Package 'TDA'

September 18, 2015

Type Package

Title Statistical Tools for Topological Data Analysis

Version 1.4.1

Date 2015-08-20

Author Brittany T. Fasy, Jisu Kim, Fabrizio Lecci, Clement Maria, Vincent Rouvreau. The included GUDHI is authored by Clement Maria, Dionysus by Dmitriy Morozov, and PHAT by Ulrich Bauer, Michael Kerber, and Jan Reininghaus.

Maintainer Jisu Kim <jisuk1@andrew.cmu.edu>

Description Tools for the statistical analysis of persistent homology and for density clustering. For that, this package provides an R interface for the efficient algorithms of the C++ libraries GUDHI, Dionysus, and PHAT.

Depends $R (= 3.1.0)$

Repository CRAN

License GPL-3

Imports FNN, igraph, parallel, scales, $\text{Rcpp} (> = 0.11.0)$

LinkingTo Rcpp, BH $(>= 1.58.0-1)$

NeedsCompilation yes

Date/Publication 2015-09-18 08:58:27

R topics documented:

2 TDA-package

TDA-package *Statistical Tools for Topological Data Analysis*

Description

Tools for Topological Data Analysis. In particular it provides functions for the statistical analysis of persistent homology and for density clustering. For that, this package provides an R interface for the efficient algorithms of the C++ libraries GUDHI, Dionysus and PHAT.

Details

Author(s)

Brittany Terese Fasy, Jisu Kim, Fabrizio Lecci, Clement Maria, Vincent Rouvreau Maintainer: Jisu Kim <jisuk1@andrew.cmu.edu>

References

Herbert Edelsbrunner, and John Harer, (2010), "Computational topology: an introduction". American Mathematical Society.

bootstrapBand 3

Brittany T. Fasy, Fabrizio Lecci, Alessandro Rinaldo, Larry Wasserman, Sivaraman Balakrishnan, and Aarti Singh. (2013), "Statistical Inference For Persistent Homology: Confidence Sets for Persistence Diagrams", (arXiv:1303.7117). To appear, Annals of Statistics.

Chazal F, Fasy BT, Lecci F, Michel B, Rinaldo A, Wasserman L (2014). "Robust Topological Inference: Distance-To-a-Measure and Kernel Distance." Technical Report.

Frederic Chazal, Brittany T. Fasy, Fabrizio Lecci, Alessandro Rinaldo, and Larry Wasserman, (2014), "Stochastic Convergence of Persistence Landscapes and Silhouettes", Proceedings of the 30th Symposium of Computational Geometry (SoCG). (arXiv:1312.0308)

Frederic Chazal, Brittany T. Fasy, Fabrizio Lecci, Bertrand Michel, Alessandro Rinaldo, and Larry Wasserman, (2014), "Subsampling Methods for Persistent Homology". (arXiv:1406.1901)

Clement Maria, "GUDHI, Simplicial Complexes and Persistent Homology Packages". https://project.inria.fr/gudhi/software/.

Dmitriy Morozov, "Dionysus, a C++ library for computing persistent homology". http://www.mrzv.org/software/dionysus/

Ulrich Bauer, Michael Kerber, Jan Reininghaus, "PHAT, a software library for persistent homology". https://code.google.com/p/phat/

bootstrapBand *Bootstrap Confidence Band*

Description

bootstrapBand computes a uniform symmetric confidence band around a function of the data X, evaluated on a Grid, using the bootstrap algorithm. See Details and References.

Usage

bootstrapBand(X, FUN, Grid, B = 30, alpha = 0.05, parallel = FALSE, $printProgress = FALSE, weight = NULL, ...)$

Arguments

Details

First, the input function FUN is evaluated on the Grid using the original data X. Then, for B times, the bootstrap algorithm subsamples n points of X (with replacement), evaluates the function FUN on the Grid using the subsample, and computes the ℓ_{∞} distance between the original function and the bootstrapped one. The result is a sequence of B values. The (1-alpha) confidence band is constructed by taking the (1-alpha) quantile of these values.

Value

Returns a list with the following elements:

Author(s)

Jisu Kim, Fabrizio Lecci

References

Larry Wasserman (2004), "All of statistics: a concise course in statistical inference", Springer.

Brittany T. Fasy, Fabrizio Lecci, Alessandro Rinaldo, Larry Wasserman, Sivaraman Balakrishnan, and Aarti Singh. (2013), "Statistical Inference For Persistent Homology: Confidence Sets for Persistence Diagrams", (arXiv:1303.7117). To appear, Annals of Statistics.

Chazal F, Fasy BT, Lecci F, Michel B, Rinaldo A, Wasserman L (2014). "Robust Topological Inference: Distance-To-a-Measure and Kernel Distance." Technical Report.

See Also

[kde](#page-18-1), [dtm](#page-12-1)

bootstrapDiagram 5

Examples

```
# Generate data from mixture of 2 normals.
n < -2000X \leq c (rnorm(n / 2), rnorm(n / 2, mean = 3, sd = 1.2))
# Construct a grid of points over which we evaluate the function
by <-0.02Grid \leq seq(-3, 6, by = by)
## bandwidth for kernel density estimator
h < -0.3## Bootstrap confidence band
band \leq bootstrapBand(X, kde, Grid, B = 80, parallel = FALSE, alpha = 0.05,
                      h = h)
plot(Grid, band[["fun"]], type = "l", lwd = 2,ylim = c(0, max(band[["band"]])), main = "kde with 0.95 confidence band")
lines(Grid, pmax(band[["band"]][, 1], 0), col = 2, lwd = 2)lines(Grid, band[["band"]][, 2], col = 2, 1wd = 2)
```


Description

bootstrapDiagram computes a (1-alpha) confidence set for the Persistence Diagram of a filtration of sublevel sets (or superlevel sets) of a function evaluated over a grid of points. The function returns the (1-alpha) quantile of B bottleneck distances (or Wasserstein distances), computed in B iterations of the bootstrap algorithm. The method is discussed in the 1st reference.

Usage

```
bootstrapDiagram(X, FUN, lim, by, maxdimension = length(lim) / 2 - 1,
                 sublevel = TRUE, library = "Dionysus", B = 30, alpha = 0.05,
                 distance = "bottleneck", dimension = min(1, maxdimension),
              p = 1, parallel = FALSE, printProgress = FALSE, weight = NULL, ...)
```
Arguments

Details

bootstrapDiagram uses gridDiag to compute the persistence diagram of the input function using the entire sample. Then the bootstrap algorithm, for B times, computes the bottleneck distance between the original persistence diagram and the one computed using a subsample. Finally the (1-alpha) quantile of these B values is returned.

