Package 'DatabionicSwarm'

November 29, 2022

Type Package

License GPL-3

Title Swarm Intelligence for Self-Organized Clustering

Version 1.1.6

Date 2022-11-26

Maintainer Michael Thrun <m.thrun@gmx.net>

Description

Algorithms implementing populations of agents that interact with one another and sense their environment may exhibit emergent behavior such as self-organization and swarm intelligence. Here, a swarm system called Databionic swarm (DBS) is introduced which was published in Thrun, M.C., Ultsch A.: ``Swarm Intelligence for Self-Organized Clustering'' (2020), Artificial Intelligence, <DOI:10.1016/j.artint.2020.103237>. DBS is able to adapt itself to structures of high-dimensional data such as natural clusters characterized by distance and/or density based structures in the data space. The first module is the parameter-free projection method called Pswarm (Pswarm()), which exploits the concepts of self-organization and emergence, game theory, swarm intelligence and symmetry considerations. The second module is the parameter-free high-dimensional data visualization technique, which generates projected points on the topographic map with hypsometric tints defined by the generalized U-matrix (GeneratePswarmVisualization()). The third module is the clustering method itself with non-critical parameters (DBSclustering()). Clustering can be verified by the visualization and vice versa. The term DBS refers to the method as a whole. It enables even a non-professional in the field of data mining to apply its algorithms for visualization and/or clustering to data sets with completely different structures drawn from diverse research fields. The comparison to common projection methods can be found in the book of Thrun, M.C.: ``Projection Based Clustering through Self-Organization and Swarm Intelligence'' (2018) <DOI:10.1007/978-3-658-20540-9>.

Imports Rcpp, deldir, GeneralizedUmatrix

Suggests DataVisualizations, knitr (>= 1.12), rmarkdown (>= 0.9), plotrix, geometry, sp, spdep, AdaptGauss, ABCanalysis, parallel, rgl, png, ProjectionBasedClustering, parallelDist, pracma, dendextend

LinkingTo Rcpp, RcppArmadillo

Depends R (>= 3.0)

NeedsCompilation yes

SystemRequirements C++11

LazyLoad yes

LazyData TRUE

URL https://www.deepbionics.org/

Encoding UTF-8

VignetteBuilder knitr

BugReports https://github.com/Mthrun/DatabionicSwarm/issues

Author Michael Thrun [aut, cre, cph] (<https://orcid.org/0000-0001-9542-5543>)

Repository CRAN

Date/Publication 2022-11-29 08:50:02 UTC

R topics documented:

`DatabionicSwarm-package`

Swarm Intelligence for Self-Organized Clustering

Description

Algorithms implementing populations of agents that interact with one another and sense their environment may exhibit emergent behavior such as self-organization and swarm intelligence. Here, a swarm system called Databionic swarm (DBS) is introduced which was published in Thrun, M.C., Ultsch A.: "Swarm Intelligence for Self-Organized Clustering" (2020), Artificial Intelligence, <DOI:10.1016/j.artint.2020.103237>. DBS is able to adapt itself to structures of high-dimensional data such as natural clusters characterized by distance and/or density based structures in the data space. The first module is the parameter-free projection method called Pswarm (Pswarm()), which exploits the concepts of self-organization and emergence, game theory, swarm intelligence and symmetry considerations. The second module is the parameter-free high-dimensional data visualization technique, which generates projected points on the topographic map with hypsometric tints defined by the generalized U-matrix (GeneratePswarmVisualization()). The third module is the clustering method itself with non-critical parameters (DBSclustering()). Clustering can be verified by the visualization and vice versa. The term DBS refers to the method as a whole. It enables even a non-professional in the field of data mining to apply its algorithms for visualization and/or clustering to data sets with completely different structures drawn from diverse research fields. The comparison to common projection methods can be found in the book of Thrun, M.C.: "Projection Based Clustering through Self-Organization and Swarm Intelligence" (2018) <DOI:10.1007/978-3-658-20540-9>.

Details

For a brief introduction to **DatabionicSwarm** please see the vignette Short Intro to the Databionic Swarm (DBS).

Package:	Databonic swarm
Type:	Package
Version:	1.1.5
Date:	2021-01-12
License:	CC BY-NC-SA 4.0

Index of help topics:

```
ClusteringAccuracy      ClusteringAccuracy
DBSclustering           Databonic swarm clustering (DBS)
DatabionicSwarm-package
                        Swarm Intelligence for Self-Organized
                        Clustering
DefaultColorSequence    Default color sequence for plots
Delaunay4Points         Adjacency matrix of the delaunay graph for
                        BestMatches of Points
```

```
DelaunayClassificationError
                        Delaunay Classification Error (DCE)
Delta3DWeightsC         Intern function
DijkstraSSSP            Internal function: Dijkstra SSSP
GeneratePswarmVisualization
                        Generates the Umatrix for Pswarm algorithm
Hepta                   Hepta is part of the Fundamental Clustering
                        Problem Suit (FCPS) [Thrun/Ultsch, 2020].
Lsun3D                  Lsun3D is part of the Fundamental Clustering
                        Problem Suit (FCPS) [Thrun/Ultsch, 2020].
ProjectedPoints2Grid    Transforms ProjectedPoints to a grid
Pswarm                  A Swarm of Databots based on polar coordinates
                        (Polar Swarm).
PswarmCurrentRadiusC2botsPositive
                        intern function, do not use yourself
RelativeDifference      Relative Difference
RobustNorm_BackTrafo    Transforms the Robust Normalization back
RobustNormalization     RobustNormalization
ShortestGraphPathsC     Shortest GraphPaths = geodesic distances
UniquePoints            Unique Points
findPossiblePositionsCsingle
                        Intern function, do not use yourself
getCartesianCoordinates
                        Intern function: Transformation of Databot
                        indizes to coordinates
getUmatrix4Projection   depricated! see GeneralizedUmatrix()
                        Generalisierte U-Matrix fuer
                        Projektionsverfahren
plotSwarm               Intern function for plotting during the Pswarm
                        annealing process
rDistanceToroidCsingle
                        Intern function for 'Pswarm'
sESOM4BMUs              Intern function: Simplified Emergent
                        Self-Organizing Map
setGridSize             Sets the grid size for the Pswarm algorithm
setPolarGrid            Intern function: Sets the polar grid
setRmin                 Intern function: Estimates the minimal radius
                        for the Databot scent
setdiffMatrix           setdiffMatrix shortens Matrix2Curt by those
                        rows that are in both matrices.
trainstepC              Internal function for sESOM
```

Note

For interactive Island Generation of a generalized Umatrix see `interactiveGeneralizedUmatrixIsland` function in the package **ProjectionBasedClustering**.

If you want to verifiy your clustering result externally, you can use `Heatmap` or `SilhouettePlot` of the CRAN package **DataVisualizations**.

Author(s)

Michal Thrun

Maintainer: Michael Thrun <m.thrun@gmx.net>

References

[Thrun/Ultsch, 2021] Thrun, M. C., and Ultsch, A.: Swarm Intelligence for Self-Organized Clustering, Artificial Intelligence, Vol. 290, pp. 103237, doi:10.1016/j.artint.2020.103237, 2021.

[Thrun/Ultsch, 2021] Thrun, M. C., & Ultsch, A.: Swarm Intelligence for Self-Organized Clustering (Extended Abstract), in Bessiere, C. (Ed.), 29th International Joint Conference on Artificial Intelligence (IJCAI), Vol. IJCAI-20, pp. 5125–5129, doi:10.24963/ijcai.2020/720, Yokohama, Japan, Jan., 2021.

