunoClust *Scatterplot of immunoClust Clustering Results*

Description

This method generates scatterplot revealing the cluster assignment.

Usage

```
## S4 method for signature 'immunoClust'
plot(x, data, subset=c(1,2), ellipse=T,
show.rm=F, include=1:(x@K), main=NULL,
col=include+1, pch=".", cex=0.6,
col.rm=1, pch.rm=1, cex.rm=0.6, ecol=col, elty=1,
npoints=501, add=F, ...)
```

Arguments

x	An object of class immunoClust as return by cell.process.
data	A matrix, data frame of observations, or object of class flowFrame. This is the object of observations on which cell.process was performed or the matrix of cell-cluster centers for the meta.process.
subset	A numeric vector of length two indicating which two parameters are selected for the scatterplot. Alternatively, a character vector containing the names of the two parameters is allowed if x@parameters is not NULL.
ellipse	A logical value indicating whether the cluster 90% percentil boundary is to be drawn or not.
show.rm	A logical value indicating whether filtered observations will be shown or not.
include	A numeric vector specifying which clusters will be shown on the plot. By default, all clusters are included.
main	Title of the plot.
col	Color(s) of the plotting points. May specify a different color for each cluster.
pch	Plotting character(s) of the plotting points. May specify a different character for each cluster.
cex	Size of the plotting characters. May specify a different size for each cluster.
col.rm	Color of the plotting characters denoting filtered observations.
pch.rm	Plotting character used to denote filtered observations.
cex.rm	Size of the plotting character used to denote filtered observations.
ecol	Color(s) of the lines representing the cluster boundaries. May specify a different color for each cluster.
elty	Line type(s) drawing the cluster boundaries. May specify a different line type for each cluster.
npoints	The number of points used to draw each cluster boundary.
add	A logical value. If TRUE, add to the current plot.
...	Further graphical parameters passed to the generic function plot.

Value

Plots the clustering assignment on an appropriatei plotting device.

Author(s)

Till Sörensen <till-antoni.soerensen@charite.de>

References

Sörensen, T., Baumgart, S., Durek, P., Grützkau, A. and Häupl, T. immunoClust - an automated analysis pipeline for the identification of immunophenotypic signatures in high-dimensional cytometric datasets. *Cytometry A* (accepted).

See Also

immunoClust-object

Examples

```
data(dat.fcs)
data(dat.exp)
dat.res <- dat.exp[[1]]
dat.trans <- trans.ApplyToData(dat.res, dat.fcs)
plot(dat.res, dat=dat.trans,N=1000)
```

---

plot.immunoMeta *Scatterplot of immunoMeta Structured Clustering Results*

Description

This method generates scatterplot revealing the cluster assignment.

Usage

```
## S3 method for class 'immunoMeta'
plot(x, pos=c(), main="", plot.childs=TRUE,
plot.unclassified=FALSE, plot.subset=c(), inc.childs=c(), plot.ellipse=TRUE,
plot.all=FALSE, ...)
```

Arguments

x	An object of class immunoMeta as return by meta.process.
pos	gives the position in the immunoMeta-hierarchy to plot (default=c() plots the root level). pos is an array of indices, which addresses the level of interest. Each level in the immunoMeta-hierarchy has an array of sub-levels and pos is the sequences of indices into these sub-levels.
main	additional title which is concatenated with the position and description path of the plotted level.
plot.subset	an array of indices for the parameter selection to be plotted.

plot.unclassified
: if set, the unclassified clusters,i.e clusters not assigned into a sub-level, are plotted rather than the classified clusters.

plot.childs
: colours the clusters by the sub-level rather than the clusters themselves. By default colours are assigned by sub-level index repeated in red, green,blue,cyan,magenta,yellow,gray,bla

inc.childs
: optionally, to restrict to a particular selection of sub-levels to plot.

plot.ellipse
: surrounds the cell-cluster center by an ellipse reflecting the meta-cluster deviation

plot.all
: plots all sub-levels. Usefull for a full annotation documentation with a pdf file.

...
: Further graphical parameters passed to the generic function `plot`.

Value

Plots the clustering assignment on an appropriated plotting device.

Author(s)

Till Sörensen <till-antoni.soerensen@charite.de>

See Also

immunoMeta-object

Examples

```
data(dat.meta)
plot(dat.meta)
```

---

splom.immunoClust *Scatterplot Matrix of immunoClust Clustering Results*

Description

This method generates scatterplot matrix revealing the cluster assignment.

Usage

```
## S4 method for signature 'immunoClust,missing'
splom(x, data, include=seq_len(x@K), ...)

## S4 method for signature 'immunoClust,flowFrame'
splom(x, data, include=seq_len(x@K),
subset=seq_len(length(attributes(x)$param)), N=NULL,label=NULL, desc=NULL,
add.param=c(), ...)

## S4 method for signature 'immunoClust,matrix'
splom(x, data, include=seq_len(x@K),
subset=seq_len(length(attributes(x)$param)), N=NULL, label=NULL,
desc=NULL, ...)

datSplom(label, data, subset=seq_len(ncol(data)),
include=seq_len(nrow(data)), ...)
```

Arguments

x	An object of class immunoClust as return by cell.process or meta.process.
data	Missing, a matrix, or object of class flowFrame. This is the object of observations on which cell.process was performed.
include	A numeric vector specifying which clusters will be shown on the plot. By default, all clusters are included.
subset	A numeric vector indicating which parameters are selected for the scatterplot matrix.
N	An integer for the maximum number of observations to be plotted. By default all observations are plotted.
label	A integer vector for the cluster mebership of the observations. By default this is x@label.
desc	A character vector for the parameter description.
add.param	A list of additional parameters to plot, which are not used for clustering.
...	Further graphical parameters passed to the generic function splom.