Value

Returns the (1-alpha) quantile of the values computed by the bootstrap algorithm.

Note

This function uses the C++ library Dionysus for the computation of bottleneck and Wasserstein distances. See references.

Author(s)

Jisu Kim, Fabrizio Lecci

bottleneck **7**

References

Chazal F, Fasy BT, Lecci F, Michel B, Rinaldo A, Wasserman L (2014). "Robust Topological Inference: Distance-To-a-Measure and Kernel Distance." Technical Report.

Larry Wasserman (2004), "All of statistics: a concise course in statistical inference", Springer.

Dmitriy Morozov, "Dionysus, a C++ library for computing persistent homology". http://www.mrzv.org/software/dionysus/

See Also

[bottleneck](#page-6-1), [bootstrapBand](#page-2-1), [distFct](#page-11-1), [kde](#page-18-1), [kernelDist](#page-19-1), [dtm](#page-12-1), [summary.diagram](#page-37-1), [plot.diagram](#page-29-1),

Examples

```
## confidence set for the Kernel Density Diagram
```

```
# input data
n < -400XX <- circleUnif(n)
## Ranges of the grid
Xlim \leftarrow c(-1.8, 1.8)Ylim \leq c(-1.6, 1.6)lim <- cbind(Xlim, Ylim)
by <-0.05h <- .3 #bandwidth for the function kde
#Kernel Density Diagram of the superlevel sets
Diag <- gridDiag(XX, kde, lim = lim, by = by, sublevel = FALSE,
                 printProgress = TRUE, h = h)
# confidence set
B \le -10 ## the number of bootstrap iterations should be higher!
              ## this is just an example
alpha \leq -0.05cc < - bootstrapDiagram(XX, kde, lim = lim, by = by, sublevel = FALSE, B = B,
          alpha = alpha, dimension = 1, printProgress = TRUE, h = h)
plot(Diag[["diagram"]], band = 2 * cc)
```
bottleneck *Bottleneck distance between two persistence diagrams*

Description

This function computes the bottleneck distance between two persistence diagrams

Usage

bottleneck(Diag1, Diag2, dimension = 1)

Arguments

Details

The bottleneck distance between two diagrams is the cost of the optimal matching between points of the two diagrams. Note that all the diagonal points are included in the persistence diagrams when computing the optimal matching. When a vector is given for dimension, then maximum among bottleneck distances using each element in dimension is returned. This function is an R wrapper of the function "bottleneck_distance" in the C++ library Dionysus. See references.

Value

Returns the value of the bottleneck distance between the two persistence diagrams.

Author(s)

Jisu Kim, Fabrizio Lecci

References

Dmitriy Morozov, "Dionysus, a C++ library for computing persistent homology". http://www.mrzv.org/software/dionysus/ Herbert Edelsbrunner and John Harer (2010), Computational topology: an introduction. American Mathematical Society.

See Also

[wasserstein](#page-39-1), [ripsDiag](#page-32-1), [gridDiag](#page-14-1), [plot.diagram](#page-29-1)

```
XX1 <- circleUnif(20)
XX2 \le circleUnif(20, r = 0.2)
DiagLim <- 5
maxdimension <- 1
Diag1 <- ripsDiag(XX1, maxdimension, DiagLim, printProgress = FALSE)
Diag2 <- ripsDiag(XX2, maxdimension, DiagLim, printProgress = FALSE)
```
circleUnif 9

```
bottleneckDist <- bottleneck(Diag1[["diagram"]], Diag2[["diagram"]],
                             dimension = 1)
print(bottleneckDist)
```
circleUnif *Uniform Sample From The Circle*

Description

This function samples n points from the circle of radius r, uniformly with respect to the circumference length.

Usage

 $circleUnif(n, r = 1)$

Arguments

Value

circleUnif returns an n by 2 matrix of coordinates.

Note

Uniform sample from sphere of arbitrary dimension can be generated using [sphereUnif](#page-36-1).

Author(s)

Fabrizio Lecci

See Also

[sphereUnif](#page-36-1), [torusUnif](#page-38-1)

Examples

X <- circleUnif(100) plot(X)

Description

Given a point cloud, or a matrix of distances, this function computes a density estimator and returns the corresponding cluster tree of superlevel sets (lambda tree and kappa tree; see references).

Usage

```
clusterTree(X, k, h = NULL, density = "knn", dist = "euclidean", d = NULL,
            Nlambda = 100, printProgress = FALSE)
```
Arguments

Details

This function is an implementation of Algorithm 1 in the first reference.

Value

This function returns an object of class clusterTree, a list with the following components

density Vector of length n: the values of the density estimator evaluated at each of the points stored in X

clusterTree 2008 and 200

Author(s)

Fabrizio Lecci

References

Brian P. Kent, Alessandro Rinaldo, and Timothy Verstynen, (2013), "DeBaCl: A Python Package for Interactive DEnsity-BAsed CLustering."arXiv:1307.8136

Fabrizio Lecci, Alessandro Rinaldo, and Larry Wasserman, (2014), "Metric Embeddings for Cluster Trees"

See Also

[plot.clusterTree](#page-27-1)

Examples

```
## Generate data: 3 clusters
n <- 1200 #sample size
Neach \leq floor(n / 4)
X1 <- cbind(rnorm(Neach, 1, .8), rnorm(Neach, 5, 0.8))
X2 <- cbind(rnorm(Neach, 3.5, .8), rnorm(Neach, 5, 0.8))
X3 <- cbind(rnorm(Neach, 6, 1), rnorm(Neach, 1, 1))
X \leftarrow \text{rbind}(X1, X2, X3)k <- 100 #parameter of knn
## Density clustering using knn and kde
Tree <- clusterTree(X, k, density = "knn")
TreeKDE \le clusterTree(X, k, h = 0.3, density = "kde")
par(mfrow = c(2, 3))plot(X, pch = 19, cex = 0.6)# plot lambda trees
plot(Tree, type = "lambda", main = "lambda Tree (knn)")
plot(TreeKDE, type = "lambda", main = "lambda Tree (kde)")
# plot clusters
plot(X, pch = 19, cex = 0.6, main = "cluster labels")for (i in Tree[["id"]]){
  points(matrix(X[Tree[["DataPoints"]][[i]],],ncol = 2), col = i, pch = 19,
         cex = 0.6}
#plot kappa trees
plot(Tree, type = "kappa", main = "kappa Tree (knn)")
plot(TreeKDE, type = "kappa", main = "kappa Tree (kde)")
```
distFct *Distance function*

Description

This function computes the distance between each point of a set Grid and the corresponding closest point of another set X.