[Thrun/Ultsch, 2020] Thrun, M. C., & Ultsch, A.: Uncovering High-Dimensional Structures of Projections from Dimensionality Reduction Methods, MethodsX, Vol. 7, pp. 101093, DOI doi:10.1016/j.mex.2020.101093, 2020.

[Thrun, 2018] Thrun, M. C.: Projection Based Clustering through Self-Organization and Swarm Intelligence, doctoral dissertation 2017, Springer, Heidelberg, ISBN: 978-3-658-20539-3, doi:10.1007/9783658205409, 2018.

[Ultsch/Thrun, 2017] Ultsch, A., & Thrun, M. C.: Credible Visualizations for Planar Projections, in Cottrell, M. (Ed.), 12th International Workshop on Self-Organizing Maps and Learning Vector Quantization, Clustering and Data Visualization (WSOM), IEEE Xplore, France, 2017.

[Thrun et al., 2016] Thrun, M. C., Lerch, F., Loetsch, J., & Ultsch, A.: Visualization and 3D Printing of Multivariate Data of Biomarkers, in Skala, V. (Ed.), International Conference in Central Europe on Computer Graphics, Visualization and Computer Vision (WSCG), Vol. 24, Plzen, http://wscg.zcu.cz/wscg2016/short/A43-full.pdf, 2016.

Successfully used in

[Thrun et al., 2018] Thrun, M. C., Breuer, L., & Ultsch, A. : Knowledge discovery from low-frequency stream nitrate concentrations: hydrology and biology contributions, Proc. European Conference on Data Analysis (ECDA), pp. 46-47, Paderborn, Germany, 2018.

[Weyer-Menkhoff et al., 2018] Weyer-Menkhoff, I., Thrun, M. C., & Loetsch, J.: Machine-learned analysis of quantitative sensory testing responses to noxious cold stimulation in healthy subjects, European Journal of Pain, Vol. 22(5), pp. 862-874, DOI doi:10.1002/ejp.1173, 2018.

[Kringel et al., 2018] Kringel, D., Geisslinger, G., Resch, E., Oertel, B. G., Thrun, M. C., Heinemann, S., & Loetsch, J. : Machine-learned analysis of the association of next-generation sequencing based human TRPV1 and TRPA1 genotypes with the sensitivity to heat stimuli and topically applied capsaicin, Pain, Vol. 159 (7), pp. 1366-1381, DOI doi:10.1097/j.pain.0000000000001222, 2018

[Thrun, 2019] Thrun, M. C.: : Cluster Analysis of Per Capita Gross Domestic Products, Entrepreneurial Business and Economics Review (EBER), Vol. 7(1), pp. 217-231, DOI: doi:10.15678/EBER.2019.070113, 2019.

[Lopez-Garcia et al., 2020] Lopez-Garcia, P., Argote, D. L., & Thrun, M. C.: Projection-based Classification of Chemical Groups and Provenance Analysis of Archaeological Materials, IEEE Access, Vol. 8, pp. 152439-152451, DOI doi:10.1109/ACCESS.2020.3016244, 2020.

Examples

```
data('Lsun3D')
##2d projection, without instant visualization of steps

#Alternative I:
#DistanceMatrix hast to be defined by the user.
InputDistances=as.matrix(dist(Lsun3D$Data))

projection=Pswarm(InputDistances)
#2d projection, with instant visualization

## Not run:
#Alternative II: DataMatrix, Distance is Euclidean per default
projection=Pswarm(Lsun3D$Data,Cls=Lsun3D$Cls,PlotIt=T)

## End(Not run)
#
##Computation of Generalized Umatrix
# If Non Euclidean Distances are used, Please Use \code{MDS}
# from the ProjectionBasedClustering package with the correct OutputDimension
# to generate a new DataMatrix from the distances (see SheppardDiagram
# or KruskalStress)
genUmatrixList=GeneratePswarmVisualization(Data = Lsun3D$Data,

projection$ProjectedPoints,projection$LC)
## Visualizuation of GenerelizedUmatrix,
# Estimation of the Number of Clusters=Number of valleys
library(GeneralizedUmatrix)#install if not installed
GeneralizedUmatrix::plotTopographicMap(genUmatrixList$Umatrix,genUmatrixList$Bestmatches)
## Automatic Clustering
# number of Cluster from dendrogram (PlotIt=TRUE) or visualization
Cls=DBSclustering(k=3, Lsun3D$Data,

genUmatrixList$Bestmatches, genUmatrixList$LC,PlotIt=FALSE)
# Verification, often its better to mark Outliers manually

GeneralizedUmatrix::plotTopographicMap(genUmatrixList$Umatrix,genUmatrixList$Bestmatches,Cls)

## Not run:
# To generate the 3D landscape in the shape of an island
# from the toroidal topograpic map visualization
# you may cut your island interactivly around high mountain ranges
Imx = ProjectionBasedClustering::interactiveGeneralizedUmatrixIsland(genUmatrixList$Umatrix,
genUmatrixList$Bestmatches,Cls)

GeneralizedUmatrix::plotTopographicMap(genUmatrixList$Umatrix,
genUmatrixList$Bestmatches, Cls=Cls,Imx = Imx)

## End(Not run)
## Not run:
library(ProjectionBasedClustering)#install if not installed
Cls2=ProjectionBasedClustering::interactiveClustering(genUmatrixList$Umatrix,
```

```
genUmatrixList$Bestmatches, Cls)

## End(Not run)
```

ClusteringAccuracy *ClusteringAccuracy*

Description

ClusteringAccuracy

Usage

```
ClusteringAccuracy(PriorCls,CurrentCls,K=9)
```

Arguments

PriorCls	[1:n] integer vector; Ground truth
CurrentCls	[1:n] integer vector with clustering result
K	Maximal number of classes for computation.

Details

Here, accuracy is defined as the normalized sum over all true positive labeled data points of a clustering algorithm. The best of all permutation of labels with the highest accuracy is selected in every trial because algorithms arbitrarily define the labels.

Value

Accuracy Between zero and one

Author(s)

Michael Thrun

References

Michael C. Thrun, Felix Pape, Alfred Ultsch: Benchmarking Cluster Analysis Methods in the Case of Distance and Density-based Structures Defined by a Prior Classification Using PDE-Optimized Violin Plots, ECDA, Potsdam, 2018

Examples

```
data(Hepta)

InputDistances=as.matrix(dist(Hepta$Data))
projection=Pswarm(InputDistances)
visualization=GeneratePswarmVisualization(Data = Hepta$Data,

projection$ProjectedPoints,projection$LC)
Cls=DBSclustering(k=7, Hepta$Data, visualization$Bestmatches,

visualization$LC,PlotIt=FALSE)
ClusteringAccuracy(Hepta$Cls,Cls,K=9)
```

`DBSclustering` *Databonic swarm clustering (DBS)*

Description

DBS is a flexible and robust clustering framework that consists of three independent modules. The first module is the parameter-free projection method Pswarm `Pswarm`, which exploits the concepts of self-organization and emergence, game theory, swarm intelligence and symmetry considerations [Thrun/Ultsch, 2021]. The second module is a parameter-free high-dimensional data visualization technique, which generates projected points on a topographic map with hypsometric colors `GeneratePswarmVisualization`, called the generalized U-matrix. The third module is a clustering method with no sensitive parameters `DBSclustering` (see [Thrun, 2018, p. 104 ff]). The clustering can be verified by the visualization and vice versa. The term DBS refers to the method as a whole.

The `DBSclustering` function applies the automated Clustering approach of the Databonic swarm using abstract U distances, which are the geodesic distances based on high-dimensional distances combined with low dimensional graph paths by using `ShortestGraphPathsC`.

