

Package ‘DatabionicSwarm’

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Type Package

Title Swarm Intelligence for Self-Organized Clustering

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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>. A comparison to 26 common clustering algorithms on 15 datasets is presented on the website.

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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

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LazyData TRUE

URL <http://www.deepbionics.org>

Encoding UTF-8

VignetteBuilder knitr

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

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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>. A comparison to 26 common clustering algorithms on 15 datasets is presented on the website.

Details

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

Package: Databionic swarm
 Type: Package
 Version: 1.1.5
 Date: 2021-01-12
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Index of help topics:

ClusteringAccuracy	ClusteringAccuracy
DBSclustering	Databionic 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
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 verify 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

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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 GeneralizedUmatrix,
# 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 interactively 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	
CurrentCls	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=DBScustering(k=7, Hepta$Data, visualization$Bestmatches,

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

```

DBScustering

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](#), 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 [DBScustering](#) (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 [DBScustering](#) 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

```

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

```

Arguments

k	number of clusters, how many to you see in the topographic map (3D landscape)?
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 vor 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 interactively 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, CIs)` for verification.

Note

If you want to verify 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](https://doi.org/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
## thorough 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	<i>Adjacency matrix of the delaunay graph for BestMatches of Points</i>
-----------------	---

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](https://doi.org/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]
ProjectedPoints	[1:n,1:2]
Cls	[1:n,1]
LC	Optional, default NULL, Wenn toroid, muss c(Lines,Columns) angegeben werden

Details

Delaunay classification error (DCE) makes an unbiased evaluation of distance and densitybased 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: $DCE = \text{mean}(DCEperPoint)$
nn the number of points in a relevant neighborhood: $0.5 * 85\text{percentile}(AnzNN)$
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	<i>Intern function</i>
-----------------	------------------------

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](https://doi.org/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	int, 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 $O(E*\text{Log}(V))$

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 and a 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, jumplength 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, indices 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](https://doi.org/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 reduce computational 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 $x \times \text{res} \times \text{LC}$ 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	matrix [1:n,1:2], BestMatches of the Umatrix, contrary to ESOM they are always fixed, because predefined by GridPoints.
Umatrix	matrix [1:Lines,1:Columns],
WeightsOfNeurons	array [1:Lines,1:Columns,1:d], d is the dimension of the weights, the same as in the ESOM algorithm
GridPoints	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 plotting 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 `interactiveGeneralizedUmatrixIsland` 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](https://doi.org/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](https://doi.org/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,Columns	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] array of data: 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, default=FALSE, if =TRUE: U-Marix of every current Position of Dababots 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 discontinuities, 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 progress of the Pswarm algorithm after every nash equilibrium. 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, xlabel, ylabel, 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 cartesian coordinates of ProjectedPoints

Usage

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

Arguments

ProjectedPoints	[1:n,1:2] 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](https://doi.org/10.1007/9783658205409), 2018.

See Also

[GeneratePswarmVisualization](#)

Pswarm

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

Description

This projection method is a part of the databionic swarm which uses the nash equilibrium [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	matrix, DataOrDistance[1:n,1:n] symmetric matrix of dissimilarities, if variable unsymmetric DataOrDistance[1:d,1:n] 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 equilbirum
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, deprecated for CRAN, because cout is not allowed.
LC	Optional, grid size c(Lines, Columns), sometimes it is better to call <code>setGridSize</code> separately.
method	Optional, one of 39 distance methods of <code>parDist</code> of package <code>parallelDist</code> , if Data matrix is chosen above
...	Further arguments passed on to the <code>parDist</code> 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 `DBScustering`. 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](https://doi.org/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](https://doi.org/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 equilibrium 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-Equilibrium
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 eepoch (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 equilibrium 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](https://doi.org/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](https://doi.org/10.1007/9783658205409), 2018.

See Also[Pswarm](#)

RelativeDifference	<i>Relative Difference</i>
--------------------	----------------------------

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 of X 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=FALSE) 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 besto 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](https://doi.org/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 between 1 to x
ComputeInR	=T: Rcode, =F Cpp Codenumber between 1 to x

Details

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

Value

esom	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](https://doi.org/10.1007/9783658205409), 2018.

See Also

[GeneratePswarmVisualization](#)

setdiffMatrix	<i>setdiffMatrix shortens Matrix2Curt by those rows that are in both matrices.</i>
---------------	--

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	<i>Sets the grid size for the Pswarm algorithm</i>
-------------	--

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](https://doi.org/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](https://doi.org/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](https://doi.org/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 $O(n \cdot E \cdot \log(V))$, see also [Jungnickel, 2013, p. 87]. Further details can be found 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 all 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

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

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[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](https://doi.org/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](https://doi.org/10.1007/9783658205409), 2018.

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