Package ‘diffusionMap’

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Title Diffusion Map
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Maintainer ORPHANED
Description Implements diffusion map method of data parametrization, including creation and visualization of diffusion map, clustering with diffusion K-means and regression using adaptive regression model.
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Description

Non-parametric adaptive regression method for diffusion map basis.

Usage

```r
adapreg(D, y, mmax = min(50, length(y)), fold = NULL, nfolds = 10, nrep = 5)
```

Arguments

- `D`: n-by-n pairwise distance matrix for a data set with n points, or alternatively output from the `dist()` function.
- `y`: vector of responses to model
- `mmax`: maximum model size to consider
- `fold`: vector of integers of size n specifying the k-fold cross-validation allocation. Default does `nfolds`-fold CV by `sample(1:nfolds,length(y),replace=T)`
- `nfolds`: number of folds to do CV. If fold is supplied, nfolds is ignored
- `nrep`: number of times optimization algorithm is run (with random initializations). Higher nrep allows algorithm to avoid getting stuck in local minima

Details

Fits an adaptive regression model leaving as free parameters both the diffusion map localness parameter, epsilon, and the size of the regression model, m. The adaptive regression model is the expansion of the response function on the first m diffusion map basis functions.

This routine searches for the optimal (epsilon,m) by minimizing the cross-validation risk (CV MSE) of the regression estimate. The function uses `optimize` to search over an appropriate range of epsilon and calls the function `adapregNm` to find the optimal m for each epsilon.

Default uses 10-fold cross-validation to choose the optimal model size. User may also supply a vector of fold allocations. For instance, `sample(1:10,length(y),replace=T)` does 10-fold CV while `1:length(y)` performs leave-one-out CV.
Value

The returned value is a list with components

- **mincvrisk**: minimum cross-validation risk for the adaptive regression model for the given epsilon
- **mopt**: size of the optimal regression model. If mopt == mmax, it is advised to increase mmax.
- **epsopt**: optimal value of epsilon used in diffusion map construction
- **y.hat**: predictions of the response, y-hat, for the optimal model
- **coeff**: coefficients of the optimal model

Author(s)

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References


See Also

diffuse, adapreg.m

Examples

```
library(scatterplot3d)
# trig function on circle
x = cbind(cos(t), sin(t))
y = cos(3*x) + rnorm(length(t), 0, 1)
tcol = topo.colors(32)
colvec = floor((y-min(y))/(max(y)-min(y))*32); colvec[colvec==0] = 1
scatterplot3d(x[,1], x[,2], y, color=tcol[colvec], pch=20,
              main="Cosine function supported on circle", angle=55,
              cex.main=2, col.axis="gray", cex.symbols=2, cex.lab=2,
              xlab=expression("x"[1]), ylab=expression("x"[2]), zlab="y")

D = as.matrix(dist(x))
# do 10-fold cross-validation to optimize (epsilon, m):
AR = adapreg(D, y, mmax=5, nfolds=2, nrep=2)
print(paste("optimal model size:" , AR$mopt, "; optimal epsilon:" ,
            round(AR$epsopt, 4), "; min. CV risk:" ,
            round(AR$mincvrisk, 5))))
plot(y, AR$y.hat, ylab=expression(hat("y")), cex.lab=1.5, cex.main=1.5,
     main="Predictions")
abline(0,1,col=2,lwd=2)
```
Description

Non-parametric adaptive regression method for diffusion map basis.

Usage

adapreg.m(epsilon,D,y,mmax=min(50,length(y)),fold=NULL,nfolds=10,objcfun=FALSE)

Arguments

epsilon  diffusion map kernel parameter
D       n-by-n pairwise distance matrix for a data set with n points, or alternatively
        output from the dist() function.
y       vector of responses to model
mmax    maximum model size to consider
fold    vector of integers of size n specifying the k-fold cross-validation allocation. De-
        fault does nfolds-fold CV by sample(1:nfolds,length(y),replace=T)
nfolds  number of folds to do CV. If fold is supplied, nfolds is ignored
objcfun if the function is to be passed into an optimization routine (such as minimize()),
        then this needs to be set to TRUE, so that only the minimal CV risk is returned

Details

Fits an adaptive regression model using the estimated diffusion map coordinates of a data set, while
holding epsilon fixed and optimizing over m. The adaptive regression model is the expansion of the
response function on the first m diffusion map basis functions.