Usage

```
DBSclustering(k, DataOrDistance, BestMatches, LC, StructureType = TRUE,
PlotIt = FALSE, method = "euclidean",...)
```

Arguments

`k`	number of clusters, how many to you see in the topographic map
`DataOrDistance`	Either [1:n,1:d] Matrix of Data (n cases, d dimensions) that will be used. One DataPoint per row or symmetric Distance matrix [1:n,1:n]
`BestMatches`	[1:n,1:2] Matrix with positions of Bestmatches or ProjectedPoints, one matrix line per data point
`LC`	grid size c(Lines,Columns), please see details

StructureType	Optional, bool; = TRUE: compact structure of clusters assumed, =FALSE: connected structure of clusters assumed. For the two options for Clusters, see [Thrun, 2018] or Handl et al. 2006
PlotIt	Optional, bool, Plots Dendrogramm
method	Optional, one of 39 distance methods of parDist of package parallelDist, if Data matrix is chosen above
...	Further arguments passed on to the parDist function, e.g. user-defined distance functions

Details

The input of the LC parameter depends on the choice of Bestmatches input argument. Usually as the name of the argument states, the Bestmatches of the GeneratePswarmVisualization function are used which is define in the notation of self-organizing map. In this case please see example one. However, as written above, clustering and visualization can be applied independently of each other. In this case the places of Lines L and Columns C are switched. Hence, one should give DBSclustering the argument LC[2,1] as shown in example 2.

Often it is better to mark the outliers manually after the prozess of clustering and sometimes a clustering can be improved through human interaction [Thrun/Ultsch,2017] <DOI:10.13140/RG.2.2.13124.53124>; use in this case the visualization plotTopographicMap of the package GeneralizedUmatrix. If you would like to mark the outliers interactivly in the visualization use the **ProjectionBasedClustering** package with the function interactiveClustering(), or for full interactive clustering IPBC(). The package is available on CRAN. An example is shown in case of interactiveClustering() function in the third example.

Value

1:n numerical vector of numbers defining the classification as the main output of this cluster analysis for the n cases of data corresponding to the n bestmatches. It has k unique numbers representing the arbitrary labels of the clustering. You can use plotTopographicMap(Umatrix,Bestmatches,Cls) for verification.

Note

If you want to verifiy your clustering result externally, you can use Heatmap or SilhouettePlot of the package **DataVisualizations** available on CRAN.

Author(s)

Michael Thrun

References

[Thrun/Ultsch, 2021] Thrun, M. C., and Ultsch, A.: Swarm Intelligence for Self-Organized Clustering, Artificial Intelligence, Vol. 290, pp. 103237, doi:10.1016/j.artint.2020.103237, 2021.

Examples

```
data("Lsun3D")
Data=Lsun3D$Data
InputDistances=as.matrix(dist(Data))
projection=Pswarm(InputDistances)
## Example One
genUmatrixList=GeneratePswarmVisualization(Data,

projection$ProjectedPoints,projection$LC)

Cls=DBSclustering(k=3, Data,

genUmatrixList$Bestmatches, genUmatrixList$LC,PlotIt=TRUE)


## Example Two
#automatic Clustering without GeneralizedUmatrix visualization
Cls=DBSclustering(k=3, Data,

projection$ProjectedPoints, projection$LC[c(2,1)],PlotIt=TRUE)

## Not run:
## Example Three
## Sometimes an automatic Clustering can be improved
## thorugh an interactive approach,
## e.g. if Outliers exist (see [Thrun/Ultsch, 2017])
library(ProjectionBasedClustering)
Cls2=ProjectionBasedClustering::interactiveClustering(genUmatrixList$Umatrix,
genUmatrixList$Bestmatches, Cls)

## End(Not run)
```

DefaultColorSequence *Default color sequence for plots*

Description

Defines the default color sequence for plots made within the Projections package.

Usage

```
data("DefaultColorSequence")
```

Format

A vector with 562 different strings describing colors for plots.

`Delaunay4Points` *Adjacency matrix of the delaunay graph for BestMatches of Points*

Description

Calculates the adjacency matrix of the delaunay graph for BestMatches (BMs) in tiled form if BestMatches are located on a toroid grid.

Usage

```
Delaunay4Points(Points, IsToroid = TRUE,Grid=NULL,PlotIt=FALSE,
Gabriel=FALSE)
```

Arguments

`Points`	[1:n,1:3] matrix containing the BMKey, X and Y coordinates of the n, BestMatches NEED NOT to be UNIQUE, however, there is an edge in the Deaunay between duplicate points!
`IsToroid`	Optional, logical, indicating if BM's are on a toroid grid. Default is True
`Grid`	Optional, A vector of length 2, containing the number of lines and columns of the Grid
`PlotIt`	Optional, bool, Plots the graph
`Gabriel`	Optional, bool, default: FALSE, If TRUE: calculates the gabriel graph instead of the delaunay graph

Value

Delaunay[1:n,1:n] adjacency matrix of the Delaunay-Graph

Author(s)

Michael Thrun

References

[Thrun, 2018] Thrun, M. C.: Projection Based Clustering through Self-Organization and Swarm Intelligence, doctoral dissertation 2017, Springer, Heidelberg, ISBN: 978-3-658-20539-3, doi:10.1007/9783658205409, 2018.

`DelaunayClassificationError` *Delaunay Classification Error (DCE)*

Description

DCE searches for the k-nearest neighbors of the first delaunay neighbors weighted by the Euclidean Distances of the Inputspace. DCE evaluates these neighbors in the Output space. A low value indicates a better two-dimensional projection of the high-dimensional Input space.

Usage

```
DelaunayClassificationError(Data,ProjectedPoints,Cls,LC=NULL)
```

Arguments

`Data`	[1:n,1:d] Numeric matrix
`ProjectedPoints`	[1:n,1:2]
`Cls`	[1:n,1]
`LC`	Optional, default NULL, Wenn toroid, muss c(Lines,Columns) angeben werden

Details

Delaunay classification error (DCE) makes an unbiased evaluation of distance and densitiybased structure which ma be even non-linear seperable. First, DCE utilizes the information provided by a prior classification to assess projected structures. Second, DCE applies the insights drawn from graph theory. Details are described in [Thrun/Ultsch, 2018]

Value

list of

`DCE`	DelaunayClassificationError NOTE the rest is just for development purposes
`DCEperPoint`	[1:n] unnormalized DCE of each point: DCE = mean(DCEperPoint)
`nn`	the number of points in a relevant neghborhood: 0.5 * 85percentile(AnzNN)
`AnzNN`	[1:n] the number of points with a delaunay graph neighborhood
`NNdists`	[1:n,1:nn] the distances within the relevant neighborhood, 0 for inner cluster distances
`HD`	[1:nn] HD = HarmonicDecay(nn) i.e weight function for the NNdists: DCEperPoint = HD*NNdists

Note

see also chapter 6 of [Thrun, 2018]

Author(s)

Michael Thrun

References

[Thrun/Ultsch, 2018] Thrun, M. C., & Ultsch, A. : Investigating Quality measurements of projections for the Evaluation of Distance and Density-based Structures of High-Dimensional Data, Proc. European Conference on Data Analysis (ECDA), pp. accepted, Paderborn, Germany, 2018.

Examples

```
data(Hepta)

InputDistances=as.matrix(dist(Hepta$Data))
projection=Pswarm(InputDistances)
DelaunayClassificationError(Hepta$Data,projection$ProjectedPoints,Hepta$Cls,LC=projection$LC)$DCE
```

Delta3DWeightsC *Intern function*

Description

Implementation of the main equation for SOM, ESOM or the sESOM algorithms

Usage

```
Delta3DWeightsC(vx,Datasample)
```

Arguments

vx	array of weights [1:Lines,1:Columns,1:Weights]
Datasample	NumericVector of one Datapoint[1:n]

Details

intern function in case of `ComputeInR==FALSE` in `GeneratePswarmVisualization`, see chapter 5.3 of [Thrun, 2018] for generalized Umatrix and especially the `sESOM4BMUs` algorithm.