Usage

distFct(X, Grid)

Arguments

Details

Given a set of points X , the distance function computed at q is defined as

$$
d(g) = \inf_{x \in X} ||x - g||_2
$$

Value

Returns a numeric vector of length n , where n is the number of points stored in Grid.

Author(s)

Fabrizio Lecci

See Also

[kde](#page-18-1),[kernelDist](#page-19-1), [dtm](#page-12-1)

Examples

```
## Generate Data from the unit circle
n <- 300
X <- circleUnif(n)
## Construct a grid of points over which we evaluate the function
by <- 0.065
Xseq \leq -seq(-1.6, 1.6, by = by)Yseq <- seq(-1.7, 1.7, by = by)Grid <- expand.grid(Xseq, Yseq)
## distance fct
distance <- distFct(X, Grid)
```
dtm *Distance to Measure Function*

Description

This function computes the "distance to measure function" on a set of points Grid, using the uniform empirical measure on a set of points X. Given a probability measure P , The distance to measure function, for each $y \in R^d$, is defined by

$$
d_{m_0}(y) = \sqrt{\frac{1}{m_0} \int_0^{m_0} (G_y^{-1}(u))^2 du},
$$

where $G_y(t) = P(||X - y|| \le t)$ and $0 < m_0 < 1$ is a smoothing parameter. See Details and References.

Given $X = \{x_1, \ldots, x_n\}$, the empirical version of the distance to measure is

$$
\hat{d}_{m_0}(y) = \sqrt{\frac{1}{k} \sum_{x_i \in N_k(y)} ||x_i - y||^2},
$$

where $k = \lfloor m_0 n \rfloor$ and $N_k(y)$ is the set containing the k nearest neighbors of y among x_1, \ldots, x_n .

Usage

 $dtm(X, Grid, m0, weight = 1)$

Arguments

Details

See Definition 3.2 of the reference for a formal definition of the "distance to measure" function.

Value

dtm returns a vector of length m (the number of points stored in Grid) containing the value of the distance to measure function evaluated at each point of Grid.

Author(s)

Jisu Kim, Fabrizio Lecci

References

Frederic Chazal, David Cohen-Steiner, and Quentin Merigot. "Geometric inference for probability measures." Foundations of Computational Mathematics 11.6 (2011): 733-751.

Chazal F, Fasy BT, Lecci F, Michel B, Rinaldo A, Wasserman L (2014). "Robust Topological Inference: Distance-To-a-Measure and Kernel Distance." Technical Report.

See Also

[kde](#page-18-1), [kernelDist](#page-19-1), [distFct](#page-11-1)

gridDiag 15

Examples

```
## Generate Data from the unit circle
n < -300X <- circleUnif(n)
## Construct a grid of points over which we evaluate the function
by <-0.065Xseq \leftarrow seq(-1.6, 1.6, by = by)Yseq <- seq(-1.7, 1.7, by = by)Grid <- expand.grid(Xseq, Yseq)
## distance to measure
m0 < -0.1DTM <- dtm(X, Grid, m0)
```
gridDiag *Persistence Diagram of a function over a Grid*

Description

gridDiag computes the Persistence Diagram of a filtration of sublevel sets (or superlevel sets) of a function evaluated over a grid of points in arbitrary dimension d.

Usage

```
gridDiag(X = NULL, FUN = NULL, lim = NULL, by = NULL, FUNvalues = NULL,maxdimension = max(NCOL(X), length(dim(FUNvalues))) - 1,sublevel = TRUE, library = "Dionysus", location = FALSE,
         printProgress = FALSE, diagLimit = NULL, ...)
```
Arguments

Details

If the values of X, FUN, lim, and by are set, then FUNvalues should be NULL. In this case, gridDiag evaluates the function FUN over a grid. If the value of FUNvalues is set, then X, FUN, lim, and by should be NULL. In this case, FUNvalues is used as function values over the grid.

Once function values are either computed or given, gridDiag constructs a filtration by triangulating the grid and considering the simplices determined by the values of the function of dimension up to maxdimension+1.

Value

gridDiag returns a list with the following components:

gridDiag and the state of t

```
cycleLocation only if location = TRUE and library = "Dionysus": a list of length P, where
                  P is the number of points in the resulting persistence diagram. Each element is
                  a P_i by d matrix and represents location of P_i grid points on a representative
                  cycle of each homological feature.
```
Note

The user can decide to use either the C++ library Dionysus or the C++ library PHAT. See references.

Since dimension of simplicial complex from grid points in R^d is up to d, homology of dimension $>= d$ is trivial. Hence setting maxdimension with values $>= d$ is equivalent to maxdimension=d-1.

Author(s)

Brittany T. Fasy, Jisu Kim, and Fabrizio Lecci

References

Brittany Fasy, Fabrizio Lecci, Alessandro Rinaldo, Larry Wasserman, Sivaraman Balakrishnan, and Aarti Singh. (2013), "Statistical Inference For Persistent Homology", (arXiv:1303.7117). To appear, Annals of Statistics.

Dmitriy Morozov, "Dionysus, a C++ library for computing persistent homology". http://www.mrzv.org/software/dionysus/

Ulrich Bauer, Michael Kerber, Jan Reininghaus, "PHAT, a software library for persistent homology". https://code.google.com/p/phat/

See Also

[summary.diagram](#page-37-1), [plot.diagram](#page-29-1), [distFct](#page-11-1), [kde](#page-18-1), [kernelDist](#page-19-1), [dtm](#page-12-1), [ripsDiag](#page-32-1)

Examples

Distance Function Diagram and Kernel Density Diagram

```
# input data
n <- 300
XX <- circleUnif(n)
## Ranges of the grid
Xlim \leftarrow c(-1.8, 1.8)Ylim \leq c(-1.6, 1.6)lim <- cbind(Xlim, Ylim)
by <-0.05h <- .3 #bandwidth for the function kde
#Distance Function Diagram of the sublevel sets
Diag1 <- gridDiag(XX, distFct, lim = lim, by = by, sublevel = TRUE,
                  printProgress = TRUE)
#Kernel Density Diagram of the superlevel sets
Diag2 <- gridDiag(XX, kde, lim = lim, by = by, sublevel = FALSE,
```

```
location = TRUE, printProgress = TRUE, h = h)
#plot
par(mfrow = c(2, 2))plot(XX, cex = 0.5, pch = 19)title(main = "Data")
plot(Diag1[["diagram"]])
title(main = "Distance Function Diagram")
plot(Diag2[["diagram"]])
title(main = "Density Persistence Diagram")
one <- which(Diag2[["diagram"]][, 1] == 1)
plot(XX, col = 2, main = "Representative loop of grid points")
for (i in seq(along = one))
{
 points(Diag2[["birthLocation"]][one[i], ], pch = 15, cex = 3, col = i)
 points(Diag2[["deathLocation"]][one[i], ], pch = 17, cex = 3, col = i)
 points(Diag2[["cycleLocation"]][[one[i]]], pch = 19, cex = 1, col = i)
}
```
hausdInterval *Subsampling Confidence Interval for the Hausdorff Distance between a Manifold and a Sample*

Description

hausdInterval computes a confidence interval for the Hausdorff distance between a point cloud X and the underlying manifold from which X was sampled. See Details. The validity of the method is proved in the 1st Reference.