For a given epsilon value, this routine finds the optimal m by minimizing the cross-validation risk
(CV MSE) of the regression estimate. To optimize over (epsilon,m), use the function adapreg.
Default uses 10-fold cross-validation to choose the optimal model size. User may also supply a
vector of fold allocations. For instance, sample(1:10,length(y),replace=T) does 10-fold CV while
1:length(y) does leave-one-out CV.

Value

The returned value is a list with components

mincvrisk minimum cross-validation risk for the adaptive regression model for the given
epsilon
mopt     size of the optimal regression model. If mopt equals mmax, it is advised to
        increase mmax.
cvrisk   vector of CV risk estimates for model sizes from 1:mmax
epsilon

describes the value of epsilon used in diffusion map construction.

y.hat

describes predictions of the response, y.hat, for the optimal model.

coeff

describes coefficients of the optimal model.

If objfun is set to TRUE, then the returned value is the minimum cross-validation risk for the adap-
tive regression model for the given epsilon.

Author(s)

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References


See Also

diffuse, adapreg

Examples

library(scatterplot3d)

## trig function on circle

t = seq(-pi, pi, .01)
x = cbind(cos(t), sin(t))
y = cos(3*tau) + rnorm(length(t), 0, 1)
tcol = topo.colors(32)
colvec = floor((y - min(y))/(max(y) - min(y))*32); colvec[colvec==0] = 1
scatterplot3d(x[, 1], x[, 2], y, color = tcol[colvec], pch = 20,
main = "Cosine function supported on circle", angle = 55,
cex.main = 2, col.axis = "gray", cex.symbols = 2, cex.lab = 2,
xlab = expression("x[1]"), ylab = expression("x[2]"), zlab = "y")

d = as.matrix(dist(x))

# leave-one-out cross-validation:
AR = adapreg.m(.01, D, y, fold = 1: length(y))
print(paste("optimal model size:
AR$mopt,"; min. CV risk:\nround(AR$mincvrisk, 4))))
par(mfrow = c(2, 1), mar = c(5, 5, 4, 1))
plot(AR$cvrisks, typc = 'b', xlab = "Model size", ylab = "CV risk",
cex.lab = 1.5, cex.main = 1.5, main = "CV risk estimates")
plot(y, AR$y.hat, ylab = expression(hat("y")), cex.lab = 1.5, cex.main = 1.5,
main = "Predictions")
abline(0, 1, col = 2, lwd = 2)

## swiss roll data

N = 2000

t = (3*pi/2)*(1+2*runif(N)); height = runif(N);
X = cbind(t*cos(t), height, t*sin(t))
X = scale(X) + matrix(rnorm(N*3,0,0.05),N,3)
tcol = topo.colors(32)
colvec = floor((t-min(t))/(max(t)-min(t))*32); colvec[colvec==0] = 1
scatterplot3d(X,pch=18,color=tcol[colvec],
               xlab=expression("x"[1]),ylab=expression("x"[2]),
               zlab=expression("x"[3]),cex.lab=1.5,
               main="Swiss Roll, Noise = 0.05",cex.main=1.5,xlim=c(-2,2),
               ylim=c(-2,2),zlim=c(-2,2),col.axis="gray")
D = as.matrix(dist(X))

# 10-fold cross-validation:
AR = adapreg.m(.2,D,t,mmax=25,nfolds=5)
print(paste("optimal model size:"Dmopt,"; min. CV risk:"Dround(AR$mincvrisk,4)))
par(mfrow=c(2,1),mar=c(5,5,4,1))
plot(AR$cvrisks,tyb"Model size",ylab="CV risk",
     cex.lab=1.5,cex.main=1.5,main="CV risk estimates")
plot(t,AR$y.hat,ylab=expression(hat("t")),cex.lab=1.5,cex.main=1.5,
     main="Predictions")
abline(0,1,col=2,lwd=2)

annulus

Annulus toy data set

Description

The annulus data frame has 1000 rows and 2 columns. 500 data points are from the noisy annulus and 500 data points reside within the annulus.