Value

modified array of weights [1:Lines,1:Columns,1:]

Author(s)

Michael Thrun

References

[Thrun, 2018] Thrun, M. C.: Projection Based Clustering through Self-Organization and Swarm Intelligence, doctoral dissertation 2017, Springer, Heidelberg, ISBN: 978-3-658-20539-3, doi:10.1007/9783658205409, 2018.

`DijkstraSSSP` *Internal function: Dijkstra SSSP*

Description

Dijkstra's SSSP (Single source shortest path) algorithm:

gets the shortest path (geodesic distance) from source vertice(point) to all other vertices(points) defined by the edges of the adjasency matrix

Usage

```
DijkstraSSSP(Adj, Costs, source)
```

Arguments

`Adj`	[1:n,1:n] 0/1 adjascency matrix, e.g. from delaunay graph or gabriel graph
`Costs`	[1:n,1:n] matrix, distances between n points (normally euclidean)
`source`	integer vertice(point) from which to calculate the geodesic distance to all other points

Details

Preallocating space for DataStructures accordingly to the maximum possible number of vertices which is fixed set at the number 10001. This is an internal function of `ShortestGraphPathsC`, no errors or mis-usage is caught here.

Value

ShortestPaths[1:n] vector, shortest paths (geodesic) to all other vertices including the source vertice itself

Note

runs in O(E*Log(V))

Author(s)

Michael Thrun

References

uses a changed code which is inspired by Shreyans Sheth 28.05.2015, see `https://ideone.com/qkmt31`

`findPossiblePositionsCsingle` *Intern function, do not use yourself*

Description

Finds all possible jumping position regarding a grid anda Radius for DataBots

Usage

```
findPossiblePositionsCsingle(RadiusPositionsschablone,
jumplength, alpha, Lines)
```

Arguments

`RadiusPositionsschablone`	NumericMatrix, see `setPolarGrid`
`jumplength`	double radius of databots regarding neighborhood, they can jump to
`alpha`	double, zu streichen
`Lines`	double, jumpinglength has to smaller than Lines/2 and Lines/2 has to yield to a integer number.

Details

Algorithm is described in [Thrun, 2018, p. 95, Listing 8.1].

Value

`OpenPositions`	NumericMatrix, indizes of open positions

Author(s)

Michael Thrun

References

[Thrun, 2018] Thrun, M. C.: Projection Based Clustering through Self-Organization and Swarm Intelligence, doctoral dissertation 2017, Springer, Heidelberg, ISBN: 978-3-658-20539-3, doi:10.1007/9783658205409, 2018.

See Also

`setPolarGrid`

GeneratePswarmVisualization

Generates the Umatrix for Pswarm algorithm

Description

DBS is a flexible and robust clustering framework that consists of three independent modules. The first module is the parameter-free projection method Pswarm `Pswarm`, which exploits the concepts of self-organization and emergence, game theory, swarm intelligence and symmetry considerations. The second module is a parameter-free high-dimensional data visualization technique, which generates projected points on a topographic map with hypsometric colors `GeneratePswarmVisualization`, called the generalized U-matrix. The third module is a clustering method with no sensitive parameters `DBSclustering`. The clustering can be verified by the visualization and vice versa. The term DBS refers to the method as a whole.

The `GeneratePswarmVisualization` function generates the special case (please see [Thrun, 2018]) of the generalized Umatrix with the help of an unsupervised neural network (simplified emergent self-organizing map published in [Thrun/Ultsch, 2020]). From the generalized Umatrix a topographic map with hypsometric tints can be visualized. To see this visualization use `plotTopographicMap` of the package **GeneralizedUmatrix**.

Usage

```
GeneratePswarmVisualization(Data,ProjectedPoints,LC,PlotIt=FALSE,
ComputeInR=FALSE)
```

Arguments

`Data`	[1:n,1:d] array of data: n cases in rows, d variables in columns
`ProjectedPoints`	matrix, ProjectedPoints[1:n,1:2] n by 2 matrix containing coordinates of the Projection: A matrix of the fitted configuration. See output of `Pswarm` for further details
`LC`	size of the grid c(Lines,Columns), number of Lines and Columns automatic calculated by `setGridSize` in `Pswarm` Sometimes is better to choose a different grid size, e.g. to to reduce computional effort contrary to SOM, here the grid size defined only the resolution of the visualizations. The real grid size is predefined by Pswarm, but you may choose a factor x*res$LC if you so desire. Therefore, The resulting grid size is given back in the Output.
`PlotIt`	Optional, default(FALSE), If TRUE than uses `plotTopographicMap` of the package GeneralizedUmatrix is plotted as a topview in the tiled option, see details for explanation.
`ComputeInR`	Optional, =TRUE: Rcode, =FALSE C++ implementation

Details

Tiled: The topographic map is visualized 4 times because the projection is toroidal. The reason is that there are no border in the visualizations and clusters (if they exist) are not disrupted by borders of the plot.

If you used Pswarm with distance matrix instead of a data matrix (in the sense that you do not have any data matrix available), you may transform your distances into data by using MDS of the **ProjectionBasedClustering** package in order to use the GeneratePswarmVisualization function. The correct dimension can be found through the Sheppard diagram or kruskals stress.

Value

list of

Bestmatches	Numeric matrix [1:n,1:2], BestMatches of the Umatrix, contrary to ESOM they are always fixed, because predefined by GridPoints.
Umatrix	Numeric matrix [1:Lines,1:Columns],
WeightsOfNeurons	Numeric 3D array [1:Lines,1:Columns,1:d], d is the dimension of the weights, the same as in the ESOM algorithm
GridPoints	Integer matrix [1:n,1:2], quantized projected points: projected points now lie on a predefined grid.
LC	c(Lines,Columns), normally equal to grid size of Pswarm, sometimes it a better or a lower resolution for the visualization is better. Therefore here the grid size of the neurons is given back.
PlotlyHandle	If PlotIt=FALSE: NULL, otherwise plotly object for ploting topview of topographic map.

Note

If you used pswarm with distance matrix instead of a data matrix you can mds transform your distances into data (see the MDS function of the ProjectionBasedClustering package.). The correct dimension can be found through the Sheppard diagram or kruskals stress.

Note

The extraction of an island out of the generalized Umatrix can be performed using the interactiveGeneralizedUmatrixIsl function in the package **ProjectionBasedClustering**.

The main code of both functions GeneralizedUmatrix and GeneratePswarmVisualization is the same C++ function sESOM4BMUs which is described in [Thrun/Ultsch, 2020].

Author(s)

Michael Thrun

References

[Thrun, 2018] Thrun, M. C.: Projection Based Clustering through Self-Organization and Swarm Intelligence, doctoral dissertation 2017, Springer, Heidelberg, ISBN: 978-3-658-20539-3, doi:10.1007/9783658205409, 2018.

[Thrun/Ultsch, 2020] Thrun, M. C., & Ultsch, A.: Uncovering High-Dimensional Structures of Projections from Dimensionality Reduction Methods, MethodsX, Vol. 7, pp. 101093, doi:10.1016/j.mex.2020.101093, 2020.