Usage

```
hausdInterval(X, m, B = 30, alpha = 0.05, parallel = FALSE,
              printProgress = FALSE)
```
Arguments

Details

For B times, the subsampling algorithm subsamples m points of X (without replacement) and computes the Hausdorff distance between the original sample X and the subsample. The result is a sequence of B values. Let q be the (1-alpha) quantile of these values and let $c = 2 * q$. The interval $[0, c]$ is a valid (1-alpha) confidence interval for the Hausdorff distance between X and the underlying manifold, as proven in Theorem 3 of the first reference.

kde te beste b

Value

Returns a number c. The confidence interval is $[0, c]$.

Author(s)

Fabrizio Lecci

References

Brittany T. Fasy, Fabrizio Lecci, Alessandro Rinaldo, Larry Wasserman, Sivaraman Balakrishnan, and Aarti Singh. (2013), "Statistical Inference For Persistent Homology: Confidence Sets for Persistence Diagrams", (arXiv:1303.7117). To appear, Annals of Statistics.

See Also

[bootstrapBand](#page-2-1)

Examples

X <- circleUnif(1000) $interval \leftarrow$ hausdInterval(X, $m = 800$) print(interval)

kde *Kernel Density Estimator over a Grid of Points*

Description

Given a point cloud X (n points), this function computes the Kernel Density Estimator over a grid of points. The kernel is a Gaussian Kernel with smoothing parameter h. For each $x \in R^d$, the Kernel Density estimator is defined as

$$
p_X(x) = \frac{1}{n(\sqrt{2\pi}h)^d} \sum_{i=1}^n \exp\left(\frac{-\|x - X_i\|_2^2}{2h^2}\right).
$$

Usage

```
kde(X, Grid, h, weight = 1, printProgress = FALSE)
```
Arguments

Value

kde returns a vector of length m (the number of points in the grid) containing the value of the kernel density estimator for each point in the grid.

Author(s)

Jisu Kim, Fabrizio Lecci

References

Larry Wasserman (2004), "All of statistics: a concise course in statistical inference", Springer.

Brittany T. Fasy, Fabrizio Lecci, Alessandro Rinaldo, Larry Wasserman, Sivaraman Balakrishnan, and Aarti Singh. (2013), "Statistical Inference For Persistent Homology: Confidence Sets for Persistence Diagrams", (arXiv:1303.7117). To appear, Annals of Statistics.

See Also

[kernelDist](#page-19-1), [distFct](#page-11-1), [dtm](#page-12-1)

Examples

```
## Generate Data from the unit circle
n < -300X <- circleUnif(n)
## Construct a grid of points over which we evaluate the function
by <-0.065Xseq \leftarrow seq(-1.6, 1.6, by=by)Yseq <- seq(-1.7, 1.7, by=by)
Grid <- expand.grid(Xseq,Yseq)
## kernel density estimator
h < -0.3KDE <- kde(X, Grid, h)
```


kernelDist *Kernel distance over a Grid of Points*

Description

Given a point cloud X, this function computes the kernel distance over a grid of points. The kernel is a Gaussian Kernel with smoothing parameter h:

$$
K_h(x, y) = \exp \left(\frac{-\|x - y\|_2^2}{2h^2} \right).
$$

For each $x \in R^d$ the Kernel distance is defined by

$$
\kappa_X(x) = \sqrt{\frac{1}{n^2} \sum_{i=1}^n \sum_{j=1}^n K_h(X_i, X_j) + K_h(x, x) - 2 \frac{1}{n} \sum_{i=1}^n K_h(x, X_i)}.
$$

kernelDist 21

Usage

```
kernelDist(X, Grid, h, weight = 1, printProgress = FALSE)
```
Arguments

Value

kernelDist returns a vector of lenght m (the number of points in the grid) containing the value of the Kernel distance for each point in the grid.

Author(s)

Jisu Kim, Fabrizio Lecci

References

Jeff M. Phillips, Bei Wang, and Yan Zheng (2013), "Geometric Inference on Kernel Density Estimates," arXiv:1307.7760.

Chazal F, Fasy BT, Lecci F, Michel B, Rinaldo A, Wasserman L (2014). "Robust Topological Inference: Distance-To-a-Measure and Kernel Distance." Technical Report.

See Also

[kde](#page-18-1), [dtm](#page-12-1), [distFct](#page-11-1)

Examples

```
## Generate Data from the unit circle
n < -300X <- circleUnif(n)
```

```
## Construct a grid of points over which we evaluate the functions
by <-0.065Xseq \leq -seq(-1.6, 1.6, by = by)Yseq <- seq(-1.7, 1.7, by = by)Grid <- expand.grid(Xseq, Yseq)
## kernel distance estimator
```
 $h < -0.3$ Kdist <- kernelDist(X, Grid, h)

Description

Given a point cloud X (*n* points), this function computes the k Nearest Neighbors Density Estimator over a grid of points. For each $x \in R^d$, the knn Density Estimator is defined by

$$
p_X(x) = \frac{k}{n v_d r_k^d(x)},
$$

where v_n is the volume of the Euclidean d dimensional unit ball and $r_k^d(x)$ is the Euclidean distance form point x to its k 'th closest neighbor.

Usage

knnDE(X, Grid, k)

Arguments

Value

knnDE returns a vector of length m (the number of points in the grid) containing the value of the knn Density Estimator for each point in the grid.

Author(s)

Fabrizio Lecci

See Also

[kde](#page-18-1),[kernelDist](#page-19-1), [distFct](#page-11-1), [dtm](#page-12-1)

```
## Generate Data from the unit circle
n <- 300
X <- circleUnif(n)
## Construct a grid of points over which we evaluate the function
by <- 0.065
Xseq \leq -seq(-1.6, 1.6, by = by)Yseq \leq seq(-1.7, 1.7, by = by)
```
landscape 23

```
Grid <- expand.grid(Xseq, Yseq)
## kernel density estimator
k < -50KNN <- knnDE(X, Grid, k)
```
landscape *The Persistence Landscape Function*

Description

This function computes the landscape function corresponding to a given persistence diagram.