Usage

annulus

Format

Data are in two dimensions.

Chainlink

Chainlink toy clustering data set

Description

The Chainlink data frame has 1000 rows and 3 columns. The data are of two interlocking 3-dimensional rings. 500 data points are from one ring and 500 from the other ring.
**diffuse**

**Usage**
Chainlink

**Format**
The data are in 3 dimensions, C1, C2, and C3.

**Source**
http://www.uni-marburg.de/fb12/datenbionik/data?language_sync=1

**References**

---

**diffuse**  
*Compute diffusion map coordinates from pair-wise distances.*

---

**Description**
Uses the pair-wise distance matrix for a data set to compute the diffusion map coefficients. Computes the Markov transition probability matrix, and its eigenvalues and left & right eigenvectors. Returns a ’dmap’ object.

**Usage**
diffuse(D, eps.val = epsilonCompute(D), neigen = NULL, t = 0, maxdim = 50, delta=10^-5)

**Arguments**

- **D**  
n-by-n pairwise distance matrix for a data set with n points, or alternatively output from the dist() function.

- **eps.val**  
epsilon parameter for the diffusion weight matrix, exp(-D$^2$/(eps.val)). Default is to use the epsilon corresponding to the median distance to the 0.01*n nearest neighbor

- **neigen**  
number of dimensions of final diffusion map representation. Default uses number of dimensions corresponding to a 95% drop-off in eigenvalue multiplier.

- **t**  
onoptional time-scale parameter in the diffusion map. The (recommended) default uses multiscale geometry.

- **maxdim**  
the maximum number of diffusion map dimensions returned if 95% drop-off is not attained.

- **delta**  
sparsity cut-off for the symmetric graph Laplacian. Default of 10^-5 is used. Higher value induces more sparsity in Laplacian (and faster computations)
Details

Diffusion map is a powerful tool for data parametrization that exploits the natural geometry of a data set. Diffusion map uses local interactions between data points, propagated to larger scales, to construct a global representation of the data.

The parameter $\text{eps.val}$ controls the degree of localness in the diffusion weight matrix. For most statistical inference problems using diffusion map, results should be optimized over $\text{eps.val}$. Generally a good starting point is to pick $\text{eps.val} = 2*\text{med.knn}^2$, where $\text{med.knn}$ is the median distance to the $k$th nearest neighbor, and $k$ is chosen 1-2% of $n$. The default uses 1% of $n$.

Computation of the diffusion map coordinates requires singular value decomposition of the normalized graph Laplacian. This operation is optimized for speed by exploiting the sparseness of the graph Laplacian and by using ARPACK for fast matrix decomposition. Increasing the sparseness parameter, $\text{delta}$, will speed up the algorithm.

Value

The returned value is an object of 'class' 'dmap'.

The function 'plot' is used to plot the diffusion coordinates in 1, 2, or 3 dimensions. The function 'print' displays the computed eigen-multipliers and the value of epsilon used.

An object of class 'dmap' is a list containing the following components:

- $\mathbf{X}$: matrix of $n$ diffusion map coordinates, entered column-wise (does not include the trivial coordinate)
- $\mathbf{\phi0}$: trivial left eigenvector of Markov matrix (stationary distribution of Markov random walk) in diffusion map construction
- $\text{eigenvals}$: eigen-values of the svd of the symmetric graph Laplacian
- $\text{eigenmult}$: eigen-multipliers of the diffusion map
- $\mathbf{\psi}$: right eigenvectors of the Markov matrix (first row is the trivial right eigenvector)
- $\mathbf{\phi}$: left eigenvectors of the Markov matrix (first row is the trivial left eigenvector)
- neigen: number of diffusion map dimensions used
- epsilon: the value of epsilon used

Author(s)