See Also

`Pswarm` and `plotTopographicMap` and `GeneralizedUmatrix` of the package **GeneralizedUmatrix**

Examples

```
data("Lsun3D")
Data=Lsun3D$Data
Cls=Lsun3D$Cls
InputDistances=as.matrix(dist(Data))

projList=Pswarm(InputDistances)
genUmatrixList=GeneratePswarmVisualization(Data,projList$ProjectedPoints,projList$LC)
library(GeneralizedUmatrix)
plotTopographicMap(genUmatrixList$Umatrix,genUmatrixList$Bestmatches,Cls)
```

---

getCartesianCoordinates

Intern function: Transformation of Databot indizes to coordinates

---

Description

Transforms Databot indizes to exact cartesian coordinates on an toroid two dimensional grid.

Arguments

`DataBotsPos`	[1:N] complex vector Two Indizes per Databot describing its positions in an two dimensional grid
`GridRadius`	[Lines,Columns] Radii Matrix of all possible Positions of DataBots in Grid, see also documentation of `setPolarGrid`
`GridAngle`	[Lines,Columns] Angle Matrix of all possible Positions of DataBots in Grid, see also documentation of `setPolarGrid`
`Lines`	Defines Size of planar toroid two dimensional grid
`Columns`	Defines Size of planar toroid two dimensional grid
`QuadOrHexa`	Optional, FALSE=If DataPos on hexadiagonal grid, round to 2 decimals after value, Default=TRUE

Details

Transformation is described in [Thrun, 2018, p. 93].

Value

BestMatchingUnits[1:N,2] coordinates on an two dimensional grid for each databot excluding unique key, such that by using `GeneratePswarmVisualization` a visualization of the Pswarm projection is possible

Author(s)

Michael Thrun

References

[Thrun, 2018] Thrun, M. C.: Projection Based Clustering through Self-Organization and Swarm Intelligence, doctoral dissertation 2017, Springer, Heidelberg, ISBN: 978-3-658-20539-3, doi:10.1007/9783658205409, 2018.

`getUmatrix4Projection` *depricated! see GeneralizedUmatrix() Generalisierte U-Matrix fuer Projektionsverfahren*

Description

depricated! see GeneralizedUmatrix()

Usage

```
getUmatrix4Projection(Data,ProjectedPoints,
PlotIt=TRUE,Cls=NULL,toroid=T,Tiled=F,ComputeInR=F)
```

Arguments

`Data`	[1:n,1:d] Numeric matrix: n cases in rows, d variables in columns
`ProjectedPoints`	[1:n,2]n by 2 matrix containing coordinates of the Projection: A matrix of the fitted configuration.
`PlotIt`	Optional,bool, defaut=FALSE, if =TRUE: U-Marix of every current Position of Databots will be shown
`Cls`	Optional, For plotting, see `plotUmatrix` in package Umatrix
`toroid`	Optional, Default=FALSE, ==FALSE planar computation ==TRUE: toroid borderless computation, set so only if projection method is also toroidal
`Tiled`	Optional,For plotting see `plotUmatrix` in package Umatrix
`ComputeInR`	Optional, =T: Rcode, =F Cpp Code

Value

List with

Umatrix	[1:Lines,1:Columns] (see ReadUMX in package DataIO)
EsomNeurons	[Lines,Columns,weights] 3-dimensional numeric array (wide format), not wts (long format)
Bestmatches	[1:n,OutputDimension] GridConverted Projected Points information converted by convertProjectionProjectedPoints() to predefined Grid by Lines and Columns
gplotres	Ausgabe von ggplot
unbesetztePositionen	Umatrix[unbesetztePositionen] = NA

Author(s)

Michael Thrun

References

[Thrun, 2018] Thrun, M. C.: Projection Based Clustering through Self-Organization and Swarm Intelligence, doctoral dissertation 2017, Springer, ISBN: 978-3-658-20539-3, Heidelberg, 2018.

Examples

```
data("Lsun3D")
Data=Lsun3D$Data
Cls=Lsun3D$Cls
InputDistances=as.matrix(dist(Data))
res=cmdscale(d=InputDistances, k = 2, eig = TRUE, add = FALSE, x.ret = FALSE)
ProjectedPoints=as.matrix(res$points)
# Stress = KruskalStress(InputDistances, as.matrix(dist(ProjectedPoints)))
#resUmatrix=GeneralizedUmatrix(Data,ProjectedPoints)
#plotTopographicMap(resUmatrix$Umatrix,resUmatrix$Bestmatches,Cls)
```

Hepta

Hepta is part of the Fundamental Clustering Problem Suit (FCPS) [Thrun/Ultsch, 2020].

Description

clearly defined clusters, different variances

Usage

```
data("Hepta")
```

Details

Size 212, Dimensions 3, stored in `Hepta$Data`

Classes 7, stored in `Hepta$Cls`

References

[Thrun/Ultsch, 2020] Thrun, M. C., & Ultsch, A.: Clustering Benchmark Datasets Exploiting the Fundamental Clustering Problems, Data in Brief,Vol. 30(C), pp. 105501, DOI 10.1016/j.dib.2020.105501 , 2020.

Examples

```
data(Hepta)
str(Hepta)
```

Lsun3D *Lsun3D is part of the Fundamental Clustering Problem Suit (FCPS) [Thrun/Ultsch, 2020].*

Description

clearly defined clusters, different variances

Usage

```
data("Lsun3D")
```

Details

Size 404, Dimensions 3

Dataset defined discontinuites, where the clusters have different variances. Three main Clusters, and four Outliers (in Cluster 4). See for a more detailed description in [Thrun, 2018].

References

[Thrun/Ultsch, 2020] Thrun, M. C., & Ultsch, A.: Clustering Benchmark Datasets Exploiting the Fundamental Clustering Problems, Data in Brief,Vol. 30(C), pp. 105501, DOI 10.1016/j.dib.2020.105501 , 2020.

Examples

```
data(Lsun3D)
str(Lsun3D)
Cls=Lsun3D$Cls
Data=Lsun3D$Data
```

plotSwarm *Intern function for plotting during the Pswarm annealing process*

Description

Intern function, generates a scatter plot of the progess of the Pswarm algorithm after every nash equlibirum. Every point symbolizes a Databot. If a prior classification is given (`Cls`) then the Databots have the colors defined by the class labels.

Usage

```
plotSwarm(Points,Cls,xlab,ylab,main)
```

Arguments

`Points`	ProjectedPoints or DataBot positions in cartesian coordinates
`Cls`	optional, Classification as a numeric vector, if given
`xlab`	='X', optional, string
`ylab`	='Y', optional, string
`main`	="DataBots", optional, string

Author(s)

Michael Thrun

See Also

`Pswarm` with `PlotIt=TRUE`

ProjectedPoints2Grid *Transforms ProjectedPoints to a grid*

Description

quantized xy cartesianncoordinates of ProjectedPoints

Usage

```
ProjectedPoints2Grid(ProjectedPoints, Lines, Columns,PlotIt)
```

Arguments

ProjectedPoints	[1:n,1:2] numeric matrix of cartesian xy coordinates
Lines	double, length of small side of the rectangular grid
Columns	double, length of big side of the rectangular grid
PlotIt	optional, bool, shows the result if TRUE

Details

intern function, described in [Thrun, 2018, p.47]

Value

BestMatches[1:n,1:3] columns in order: Key,Lines,Columns

Author(s)

Michael Thrun

References

[Thrun, 2018] Thrun, M. C.: Projection Based Clustering through Self-Organization and Swarm Intelligence, doctoral dissertation 2017, Springer, Heidelberg, ISBN: 978-3-658-20539-3, doi:10.1007/9783658205409, 2018.

See Also

GeneratePswarmVisualization

Pswarm *A Swarm of Databots based on polar coordinates (Polar Swarm).*

Description

This projetion method is a part of the databionic swarm which uses the nash equlibrium [Thrun/Ultsch, 2021]. Using polar coordinates for agents (here Databots) in two dimensions has many advantages, for further details see [Thrun, 2018] and [Thrun/Ultsch, 2021].