Usage

landscape(Diag, dimension = 1 , KK = 1 , tseq = seq(min(Diag[,2:3]), max(Diag[,2:3]), length=500))

Arguments

Value

Returns a numeric matrix with the number of row as the length of tseq and the number of column as the length of KK. The value at ith row and jth column represents the value of the KK[j]-th landscape function evaluated at tseq[i].

Author(s)

Fabrizio Lecci

References

Peter Bubenik, (2012), "Statistical topology using persistence landscapes", arXiv1207.6437.

Frederic Chazal, Brittany T. Fasy, Fabrizio Lecci, Alessandro Rinaldo, and Larry Wasserman, (2014), "Stochastic Convergence of Persistence Landscapes and Silhouettes", Proceedings of the 30th Symposium of Computational Geometry (SoCG). (arXiv:1312.0308)

See Also

[silhouette](#page-35-1)

Examples

```
Diag \le matrix(c(0, 0, 10, 1, 0, 3, 1, 3, 8), ncol = 3, byrow = TRUE)
DiagLim <- 10
colnames(Diag) <- c("dimension", "Birth", "Death")
#persistence landscape
tseq <- seq(0,DiagLim, length = 1000)
Land \leq landscape(Diag, dimension = 1, KK = 1, tseq)
par(mfrow = c(1,2))plot.diagram(Diag)
plot(tseq, Land, type = "l", xlab = "t", ylab = "landscape", asp = 1)
```
maxPersistence *Maximal Persistence Method*

Description

Given a point cloud and a function built on top of the data, we are interested in studying the evolution of the sublevel sets (or superlevel sets) of the function, using persistent homology. The Maximal Persistence Method selects the optimal smoothing parameter of the function, by maximizing the number of significant topological features, or by maximizing the total significant persistence of the features. For each value of the smoothing parameter, this function computes a persistence diagram using gridDiag and returns the values of the two criteria, the dimension of detected features, their persistence, and a bootstrapped confidence band. The features that fall outside of the band are statistically significant. See References.

Usage

```
maxPersistence(FUN, parameters, X, lim, by, maxdimension = length(lim) / 2 - 1,
               sublevel = TRUE, library = "Dionysus", B = 30, alpha = 0.05,
               bandFUN = "bootstrapBand", distance = "bottleneck",
               dimension = min(1, maxdimension), p = 1, parallel = FALSE,
               printProgress = FALSE, weight = NULL)
```
Arguments

Details

maxPersistence calls the [gridDiag](#page-14-1) function, which computes the persistence diagram of sublevel (or superlevel) sets of a function, evaluated over a grid of points.

Value

The function returns an object of the class "maxPersistence", a list with the following components

Author(s)

Jisu Kim, Fabrizio Lecci

References

Frederic Chazal, Jessi Cisewski, Brittany T. Fasy, Fabrizio Lecci, Bertrand Michel, Alessandro Rinaldo, and Larry Wasserman, (2014), "Robust Topological Inference: distance-to-a-measure and kernel distance"

Brittany T. Fasy, Fabrizio Lecci, Alessandro Rinaldo, Larry Wasserman, Sivaraman Balakrishnan, and Aarti Singh. (2013), "Statistical Inference For Persistent Homology", (arXiv:1303.7117). To appear, Annals of Statistics.

See Also

[gridDiag](#page-14-1), [kde](#page-18-1), [kernelDist](#page-19-1), [dtm](#page-12-1), [bootstrapBand](#page-2-1)

```
## input data: circle with clutter noise
n < - 600percNoise <- 0.1
XX1 <- circleUnif(n)
noise \le cbind(runif(percNoise * n, -2, 2), runif(percNoise * n, -2, 2))
X <- rbind(XX1, noise)
## limits of the Gird at which the density estimator is evaluated
Xlim < -c(-2, 2)Ylim <-c(-2, 2)lim <- cbind(Xlim, Ylim)
by <-0.2B < - 80alpha <-0.05## candidates
parametersKDE \leq seq(0.1, 0.5, by = 0.2)
maxKDE <- maxPersistence(kde, parametersKDE, X, lim = lim, by = by,
                         bandFUN = "bootstrapBand", B = B, alpha = alpha,
                         parallel = FALSE, printProgress = TRUE)
print(summary(maxKDE))
par(mfrow = c(1,2))plot(X, pch = 16, cex = 0.5, main = "Circle")
```
plot(maxKDE)

multipBootstrap *Multiplier Bootstrap for Persistence Landscapes and Silhouettes*

Description

This function computes a confidence band for the average landscape (or the average silhouette) using the multiplier bootstrap.

Usage

```
multipBootstrap(Y, B = 30, alpha = 0.05, parallel = FALSE, printProgress = FALSE)
```
Arguments

Details

See Algorithm 1 in the reference.

Value

Returns a list with the following elements:

Author(s)

Fabrizio Lecci

References

Chazal, F., Fasy, B.T., Lecci, F., Rinaldo, A., and Wasserman, L., (2014), "Stochastic Convergence of Persistence Landscapes and Silhouettes", Proceedings of the 30th Symposium of Computational Geometry (SoCG). (arXiv:1312.0308)

See Also

[landscape](#page-22-1), [silhouette](#page-35-1)

```
nn <- 3000 #large sample size
mm <- 50 #small subsample size
NN <- 5 #we will compute NN diagrams using subsamples of size mm
XX <- circleUnif(nn) ## large sample from the unit circle
DiagLim <- 2
maxdimension <- 1
tseq <- seq(0, DiagLim, length = 1000)
Diags <- list() #here we will store the NN rips diagrams
                 #constructed using different subsamples of mm points
#here we'll store the landscapes
Lands \leq matrix(0, nrow = NN, ncol = length(tseq))
for (i in seq_len(NN)){
  subXX <- XX[sample(seq_len(nn), mm), ]
  Diags[[i]] <- ripsDiag(subXX, maxdimension, DiagLim)
  Lands[i, ] <- landscape(Diags[[i]][["diagram"]], dimension = 1, KK = 1, tseq)
}
## now we use the NN landscapes to construct a confidence band
B < -50alpha <- 0.05
boot <- multipBootstrap(Lands, B, alpha)
LOWband <- boot[["band"]][, 1]
UPband <- boot[["band"]][, 2]
MeanLand <- boot[["mean"]]
plot(tseq, MeanLand, type = "1", lwd = 2, xlab = "", ylab = "",
     main = "Mean Landscape with band", ylim = c(0, 1.2))
polygon(c(tseq, rev(tseq)), c(LOWband, rev(UPband)), col = "pink")
lines(tseq, MeanLand, lwd = 1, col = 2)
```
plot.clusterTree 29

Description

This function plots the Cluster Tree stored in an object of class clusterTree.