Value

An object of class trellis as returned by the generic splom function of the lattice-package. The print method (called by default) will plot it on an appropriate plotting device.

Author(s)

Till Sörensen <till-antoni.soerensen@charite.de>

References

Sörensen, T., Baumgart, S., Durek, P., Grützkau, A. and Häupl, T. immunoClust - an automated analysis pipeline for the identification of immunophenotypic signatures in high-dimensional cytometric datasets. *Cytometry A* (accepted).

See Also

immunoClust-object

Examples

```
data(dat.fcs)
data(dat.exp)
# cell clustering results of dat.fcs
dat.res <- dat.exp[[1]]
dat.trans <- trans.ApplyToData(dat.res, dat.fcs)
splom(dat.res, data=dat.trans, N=1000)
```

`trans.ApplyToData` *immunoClust asinh-Transformation*

Description

Applies the transformation information of the `immunoClust` object to the raw observed FC dataset.

Usage

```
trans.ApplyToData(x, data, add.param=c(), max.decade=attr(x,"trans.decade"),
    lin.scale=attr(x,"trans.scale") )
```

Arguments

`x`	The `immunoClust` object containing the estimators for the transformation `trans.a` and `trans.b`.
`data`	The numeric matrix, data frame of observations, or object of class `flowFrame`.
`add.param`	A list of additional parameters in the `flowFrame`, which are not used for clustering but should be included in the final transformed resulting `flowFrame`.
`max.decade`	A numeric scale for the maximum transformed observation value; if missing or below 0, no scaling of the transformed values is apllied, which is the default in *immuno*Clust.
`lin.scale`	A numeric scaling factor for the linear, i.e. not transformed, parameters; if missing no scaling, i.e. $lin.scale = 1$, is applied, which is the default in *immuno*Clust.

Details

In *immuno*Clust an $asinh$-transformation $h(y) = asinh(a \cdot y + b)$ is applied to the fluorescence parameter in the observed data. The scatter parameter are assumed to be linear.

Value

A matrix or `flowFrame` with replaced transformed oberservation values.

Author(s)

Till Sörensen <till-antoni.soerensen@charite.de>

References

Sörensen, T., Baumgart, S., Durek, P., Grützkau, A. and Häupl, T. immunoClust - an automated analysis pipeline for the identification of immunophenotypic signatures in high-dimensional cytometric datasets. *Cytometry A* (accepted).

See Also

`immunoClust`, `trans.FitToData`, `cell.process`

Examples

```
data(dat.fcs)
data(dat.exp)
dat.trans <- trans.ApplyToData(dat.exp[[1]], dat.fcs)
#
#plot(dat.exp[[1]], data=dat.trans)
#
```

`trans.FitToData` *immunoClust asinh-Transformation Optimization*

Description

Performs variance stabilization transformation estimation on the fluorescense parameters of the observed cell events. It is integrated in the interative cell event clustering approach of *immuno*Clust when transformation estimation should be applied.

Usage

```
trans.FitToData(x, data, B=10, tol=1e-5, certainty=0.3, proc="vsHtransAw")
```

Arguments

`x`	The `immunoClust` object of the fitted mixture model and initial estimators for the transformation.
`data`	The numeric matrix, data frame of observations, or object of class flowFrame.
`B`	The maximum number of BFG2 minimizer iterations.
`tol`	The tolerance used to assess the convergence for the BFG2 minimizer.
`certainty`	Minimum probability for cluster membership of an observation to be taken into account.
`proc`	An experimental switch for alternative procedures; should be "vsHtransAw".

Details

In *immuno*Clust an $asinh$-transformation $h(y) = asinh(a \cdot y + b)$ is applied for all fluorescence parameter in the observed data.

The transformation optimization `trans.FitToData` requires a fitted model of cluster information together with suitable initial transformation estimation in an `immunoClust` object. It fits the transformation based on the initial scaling values `trans.a` and translation values `trans.b` to the observed data. It returns the optimized transformation parameter in a $2 \times P$-dimensional matrix, first row for the scaling and second row for the translation values. A scaling value of $a = 0$ on input and output indicates, that a parameter should not be transformed.

The presented transformation optimization ("vsHtransAw") fits only the scaling value. An alternative procedure ("vsHtrans_w") fits both, the scaling and the translation value, but turns out to be less robust.

Value

Optimized transformation scaling and translation values in a $2 \times P$-dimensional matrix, first row for the scaling and second row for the translation values.

Author(s)

Till Sörensen <till-antoni.soerensen@charite.de>

References

Sörensen, T., Baumgart, S., Durek, P., Grützkau, A. and Häupl, T. immunoClust - an automated analysis pipeline for the identification of immunophenotypic signatures in high-dimensional cytometric datasets. *Cytometry A* (accepted).

See Also

trans.ApplyToData, cell.process

Examples

```
data(dat.fcs)
data(dat.exp)
## in dat.exp the z-matrices of the immunoClust-object are removed
## so we have to re-calculate it first ...
dat.trans <- trans.ApplyToData(dat.exp[[1]], dat.fcs)
res <- cell.Classify(dat.exp[[1]], dat.trans)
## ... now the transformation parameter can be optimzed
trans.FitToData(res, dat.fcs)
```

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