Usage

```
Pswarm(DataOrDistance,PlotIt=F,Cls=NULL,Silent=T,
Debug=FALSE,LC=c(NULL,NULL),method= "euclidean",...)
```

Arguments

DataOrDistance	Numeric matrix [1:n,1:n]: symmetric matrix of dissimilarities, if variable unsymmetric (Numeric matrix [1:d,1:n]) it is assumed as a dataset and the euclidean distances are calculated of d variables and n cases.
PlotIt	Optional, bool, default=FALSE, If =TRUE, Plots the projection during the computation prozess after every nash equlibirum.
Cls	Optional, numeric vector [1:n], given Classification in numbers, only for plotting if PlotIt=TRUE, irrelevant for computations.
Silent	Optional, bool, default=FALSE, If =TRUE results in various console messages
Debug	Optional, Debug, default=FALSE, =TRUE results in various console messages, depricated for CRAN, because cout is not allowed.
LC	Optional, grid size c(Lines, Columns), sometimes it is better to call setGridSize separately.
method	Optional, one of 39 distance methods of parDist of package parallelDist, if Data matrix is chosen above
...	Further arguments passed on to the parDist function, e.g. user-defined distance functions

Details

DBS is a flexible and robust clustering framework that consists of three independent modules. The first module is the parameter-free projection method Pswarm Pswarm, which exploits the concepts of self-organization and emergence, game theory, swarm intelligence and symmetry considerations. The second module is a parameter-free high-dimensional data visualization technique, which generates projected points on a topographic map with hypsometric colors GeneratePswarmVisualization, called the generalized U-matrix. The third module is a clustering method with no sensitive parameters DBSclustering. The clustering can be verified by the visualization and vice versa. The term DBS refers to the method as a whole.

Value

List with

ProjectedPoints	[1:n,1:2] xy cartesian coordinates of projection
LC	number of Lines and Columns in c(Lines,Columns)
Control	List, only for intern debugging

Note

LC is now automatically estimated; LC is the size of the grid c(Lines,Columns), number of Lines and Columns, default c(NULL,NULL) and automatic calculation by setGridSize

Author(s)

Michael Thrun

References

[Thrun, 2018] Thrun, M. C.: Projection Based Clustering through Self-Organization and Swarm Intelligence, doctoral dissertation 2017, Springer, Heidelberg, ISBN: 978-3-658-20539-3, doi:10.1007/9783658205409, 2018.

[Thrun/Ultsch, 2021] Thrun, M. C., and Ultsch, A.: Swarm Intelligence for Self-Organized Clustering, Artificial Intelligence, Vol. 290, pp. 103237, doi:10.1016/j.artint.2020.103237, 2021.

Examples

```
data("Lsun3D")
Data=Lsun3D$Data
Cls=Lsun3D$Cls
InputDistances=as.matrix(dist(Data))
#If not called separately setGridSize() is called in Pswarm
LC=setGridSize(InputDistances)
res=Pswarm(InputDistances,LC=LC,Cls=Cls,PlotIt=TRUE)
```

PswarmCurrentRadiusC2botsPositive

intern function, do not use yourself

Description

Finds the weak Nash equilibirium for DataBots in one epoch(Radius), requires the setting of constants, grid, and so on in Pswarm

Usage

```
PswarmCurrentRadiusC2botsPositive( AllDataBotsPosOld, Radius, DataDists,
IndPossibleDBPosR, RadiusPositionsschablone, pp, Nullpunkt, Lines, Columns,
nBots, limit, steigungsverlaufind, StressConstAditiv, debug)
```

Arguments

AllDataBotsPosOld	ComplexVector [1:n,1], DataBots position in the last Nash-Equlibriuum
Radius	double, Radius of payoff function, neighborhood, where other DatsBots can be smelled
DataDists	NumericMatrix, Inputdistances[1:n,1:n]
IndPossibleDBPosR	ComplexVector, see output of findPossiblePositionsCsingle
RadiusPositionsschablone	NumericMatrix, see AllallowedDBPosR0 in setPolarGrid

pp	NumericVector, number of jumping simultaneously DataBots of one epoch (per nash-equilibirum), this vector is linearly monotonically decreasing
Nullpunkt	NumericVector, equals `which(AllallowedDBPosR0==0,arr.ind=T)`, see see `AllallowedDBPosR0` in setPolarGrid
Lines	double, small edge length of rectangulare grid
Columns	double, big edge length of rectangulare grid
nBots	double, intern constant, equals `round(pp[Radius]*DBAnzahl)`
limit	int, intern constant, equals `ceiling(1/pp[Radius])`
steigungsverlaufind	int, intern constant
StressConstAditiv	double, intern constant, sum of payoff of all databots in random condition before the algorithm starts
debug	optional, bool: If TRUE prints status every 100 iterations

Details

Algorithm is described in [Thrun, 2018, p. 95, Listing 8.1].

Value

list of

AllDataBotsPos	ComplexVector, indizes of DataBot Positions after a weak Nash equlibrium is found
stressverlauf	NumericVector, intern result, for debugging only
fokussiertlaufind	NumericVector, intern result, for debugging only

Author(s)

Michael Thrun

References

[Thrun, 2018] Thrun, M. C.: Projection Based Clustering through Self-Organization and Swarm Intelligence, doctoral dissertation 2017, Springer, Heidelberg, ISBN: 978-3-658-20539-3, doi:10.1007/9783658205409, 2018.

rDistanceToroidCsingle *Intern function for* Pswarm

Description

toroid distance calculation

Usage

```
rDistanceToroidCsingle(AllDataBotsPosX, AllDataBotsPosY, AllallowedDBPosR0,
Lines, Columns,  Nullpunkt)
```

Arguments

AllDataBotsPosX	NumericVector [1:n,1], positions of on grid
AllDataBotsPosY	NumericVector [1:n,1], positions of on grid
AllallowedDBPosR0	NumericMatrix
Lines	double
Columns	double
Nullpunkt	NumericVector

Details

Part of the algorithm described in [Thrun, 2018, p. 95, Listing 8.1].

Value

numeric matrix of toroid Distances[1:n,1:n]

Note

do not use yourself

Author(s)

Michael Thrun

References

[Thrun, 2018] Thrun, M. C.: Projection Based Clustering through Self-Organization and Swarm Intelligence, doctoral dissertation 2017, Springer, Heidelberg, ISBN: 978-3-658-20539-3, doi:10.1007/9783658205409, 2018.

See Also

Pswarm

RelativeDifference *Relative Difference*

Description

Calculates the difference between positive x and y values

Usage

```
RelativeDifference(X, Y, epsilon = 10^-10,na.rm=FALSE)
```

Arguments

X	either a value or numerical vector of [1:n]
Y	either a value or numerical vector of [1:n]
epsilon	Optional, If both x and y are approximatly zero the output is also zero
na.rm	Optional, function does not work with non finite values. If these cases should be automatically removed, set parameter TRUE

Details

Contrary to other approaches in this cases the range of values lies between [-2,2]. The approach is only valid for positive values ofX and Y. The realtive difference R is defined with

$$R = \frac{Y - X}{0.5 * (X + Y)}$$

Negative value indicate that X is higher than Y and positive values that X is lower than Y.

Value

R

Note

It can be combined with the DelaunayClassificationError if a clear baseline is defined.

Author(s)

Michael Thrun

References

Ultsch, A.: Is Log Ratio a Good Value for Measuring Return in Stock Investments? GfKl 2008, pp, 505-511, 2008.