Usage

S3 method for class 'clusterTree' $plot(x, type = "lambda", color = NULL, add = FALSE, ...)$

Arguments

Author(s)

Fabrizio Lecci

References

Brian P. Kent, Alessandro Rinaldo, and Timothy Verstynen, (2013), "DeBaCl: A Python Package for Interactive DEnsity-BAsed CLustering."arXiv:1307.8136

Fabrizio Lecci, Alessandro Rinaldo, and Larry Wasserman, (2014), "Metric Embeddings for Cluster Trees"

See Also

[clusterTree](#page-9-1), [print.clusterTree](#page-9-2)

```
## Generate data: 3 clusters
n <- 1200 #sample size
Neach <- floor(n / 4)
X1 <- cbind(rnorm(Neach, 1, .8), rnorm(Neach, 5, 0.8))
X2 <- cbind(rnorm(Neach, 3.5, .8), rnorm(Neach, 5, 0.8))
X3 <- cbind(rnorm(Neach, 6, 1), rnorm(Neach, 1, 1))
XX \leftarrow rbind(X1, X2, X3)k <- 100 #parameter of knn
## Density clustering using knn and kde
Tree <- clusterTree(XX, k, density = "knn")
TreeKDE \leq clusterTree(XX,k, h = 0.3, density = "kde")
```

```
par(mfrow = c(2, 3))plot(XX, pch = 19, cex = 0.6)# plot lambda trees
plot(Tree, type = "lambda", main = "lambda Tree (knn)")
plot(TreeKDE, type = "lambda", main = "lambda Tree (kde)")
# plot clusters
plot(XX, pch = 19, cex = 0.6, main = "cluster labels")for (i in Tree[["id"]]){
  points(matrix(XX[Tree[["DataPoints"]][[i]], ], ncol = 2), col = i, pch = 19,
        cex = 0.6}
#plot kappa trees
plot(Tree, type = "kappa", main = "kappa Tree (knn)")
plot(TreeKDE, type = "kappa", main = "kappa Tree (kde)")
```
plot.diagram *Plot the Persistence Diagram*

Description

This function plots the Persistence Diagram stored in an object of class diagram. Optionally, it can also represent the diagram as a persistence barcode.

Usage

```
## S3 method for class 'diagram'
plot(x, diagLim = NULL, dimension = NULL, col = NULL, rotate = FALSE,barcode = FALSE, band = NULL, lab.line = 2.2, colorBand = "pink",
     colorBer = NA, add = FALSE, ...)
```
Arguments

plot.diagram 31

Author(s)

Fabrizio Lecci

References

Brittany T. Fasy, Fabrizio Lecci, Alessandro Rinaldo, Larry Wasserman, Sivaraman Balakrishnan, and Aarti Singh. (2013), "Statistical Inference For Persistent Homology", (arXiv:1303.7117). To appear, Annals of Statistics.

Frederic Chazal, Brittany T. Fasy, Fabrizio Lecci, Alessandro Rinaldo, and Larry Wasserman, (2014), "Stochastic Convergence of Persistence Landscapes and Silhouettes", Proceedings of the 30th Symposium of Computational Geometry (SoCG). (arXiv:1312.0308)

See Also

[gridDiag](#page-14-1), [ripsDiag](#page-32-1)

```
XX1 <- circleUnif(30)
XX2 \le circleUnif(30, r = 2) + 3
XX <- rbind(XX1, XX2)
DiagLim <- 5
maxdimension <- 1
## rips diagram
Diag <- ripsDiag(XX, maxdimension, DiagLim, printProgress = TRUE)
#plot
par(mfrow = c(1, 3))plot(Diag[["diagram"]])
plot(Diag[["diagram"]], rotated = TRUE)
plot(Diag[["diagram"]], barcode = TRUE)
```
plot.maxPersistence *Summary plot for the maxPersistence function*

Description

This function plots an object of class maxPersistence, for the selection of the optimal smoothing parameter for persistent homology. For each value of the smoothing parameter, the plot shows the number of detected features, their persistence, and a bootstrap confidence band.

Usage

```
## S3 method for class 'maxPersistence'
plot(x, features = "dimension", colorBand = "pink", colorBorder = NA, ...)
```
Arguments

Author(s)

Fabrizio Lecci

References

Frederic Chazal, Jessi Cisewski, Brittany T. Fasy, Fabrizio Lecci, Bertrand Michel, Alessandro Rinaldo, and Larry Wasserman, (2014), "Robust Topological Inference: distance-to-a-measure and kernel distance"

Brittany T. Fasy, Fabrizio Lecci, Alessandro Rinaldo, Larry Wasserman, Sivaraman Balakrishnan, and Aarti Singh. (2013), "Statistical Inference For Persistent Homology", (arXiv:1303.7117). To appear, Annals of Statistics.

See Also

[maxPersistence](#page-23-1)

ripsDiag 33

Examples

```
## input data: circle with clutter noise
n < - 600percNoise <- 0.1
XX1 <- circleUnif(n)
noise \le cbind(runif(percNoise * n, -2, 2), runif(percNoise * n, -2, 2))
X <- rbind(XX1, noise)
## limits of the Gird at which the density estimator is evaluated
Xlim < -c(-2, 2)Ylim <-c(-2, 2)lim <- cbind(Xlim, Ylim)
by <-0.2B < - 80alpha <-0.05## candidates
parametersKDE \leq seq(0.1, 0.5, by = 0.2)
maxKDE <- maxPersistence(kde, parametersKDE, X, lim = lim, by = by,
                        bandFUN = "bootstrapBand", B = B, alpha = alpha,
                         parallel = FALSE, printProgress = TRUE)
print(summary(maxKDE))
par(mfrow = c(1, 2))plot(X, pch = 16, cex = 0.5, main = "Circle")plot(maxKDE)
```
ripsDiag *Rips Persistence Diagram*

Description

This function computes the persistence diagram of the Rips filtration built on top of a point cloud.

Usage

```
ripsDiag(X, maxdimension, maxscale, dist = "euclidean", library = "GUDHI",
         location = FALSE, printProgress = FALSE)
```
Arguments

Details

For Rips Diagrams based on Euclidean distance of the input point cloud, the user can decide to use either the C++ library GUDHI, the C++ library Dionysus, or the C++ library PHAT. For Rips Diagrams based on arbitrary distance, the user can decide to use either the C++ library Dionysus, or the C++ library PHAT. See refereneces.