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References


See Also

plot.dmap.print.dmap
Examples

```r
## example with noisy spiral
n=2000
t=runif(n)^.7*10
al=.15;bet=.5;
x1=bet*exp(al*t)*cos(t)+rnorm(n,0,.1)
y1=exp(al*t)*sin(t)+rnorm(n,0,.1)
plot(x1,y1,pch=20,main="Noisy spiral")
D = dist(cbind(x1,y1))
dmap = diffuse(D,neigen=10) # compute diffusion map
par(mfrow=c(2,1))
plot(t,dmap$d[,1],pch=20,axes=FALSE,xlab="spiral parameter",ylab="1st diffusion coefficient")
box()
plot(1:10,dmap$eigenmult,typ='h',xlab="diffusion map dimension",ylab="eigen-multipliers")

## example with annulus data set
data(annulus)
plot(annulus,main="Annulus Data",pch=20,cex=.7)
D = dist(annulus) # use Euclidean distance
dmap = diffuse(D,eps.val=.1) # compute diffusion map & plot
print(dmap)
plot(dmap)
```

diffusionKmeans  Diffusion K-means

Description

Clusters a data set based on its diffusion coordinates.

Usage

```r
diffusionKmeans(dmap, K, params = c(), Niter = 10, epsilon = 0.001)
```

Arguments

dmap a "dmap" object, computed by diffuse()

K number of clusters

params optional parameters for each data point. Entry can be a vector of length n, or a matrix with n rows. If this argument is given, cluster centroid parameters are returned.

Niter number of K-means iterations performed.

epsilon stopping criterion for relative change in distortion for each K-means iteration
Details

A `"dmap"` object computed by `diffuse()` is the input, so `diffuse()` must be performed first. Function is written this way so the K-means parameters may be varied without having to recompute the diffusion map coordinates in each run.

Diffusion K-means is a special form of spectral clustering. It is a unique algorithm because the eigenvectors of the symmetric Laplacian are weighted in such a way to guarantee that Euclidean distance in diffusion space will be approximately equal to the diffusion distance between objects. Clustering by Euclidean distance in diffusion space exploits this fact.

Value

The returned value is a list with components

- `part` final labelling of data from K-means. n-dimensional vector with integers between 1 and K
- `cent` K geometric centroids found by K-means
- `D` minimum of total distortion (loss function of K-means) found across K-means runs
- `DK` n by k matrix of squared (Euclidean) distances from each point to every centroid for the optimal K-means run
- `centparams` optional parameters for each centroid. Only returned if params is specified in the function call. Is a matrix with k rows.

Author(s)

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References


See Also

diffuse

Examples

```
library(scatterplot3d)

## example with annulus data set
data(annulus)
par(mfrow=c(2,1))
plot(annulus,main="Annulus Data",pch=20,cex=.7)
D = dist(annulus) # use Euclidean distance
dmap = diffuse(D,eps.val=0.05) # compute diffusion map
```
distortionMin

Distortion Minimization via K-means

description

Runs one K-means loop based on the diffusion coordinates of a data set, beginning from an initial set of cluster centers.

Usage

distortionMin(X, phi0, K, c0, epsilon = 0.001)

Arguments

X  diffusion coordinates, each row corresponds to a data point
phi0  trivial left eigenvector of Markov matrix (stationary distribution of Markov random walk) in diffusion map construction
K  number of clusters
c0  initial cluster centers
epsilon  stopping criterion for relative change in distortion

Details

Used by diffusionKmeans().
epsilonCompute

Value

The returned value is a list with components

- $S$ labelling from K-means loop. n-dimensional vector with integers between 1 and K
- $c$ K geometric centroids found by K-means
- $D$ minimum of total distortion (loss function of K-means) found in K-means run
- $DK$ n by k matrix of squared (Euclidean) distances from each point to every centroid

Author(s)

Joseph Richards <joeyrichar@gmail.com>

References


See Also

diffusionKmeans

Examples

data(annulus)
n = dim(annulus)[1]
D = dist(annulus) # use Euclidean distance
dmap = diffuse(D, 0.03) # compute diffusion map
km = distortionMin(dmap$X, dmap$phi0, 2, dmap$X[sample(n, 2), ])
plot(annulus, col = km$S, pch = 20)
table(km$S, c(rep(1, 500), rep(2, 500)))

epsilonCompute

Compute default diffusion map epsilon.