See Also

DelaunayClassificationError

Examples

```
x=c(1:5)
y=runif(5,min=1,max=10)
RelativeDifference(x,y)
```

RobustNormalization *RobustNormalization*

Description

RobustNormalization as described in [Milligan/Cooper, 1988].

Usage

```
RobustNormalization(Data,Centered=FALSE,Capped=FALSE,

na.rm=TRUE,WithBackTransformation=FALSE,

pmin=0.01,pmax=0.99)
```

Arguments

Data	[1:n,1:d] data matrix of n cases and d features
Centered	centered data around zero by median if TRUE
Capped	TRUE: outliers are capped above 1 or below -1 and set to 1 or -1.
na.rm	If TRUE, infinite vlaues are disregarded
WithBackTransformation	If in the case for forecasting with neural networks a backtransformation is required, this parameter can be set to 'TRUE'.
pmin	defines outliers on the lower end of scale
pmax	defines outliers on the higher end of scale

Details

Normalizes features either between -1 to 1 (Centered=TRUE) or 0-1 (Centered=TRUE) without changing the distribution of a feature itself. For a more precise description please read [Thrun, 2018, p.17].

"[The] scaling of the inputs determines the effective scaling of the weights in the last layer of a MLP with BP neural netowrk, it can have a large effect on the quality of the final solution. At the outset it is best to standardize all inputs to have mean zero and standard deviation 1 [(or at least the range under 1)]. This ensures all inputs are treated equally in the regularization prozess, and allows to choose a meaningful range for the random starting weights."[Friedman et al., 2012]

Value

if `WithBackTransformation=FALSE`: TransformedData[1:n,1:d] i.e., normalized data matrix of n cases and d features

if `WithBackTransformation=TRUE`: List with

`TransformedData`	[1:n,1:d] normalized data matrix of n cases and d features
`MinX`	[1:d] numerical vector used for manual back-transformation of each feature
`MaxX`	[1:d] numerical vector used for manual back-transformation of each feature
`Denom`	[1:d] numerical vector used for manual back-transformation of each feature
`Center`	[1:d] numerical vector used for manual back-transformation of each feature

Author(s)

Michael Thrun

References

[Milligan/Cooper, 1988] Milligan, G. W., & Cooper, M. C.: A study of standardization of variables in cluster analysis, Journal of Classification, Vol. 5(2), pp. 181-204. 1988.

[Friedman et al., 2012] Friedman, J., Hastie, T., & Tibshirani, R.: The Elements of Statistical Learning, (Second ed. Vol. 1), Springer series in statistics New York, NY, USA:, ISBN, 2012.

[Thrun, 2018] Thrun, M. C.: Projection Based Clustering through Self-Organization and Swarm Intelligence, doctoral dissertation 2017, Springer, Heidelberg, ISBN: 978-3-658-20539-3, doi:10.1007/9783658205409, 2018.

See Also

`RobustNorm_BackTrafo`

Examples

```
Scaled = RobustNormalization(rnorm(1000, 2, 100), Capped = TRUE)
hist(Scaled)

m = cbind(c(1, 2, 3), c(2, 6, 4))
List = RobustNormalization(m, FALSE, FALSE, FALSE, TRUE)
TransformedData = List$TransformedData

mback = RobustNorm_BackTrafo(TransformedData, List$MinX, List$Denom, List$Center)

sum(m - mback)
```

RobustNorm_BackTrafo *Transforms the Robust Normalization back*

Description

Transforms the Robust Normalization back if Capped=FALSE

Usage

```
RobustNorm_BackTrafo(TransformedData,

MinX,Denom,Center=0)
```

Arguments

TransformedData	[1:n,1:d] matrix
MinX	scalar
Denom	scalar
Center	scalar

Details

For details see RobustNormalization

Value

1:n,1:d Data matrix

Author(s)

Michael Thrun

See Also

RobustNormalization

Examples

```
data(Hepta)
Data = Hepta$Data
TransList = RobustNormalization(Data, Centered = TRUE, WithBackTransformation = TRUE)

HeptaData = RobustNorm_BackTrafo(TransList$TransformedData,
                                 TransList$MinX,
                                 TransList$Denom,
                                 TransList$Center)

sum(HeptaData - Data) #<e-15
```

sESOM4BMUs *Intern function: Simplified Emergent Self-Organizing Map*

Description

Intern function for the simplified ESOM (sESOM) algorithm for fixed BestMatchingUnits.

Usage

```
sESOM4BMUs(BMUs,Data, esom, toroid, CurrentRadius,ComputeInR)
```

Arguments

BMUs	[1:Lines,1:Columns], BestMAtchingUnits generated by ProjectedPoints2Grid()
Data	[1:n,1:d] array of data: n cases in rows, d variables in columns
esom	[1:Lines,1:Columns,1:weights] array of NeuronWeights, see ListAsEsomNeurons()
toroid	TRUE/FALSE - topology of points
CurrentRadius	number betweeen 1 to x
ComputeInR	=T: Rcode, =F Cpp Codenumber betweeen 1 to x

Details

Algorithm is described in [Thrun, 2018, p. 48, Listing 5.1].

Value

esom	numeric array [1:Lines,1:Columns,1:d], d is the dimension of the weights, the same as in the ESOM algorithm. modified esomneuros regarding a predefined neighborhood defined by a radius

Note

Usually not for seperated usage!

Author(s)

Michael Thrun

References

[Thrun, 2018] Thrun, M. C.: Projection Based Clustering through Self-Organization and Swarm Intelligence, doctoral dissertation 2017, Springer, Heidelberg, ISBN: 978-3-658-20539-3, doi:10.1007/9783658205409, 2018.

See Also

GeneratePswarmVisualization

`setdiffMatrix` *setdiffMatrix shortens Matrix2Curt by those rows that are in both matrices.*

Description

setdiffMatrix shortens Matrix2Curt by those rows that are in both matrices.

Arguments

`Matrix2Curt`	[n,k] matrix, which will be shortened by x rows
`Matrix2compare`	[m,k] matrix whose rows will be compared to those of Matrix2Curt x rows in Matrix2compare equal rows of Matrix2Curt (order of rows is irrelevant). Has the same number of columns as Matrix2Curt.

Value

V$CurtedMatrix[n-x,k] Shortened Matrix2Curt

Author(s)

CL,MT 12/2014

`setGridSize` *Sets the grid size for the Pswarm algorithm*

Description

Automatically sets the size of the grid, formula see [Thrun, 2018, p. 93-94].

Usage

```
setGridSize(InputDistances,minp=0.01,maxp=0.99,alpha=4)
```

Arguments

`InputDistances`	[1:n,1:n] symmetric matrix of input distances
`minp`	default value: 0.01,see `quantile`, first value in the vector of `probs` estimates robust minimum of distances
`maxp`	default value: 0.99, see `quantile`, last value of the vector of `probs` estimates robust maximum of distances
`alpha`	Do not change! Intern parameter, Only if Java Version of Pswarm instead of C++ version is used.

Details

grid is set such that minimum and maximum distances can be shown on the grid

Value

LC=c(Lines,Columns) size of the grid for `Pswarm`

Author(s)

Michael Thrun, Florian Lerch

References

[Thrun, 2018] Thrun, M. C.: Projection Based Clustering through Self-Organization and Swarm Intelligence, doctoral dissertation 2017, Springer, Heidelberg, ISBN: 978-3-658-20539-3, doi:10.1007/9783658205409, 2018.