Value

ripsDiag returns a list with the following elements:

feature. If dist = 'arbitrary', then each element is a vector of length P_i and represents index of P_i data points on a representative cycle of each homological feature.

Author(s)

Brittany T. Fasy, Jisu Kim, Fabrizio Lecci, and Clement Maria

References

Jean-Daniel Boissonnat, Marc Glisse, Clement Maria, Vincent Rouvreau, "GUDHI, Simplicial Complexes and Persistent Homology Packages". https://project.inria.fr/gudhi/software/.

Dmitriy Morozov, "Dionysus, a C++ library for computing persistent homology". http://www.mrzv.org/software/dionysus/

Herbert Edelsbrunner and John Harer (2010), Computational topology: an introduction. American Mathematical Society.

Brittany Fasy, Fabrizio Lecci, Alessandro Rinaldo, Larry Wasserman, Sivaraman Balakrishnan, and Aarti Singh. (2013), "Statistical Inference For Persistent Homology", (arXiv:1303.7117). To appear, Annals of Statistics.

See Also

[summary.diagram](#page-37-1), [plot.diagram](#page-29-1), [gridDiag](#page-14-1)

```
## EXAMPLE 1: rips diagram for circles (euclidean distance)
XX <- circleUnif(30)
maxscale <- 5
maxdimension <- 1
## note that the input XX is a point cloud
Diag <- ripsDiag(XX, maxdimension, maxscale, printProgress = TRUE)
```

```
## EXAMPLE 2: rips diagram with arbitrary distance
## distance matrix for triangle with edges of length: 1,2,4
distX <- matrix(c(0, 1, 2, 1, 0, 4, 2, 4, 0), ncol = 3)
maxscale <- 5
maxdimension <- 1
## note that the input distXX is a distance matrix
DiagTri <- ripsDiag(distX, maxdimension, maxscale, dist = "arbitrary",
                    printProgress = TRUE)
#points with lifetime = 0 are not shown. e.g. the loop of the triangle.
print(DiagTri[["diagram"]])
```


Description

This function computes the silhouette function corresponding to a given persistence diagram.

Usage

```
silhouette(Diag, p = 1, dimension = 1,
           tseq = seq(min(Diag[, 2:3]), max(Diag[, 2:3]), length = 500))
```
Arguments

Value

Returns a numeric matrix of with the number of row as the length of tseq and the number of column as the length of p. The value at ith row and jth column represents the value of the $p[j]-$ th power silhouette function evaluated at tseq[i].

Author(s)

Fabrizio Lecci

References

Frederic Chazal, Brittany T. Fasy, Fabrizio Lecci, Alessandro Rinaldo, and Larry Wasserman, (2014), "Stochastic Convergence of Persistence Landscapes and Silhouettes", Proceedings of the 30th Symposium of Computational Geometry (SoCG). (arXiv:1312.0308)

See Also

[landscape](#page-22-1)

sphereUnif 37

Examples

```
Diag <- matrix(c(0, 0, 10, 1, 0, 3, 1, 3, 8), ncol = 3, byrow = TRUE)
DiagLim <- 10
colnames(Diag) <- c("dimension", "Birth", "Death")
#persistence silhouette
tseq <- seq(0, DiagLim, length = 1000)
Sil \le silhouette(Diag, p = 1, dimension = 1, tseq)
par(mfrow = c(1, 2))plot.diagram(Diag)
plot(tseq, Sil, type = "l", xlab = "t", ylab = "silhouette", asp = 1)
```


Description

This function samples n points from the sphere S^d of radius r embedded in R^{d+1} , uniformly with respect to the volume measure of the sphere.

Usage

sphereUnif(n, d, $r = 1$)

Arguments

Value

sphereUnif returns an n by 2 matrix of coordinates.

Note

When $d = 1$, this function is same as using [circleUnif](#page-8-1).

Author(s)

Jisu Kim

See Also

[circleUnif](#page-8-1), [torusUnif](#page-38-1)

Examples

```
X \leq - sphereUnif(n = 100, d = 1, r = 1)
plot(X)
```
summary.diagram print *and* summary *for* diagram

Description

print.diagram prints a persistence diagram, a P by 3 matrix, where P is the number of points in the diagram. The first column contains the dimension of each feature (0 for components, 1 for loops, 2 for voids, etc.). Second and third columns are Birth and Death of the features.

summary.diagram produces basic summaries of a persistence diagrams.

Usage

S3 method for class 'diagram' $print(x, \ldots)$ ## S3 method for class 'diagram' summary(object, ...)

Arguments

Author(s)

Fabrizio Lecci

See Also

[plot.diagram](#page-29-1), [gridDiag](#page-14-1), [ripsDiag](#page-32-1),

```
# Generate data from 2 circles
XX1 <- circleUnif(30)
XX2 \leftarrow circleUnif(30, r = 2) + 3XX \leftarrow rbind(XX1, XX2)
```

```
DiagLim <- 5 # limit of the filtration
maxdimension <-1 # computes betti0 and betti1
Diag <- ripsDiag(XX, maxdimension, DiagLim, printProgress = TRUE)
print(Diag[["diagram"]])
print(summary(Diag[["diagram"]]))
```


Description

This function samples n points from the 3D torus, uniformly with respect to its surface.

Usage

torusUnif(n, a, c)

Arguments

Details

This function is an implementation of Algorithm 1 in the reference.

Value

torusUnif returns an n by 3 matrix of coordinates.

Author(s)

Fabrizio Lecci

References

Persi Diaconis, Susan Holmes, and Mehrdad Shahshahani, (2013), "Sampling from a manifold." Advances in Modern Statistical Theory and Applications: A Festschrift in honor of Morris L. Eaton. Institute of Mathematical Statistics, 102-125.

See Also

[circleUnif](#page-8-1),[sphereUnif](#page-36-1)

```
X \le - torusUnif(300, a = 1.8, c = 5)
plot(X)
```


Description

This function computes the Wasserstein distance between two persistence diagrams.

Usage

wasserstein(Diag1, Diag2, $p = 1$, dimension = 1)

Arguments

Details

The Wasserstein distance between two diagrams is the cost of the optimal matching between points of the two diagrams. When a vector is given for dimension, then maximum among bottleneck distances using each element in dimension is returned. This function is an R wrapper of the function "wasserstein_distance" in the C++ library Dionysus. See references.