Description

Uses the pair-wise distances to estimate a diffusion map epsilon value by the median p*n-th nearest neighbor

Usage

epsilonCompute(D, p = 0.01)
Arguments

- \( D \) n-by-n pairwise distance matrix for a data set with \( n \) points, or alternatively output from the \texttt{dist()} function
- \( p \) distances to \( p^n \)-th nearest neighbor are used. Default value is .01

Details

Function is used as the default value in \texttt{diffuse()}. For inference problems, it is advised that the results be optimized over \( \epsilon \).

Value

- \( \epsilon \) value of \( \epsilon \) to be used in diffusion map

Author(s)

Joseph Richards <joeyrichar@gmail.com>

See Also

- \texttt{diffuse}

Examples

```r
data(annulus)
D = dist(annulus) # use Euclidean distance
epsilonCompute(D,.005)
epsilonCompute(D,.01)
epsilonCompute(D,.05)
epsilonCompute(D,.1)
```

---

\texttt{nystrom} \hspace{1cm} \textit{Perform Nystrom Extension to estimate diffusion coordinates of data.}

Description

Given the diffusion map coordinates of a training data set, estimates the diffusion map coordinates of a new set of data using the pairwise distance matrix from the new data to the original data.

Usage

\texttt{nystrom(dmap,Dnew,\sigma=dmap$\epsilon)}
Arguments

dmap       a "dmap" object from the original data set, computed by diffuse()
Dnew       distance matrix between each new data point and every point in the training data
           set. Matrix is m-by-n, where m is the number of data points in the new set and
           n is the number of training data points
sigma      scalar giving the size of the Nystrom extension kernel. Default uses the tuning
           parameter of the original diffusion map

Details

Often, it is computationally infeasible to compute the exact diffusion map coordinates for large data
sets. In this case, one may use the exact diffusion coordinates of a training data set to extend to a
new data set using the Nystrom approximation.

A Gaussian kernel is used: exp(-D(x,y)^2/sigma). The default value of sigma is the epsilon value
used in the construction of the original diffusion map. Other methods to select sigma, such as
Algorithm 2 in Lafon, Keller, and Coifman (2006) have been proposed.

The dimensionality of the diffusion map representation of the new data set will be the same as the
dimensionality of the diffusion map constructed on the original data.

Value

The estimated diffusion coordinates for the new data, a matrix of dimensions m by p, where p is the
dimensionality of the input diffusion map

Author(s)

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References

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1784

See Also

diffuse

Examples

Norig = 1000
Next = 4000
t=runif(Norig+Next)^.7*10
al=.15; bet=.5;
x1=bet*exp(al*t)*cos(t)+rnorm(length(t),0,.1)
y1=bet*exp(al*t)*sin(t)+rnorm(length(t),0,.1)
D = as.matrix(dist(cbind(x1,y1)))
Dorig = D[1:Norig,1:Norig] # training distance matrix
DExt = D[(Norig+1):(Norig+Next),1:Norig] # new data distance matrix
# compute original diffusion map
dmap = diffuse(Dorig,neigen=2)
# use Nystrom extension
dmapExt = nystrom(dmap,DExt)
plot(dmapExt[,1:2],pch=8,col=2,
     main="Diffusion map, black = original, red = new data",
     xlab="1st diffusion coefficient",ylab="2nd diffusion coefficient")
points(dmap$X[,1:2],pch=19,cex=.5)

plot.dmap

Description

A generic function that plots the diffusion map stored in a dmap object

Usage

## S3 method for class 'dmap'
plot(x, ...)

Arguments

x  diffusion map object from diffuse()
...
other options used for plot, currently ignored

Author(s)

Joseph Richards <joeyrichar@gmail.com>

See Also

diffuse

Examples

data(annulus)
dmap = diffuse(dist(annulus)) # compute diffusion map
plot(dmap)
print.dmap

Extract diffusion map eigen-multipliers and epsilon

Description
A generic function that prints the eigen-multipliers of a dmap object and the epsilon used in its construction.

Usage
## S3 method for class 'dmap'
print(x, ...)

Arguments
x  diffusion map object from diffuse()
...  further arguments

Author(s)
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See Also
diffuse

Examples
data(annulus)
dmap = diffuse(dist(annulus))  # compute diffusion map
print(dmap)
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