See Also

automatic choice of LC for `Pswarm`

Examples

```
data("Lsun3D")
Data=Lsun3D$Data
Cls=Lsun3D$Cls
InputDistances=as.matrix(dist(Data))
#If not called separately setGridSize() is called in Pswarm
LC=setGridSize(InputDistances)
```

`setPolarGrid` *Intern function: Sets the polar grid*

Description

Sets a polar grid for a swarm in an rectangular shape

Usage

```
setPolarGrid(Lines,Columns,QuadOrHexa,PlotIt,global)
```

Arguments

`Lines`	Integer, hast to be able to be divided by 2
`Columns`	Integer, with Columns>=Lines
`QuadOrHexa`	bool, default(TRUE) If False Hexagonal grid, default quad grid
`PlotIt`	bool, default(FALSE)
`global`	bool, default(TRUE), intern parameter, how shall the radii be calculated?

Details

Part of the Algorithm described in [Thrun, 2018, p. 95, Listing 8.1].

Value

list of

`GridRadii` matrix [1:Lines,1:Columns], Radii Matrix of all possible Positions of DataBots in Grid

`GridAngle` matrix [1:Lines,1:Columns], Angle Matrix of all possible Positions of DataBots in Grid

`AllallowedDBPosR0`
matrix [1:Lines+1,1:Columns+1], Matrix of radii in polar coordinates respecting origin (0,0) of all allowed DataBots Positions in one jump

`AllallowedDBPosPhi0`
matrix [1:Lines+1,1:Columns+1], # V$AllallowedDBPosPhi0[Lines+1,Lines+1] Matrix of angle in polar coordinates respecting origin (0,0) of all allowed DataBots Positions in one jump

Author(s)

Michael Thrun

References

[Thrun, 2018] Thrun, M. C.: Projection Based Clustering through Self-Organization and Swarm Intelligence, doctoral dissertation 2017, Springer, Heidelberg, ISBN: 978-3-658-20539-3, doi:10.1007/9783658205409, 2018.

See Also

`Pswarm`

`setRmin` *Intern function: Estimates the minimal radius for the Databot scent*

Description

estimates the minimal radius on apolar grid in the automated annealing process of Pswarm, details of how can be read in [Thrun, 2018, p. 97]

Arguments

`Lines`	x-value determining the size of the map, i.e. how many open places for DataBots will be available on the 2-dimensional grid BEWARE: has to be able to be divided by 2
`Columns`	y-value determining the size of the map, i.e. how many open places for DataBots will be available on the 2-dimensional grid Columns>Lines
`AllallowedDBPosR0`	[1:Lines+1,1:Lines+1]Matrix of radii in polar coordinates respecting origin (0,0) of all allowed DataBots Positions in one jump
`p`	percent of gitterpositions, which should be considered

Value

Rmin Minimum Radius

Author(s)

Michael Thrun

References

[Thrun, 2018] Thrun, M. C.: Projection Based Clustering through Self-Organization and Swarm Intelligence, doctoral dissertation 2017, Springer, Heidelberg, ISBN: 978-3-658-20539-3, doi:10.1007/9783658205409, 2018.

`ShortestGraphPathsC` *Shortest GraphPaths = geodesic distances*

Description

Dijkstra's SSSP (Single source shortest path) algorithm, from all points to all points

Usage

```
ShortestGraphPathsC(Adj, Cost)
```

Arguments

`Adj`	[1:n,1:n] 0/1 adjascency matrix, e.g. from delaunay graph or gabriel graph.
`Cost`	[1:n,1:n] matrix, distances between n points (normally euclidean)

Details

Vertices are the points, edges have the costs defined by weights (normally a distance). The algorithm runs in runs in O(n*E*Log(V)), see also [Jungnickel, 2013, p. 87]. Further details can be foubd in [Jungnickel, 2013, p. 83-87] and [Thrun, 2018, p. 12].

Value

ShortestPaths[1:n,1:n] vector, shortest paths (geodesic) to all other vertices including the source vertice itself from al vertices to all vertices, stored as a matrix

Note

require C++11 standard (set flag in Compiler, if not set automatically)

Author(s)

Michael Thrun

References

[Dijkstra,1959] Dijkstra, E. W.: A note on two problems in connexion with graphs, Numerische mathematik, Vol. 1(1), pp. 269-271. 1959.

[Jungnickel, 2013] Jungnickel, D.: Graphs, networks and algorithms, (4th ed ed. Vol. 5), Berlin, Heidelberg, Germany, Springer, ISBN: 978-3-642-32278-5, 2013.

[Thrun/Ultsch, 2017] Thrun, M.C., Ultsch, A.: Projection based Clustering, Conf. Int. Federation of Classification Societies (IFCS),DOI:10.13140/RG.2.2.13124.53124, Tokyo, 2017.

[Thrun, 2018] Thrun, M. C.: Projection Based Clustering through Self-Organization and Swarm Intelligence, doctoral dissertation 2017, Springer, Heidelberg, ISBN: 978-3-658-20539-3, doi:10.1007/9783658205409, 2018.

See Also

`DijkstraSSSP`

`trainstepC` *Internal function for sESOM*

Description

Does the training for fixed bestmatches in one epoch of the sESOM algorithm (see [Thrun, 2018] for details).

Usage

```
trainstepC(vx,vy, DataSampled,BMUsampled,Lines,Columns, Radius, toroid)
```

Arguments

vx	array [1:Lines,1:Columns,1:Weights], WeightVectors that will be trained, internally transformed von NumericVector to cube
vy	array [1:Lines,1:Columns,1:2], meshgrid for output distance computation
DataSampled	NumericMatrix, n cases shuffled Dataset[1:n,1:d] by sample
BMUsampled	NumericMatrix, n cases shuffled BestMatches[1:n,1:2] by sample in the same way as DataSampled
Lines	double, Height of the grid
Columns	double, Width of the grid
Radius	double, The current Radius that should be used to define neighbours to the bm
toroid	bool, Should the grid be considered with cyclically connected borders?

Details

Algorithm is described in [Thrun, 2018, p. 48, Listing 5.1].

Value

WeightVectors, array[1:Lines,1:Columns,1:weights] with the adjusted Weights

Note

Usually not for seperated usage!

Author(s)

Michael Thrun

References

[Thrun, 2018] Thrun, M. C.: Projection Based Clustering through Self-Organization and Swarm Intelligence, doctoral dissertation 2017, Springer, Heidelberg, ISBN: 978-3-658-20539-3, doi:10.1007/9783658205409, 2018.

UniquePoints *Unique Points*

Description

return only the unique points in Datapoints

Usage

```
UniquePoints(Datapoints,Eps)
```

Arguments

Datapoints	[1:n,1:d] matrix of Datapoints points of dimension d, the points are in the rows
Eps	Optional,scalar above zero that defines minimum non-identical euclidean distance between two points

Details

Euclidean distance is computed and used within. Setting Eps to a very small number results in the identification of unique data points. Setting epsilon to a higher number results in the definition of mesh points within an d-dimensional R-ball graph.

Value

List with

Unique	[1:k,1:d] Datapoints points without duplicate points
IsDuplicate	[1:n,1:n] matrix,for i!=j IsDuplicate[i,j]== 1 if Datapoints[i,] == Datapoints[j,] IsDuplicate[i,i]==0
UniqueInd	[1:k] index vector such that Unique == Datapoints[UniqueInd,], it has k non-consecutive numbers or labels, each label defines a row number within Datapoints[1:n,1:d] of a unique data point
Uniq2DatapointsInd	[1:n] index vector. It has k unique index numbers representing the arbitrary labels. Each labels is mapped uniquely to a point in Unique. Logically in a way such that Datapoints == Unique[Uniq2DatapointsInd,] (will not work directly in R this way)

Author(s)

Michael Thrun

Examples

```
Datapoints2D=rbind(c(1,2),c(1,2),c(1,3),c(3,1))
V=UniquePoints(Datapoints2D)
```

Index