Value

Returns the value of the Wasserstein distance between the two persistence diagrams.

Author(s)

Jisu Kim, Fabrizio Lecci

References

Dmitriy Morozov, "Dionysus, a C++ library for computing persistent homology". http://www.mrzv.org/software/dionysus/ Herbert Edelsbrunner and John Harer (2010), Computational topology: an introduction. American Mathematical Society.

See Also

[bottleneck](#page-6-1), [ripsDiag](#page-32-1), [gridDiag](#page-14-1), [plot.diagram](#page-29-1)

wasserstein 41

```
XX1 <- circleUnif(20)
XX2 \le circleUnif(20, r = 0.2)
DiagLim <- 5
maxdimension <- 1
Diag1 <- ripsDiag(XX1, maxdimension, DiagLim, printProgress = FALSE)
Diag2 <- ripsDiag(XX2, maxdimension, DiagLim, printProgress = FALSE)
wassersteinDist <- wasserstein(Diag1[["diagram"]], Diag2[["diagram"]], p = 1,
                               dimension = 1)
print(wassersteinDist)
```
Index

∗Topic datagen circleUnif, [9](#page-8-0) sphereUnif, [37](#page-36-0) torusUnif, [39](#page-38-0) ∗Topic hplot plot.clusterTree, [28](#page-27-0) plot.diagram, [30](#page-29-0) plot.maxPersistence, [32](#page-31-0) ∗Topic htest bootstrapBand, [3](#page-2-0) bootstrapDiagram, [5](#page-4-0) hausdInterval, [18](#page-17-0) multipBootstrap, [27](#page-26-0) ∗Topic methods bottleneck, [7](#page-6-0) gridDiag, [15](#page-14-0) landscape, [23](#page-22-0) maxPersistence, [24](#page-23-0) ripsDiag, [33](#page-32-0) silhouette, [36](#page-35-0) wasserstein, [40](#page-39-0) ∗Topic nonparametric bootstrapBand, [3](#page-2-0) bootstrapDiagram, [5](#page-4-0) clusterTree, [10](#page-9-0) distFct, [12](#page-11-0) dtm, [13](#page-12-0) hausdInterval, [18](#page-17-0) kde, [19](#page-18-0) kernelDist, [20](#page-19-0) knnDE, [22](#page-21-0) multipBootstrap, [27](#page-26-0) ∗Topic optimize bottleneck, [7](#page-6-0) wasserstein, [40](#page-39-0) ∗Topic package TDA-package, [2](#page-1-0) bootstrapBand, [3,](#page-2-0) *[7](#page-6-0)*, *[19](#page-18-0)*, *[26](#page-25-0)* bootstrapDiagram, [5](#page-4-0)

bottleneck, *[7](#page-6-0)*, [7,](#page-6-0) *[40](#page-39-0)* circleUnif, [9,](#page-8-0) *[37](#page-36-0)*, *[39](#page-38-0)* clusterTree, [10,](#page-9-0) *[29](#page-28-0)* distFct, *[3](#page-2-0)*, *[5](#page-4-0)*, *[7](#page-6-0)*, [12,](#page-11-0) *[14,](#page-13-0) [15](#page-14-0)*, *[17](#page-16-0)*, *[20](#page-19-0)[–22](#page-21-0)* dtm, *[3–](#page-2-0)[5](#page-4-0)*, *[7](#page-6-0)*, *[13](#page-12-0)*, [13,](#page-12-0) *[15](#page-14-0)*, *[17](#page-16-0)*, *[20](#page-19-0)[–22](#page-21-0)*, *[24](#page-23-0)*, *[26](#page-25-0)* gridDiag, *[8](#page-7-0)*, [15,](#page-14-0) *[25,](#page-24-0) [26](#page-25-0)*, *[30,](#page-29-0) [31](#page-30-0)*, *[35](#page-34-0)*, *[38](#page-37-0)*, *[40](#page-39-0)* hausdInterval, [18](#page-17-0) kde, *[3–](#page-2-0)[5](#page-4-0)*, *[7](#page-6-0)*, *[13](#page-12-0)[–15](#page-14-0)*, *[17](#page-16-0)*, [19,](#page-18-0) *[21,](#page-20-0) [22](#page-21-0)*, *[24](#page-23-0)*, *[26](#page-25-0)* kernelDist, *[7](#page-6-0)*, *[13,](#page-12-0) [14](#page-13-0)*, *[17](#page-16-0)*, *[20](#page-19-0)*, [20,](#page-19-0) *[22](#page-21-0)*, *[24](#page-23-0)*, *[26](#page-25-0)* knnDE, [22](#page-21-0) landscape, [23,](#page-22-0) *[28](#page-27-0)*, *[36](#page-35-0)* maxPersistence, [24,](#page-23-0) *[32](#page-31-0)* multipBootstrap, [27](#page-26-0) plot.clusterTree, *[11](#page-10-0)*, [28](#page-27-0) plot.diagram, *[7,](#page-6-0) [8](#page-7-0)*, *[17](#page-16-0)*, [30,](#page-29-0) *[35](#page-34-0)*, *[38](#page-37-0)*, *[40](#page-39-0)* plot.maxPersistence, [32](#page-31-0) print.clusterTree, *[29](#page-28-0)* print.clusterTree *(*clusterTree*)*, [10](#page-9-0) print.diagram *(*summary.diagram*)*, [38](#page-37-0) print.maxPersistence *(*maxPersistence*)*, [24](#page-23-0) print.summary.diagram *(*summary.diagram*)*, [38](#page-37-0) print.summary.maxPersistence *(*maxPersistence*)*, [24](#page-23-0) ripsDiag, *[8](#page-7-0)*, *[17](#page-16-0)*, *[30,](#page-29-0) [31](#page-30-0)*, [33,](#page-32-0) *[38](#page-37-0)*, *[40](#page-39-0)* silhouette, *[23](#page-22-0)*, *[28](#page-27-0)*, [36](#page-35-0) sphereUnif, *[9](#page-8-0)*, [37,](#page-36-0) *[39](#page-38-0)* summary.diagram, *[7](#page-6-0)*, *[17](#page-16-0)*, *[35](#page-34-0)*, [38](#page-37-0)

summary.maxPersistence

*(*maxPersistence*)*, [24](#page-23-0)

I_N and $I₃$ and $I₄₃$

TDA *(*TDA-package *)* , [2](#page-1-0) TDA-package, [2](#page-1-0) torusUnif , *[9](#page-8-0)* , *[37](#page-36-0)* , [39](#page-38-0)

wasserstein , *[8](#page-7-0)* , [40](#page-39-0)