Package: bigMap (via r-universe)

November 7, 2024

Type Package

Title Big Data Mapping

Version 4.6.2

Date 2024-06-01

Description Unsupervised clustering protocol for large scale structured data, based on a low dimensional representation of the data. Dimensionality reduction is performed using a parallelized implementation of the t-Stochastic Neighboring Embedding algorithm (Garriga J. and Bartumeus F. (2018), [<arXiv:1812.09869>](https://arxiv.org/abs/1812.09869)).

License GPL-3 | file LICENSE

Depends $R (= 3.5.0)$

Imports Rcpp ($>= 0.12.0$), bigmemory ($>= 4.5.0$), parallel ($>= 3.5.0$), RColorBrewer, colorspace,

Suggests snow $(>= 0.4-2)$, knitr, rmarkdown

LinkingTo Rcpp, RcppArmadillo, BH, bigmemory

LazyData FALSE

VignetteBuilder knitr

RoxygenNote 7.3.1

SystemRequirements GNU make

NeedsCompilation yes

Author Joan Garriga [aut, cre], Frederic Bartumeus [aut]

Maintainer Joan Garriga <jgarriga@ceab.csic.es>

Config/pak/sysreqs make

Repository https://jgarriga65.r-universe.dev

RemoteUrl https://github.com/jgarriga65/bigmap

RemoteRef HEAD

RemoteSha bec112db4a3619893cd16a33952f209170cb3cb1

Contents

bdm.boxp *Clustering statistics box-plot.*

Description

Clustering statistics box-plot.

Usage

```
bdm.boxp(data, bdm, byVars = F, merged = T, clusters = NULL, layer = 1)
```


bdm.cost 3

Details

If the number of clusters is large, only the first 25 clusters will be plotted. Note that the WTT algorithm numbers the clusters based on density value at the peak cell of the cluster. Thus, the numbering of the clusters is highly correlated with their relevance in terms of partial density. Therefore, in case of more than 25 clusters, the most relevant should always be included in the plot.

Value

None.

Examples

```
bdm.example()
bdm.boxp(ex$map, data = ex$data[, 1:4])
bdm.boxp(ex$map, data = ex$data[, 1:4], byVars = TRUE)
```
bdm.cost *ptSNE cost & size plot.*

Description

ptSNE cost & size plot.

Usage

bdm.cost(bdm, x.lim = NULL)

Arguments

Value

None.

Examples

bdm.example() bdm.cost(ex\$map)

bdm.dMap *Class density maps*

Description

Compute the class density maps of a set of classes on the embedding grid. This function returns a fuzzy mapping of the set of classes on the grid cells. The classes can be whatever set of classes of interest and must be given as a vector of point-wise discrete labels (either numeric, string or factor).

Usage

```
bdm.dMap(bdm, data = NULL, threads = 2, mpi.cl = NULL, layer = 1)
```
Arguments

Details

bdm.dMap() computes the join distribution $P(V = v_i, C = c_j)$ where $V = v_1, \ldots, v_l$ is the discrete covariate and $C = c_1, \ldots, c_g$ are the grid cells of the paKDE raster. That is, this function recomputes the paKDE but keeping track of the covariate (or class) label of each data-point. This results in a fuzzy distribution of the covariate (class) at each cell.

Usually, figuring out the join distribution $P(V = v_i, C = c_j)$ entails an intensive computation. Thus bdm.dMap() performs the computation and stores the result in a dedicated element named \$dMap. Afterwards the class density maps can be visualized with the bdm.dMap.plot() function.

Value

A copy of the input bdm instance with element \$dMap, a matrix with a soft clustering of the grid cells.

bdm.dMap.plot 5

Examples

```
# --- load example dataset
bdm.example()
## Not run:
m <- bdm.dMap(ex$map, threads = 4)
## End(Not run)
```
bdm.dMap.plot *Class density maps plot.*

Description

Class density maps plot.

Usage

```
bdm.dMap.plot(
 bdm,
 classes = NULL,
  join = FALSE,
  class.pltt = NULL,
 pakde.pltt = NULL,
 pakde.lvls = 16,
 wtt.lwd = 1,
 plot.peaks = T,
 labels.cex = 1,
  layer = 1\mathcal{L}
```


Details

bdm.dMap.plot() yields a multi-plot layout where the first plot shows the dominating value of the covariate (or dominating class) in each cell, and the rest of the plots show the density map of each covariate value (or class).

The join distribution $P(V = v_i, C = c_j)$ is prone to the bias in the marginal distribution of the covariate. Therefore, the join distribution $P(V = v_i, C = c_j)$ is transformed, by default, into a conditional distribution $P(c_j | V = v_i)$ (where the c_j are the grid cells of the embedding and V is the covariate (or class)). Thus, the first plot shows a hard classification of grid-cells, (cells are coloured based on the dominating value of the covariate (or dominating class), *i.e.* the v_i for which $P(c_i | V = v_i)$ is maximum), and the rest of the plots show the conditional distributions $P(C = c_i | V = v_i)$. This makes the plots of the different classes not directly comparable but the dominant areas of each class can be more easily identified.

However, the same plots can be depicted based on the join distribution by setting join = TRUE. This makes sense when the bias in the covariate values (or classes) is not significant. In this case the hard clustering shows the real dominance of each covariate value (or class) over the embedding area and the density maps are comparable one to each other (although, individually, they are not real density functions as they do not add up to one).

The multi-plot layout can be limited to a subset of the values of the covariate (or subset of classes) specified in parameter classes.

Value

None.

Examples

```
# --- load example dataset
bdm.example()
## Not run:
m \le - bdm.dMap(ex$map, threads = 4)
bdm.dMap.plot(m)
```
End(Not run)

bdm.example *Example dataset*

Description

Loads a mapping example.

Usage

bdm.example()

Details

The object ex is a list with elements: ex\$data, a matrix with raw data; ex\$labels, a vector of datapoint labels; ex\$map, a bdm data mapping instance. A bdm instance is the basic object of the mapping protocol, i.e. a list to which new elements are added at each step of the mapping protocol.

This example is based on a small synthetic dataset with $n = 5000$ observations drawn from a 4variate Gaussian Mixture Model (GMM) with 16 Gaussian components with random means and variances.

Value

An example dataset named ex

Examples

```
# --- load example dataset
bdm.example()
str(ex)
```
bdm.hlCorr *HD/LD correlation.*

Description

Pair-wise distance correlation between HD and LD neighborhoods.

```
bdm.hlCorr(data, bdm, zSampleSize = 1000, threads = 4, mpi.cl = NULL)
```
Arguments

Value

A copy of the input bdm instance with new element bdm\$knP.

Examples

```
# --- load example dataset
## Not run:
bdm.example()
m <- bdm.hlCorr(exData[, 1:4], ex$map, threads = 4)
## End(Not run)
```
bdm.init *Embedding initialization.*

Description

Computes the precision parameters for the given perplexity (i.e. the local bandwidths for the input affinity kernels) and returns them as a bdm data mapping instance. A bdm data mapping instance is the starting object of the mapping protocol, a list to which new elements are added at each step of the mapping protocol.

```
bdm.init(
  data,
  is.distance = F,
  is.sparse = F.
 ppx = 100,
  mpi.c1 = NULL,threads = 4,
  labels = NULL
)
```
bdm.knp 9

Arguments

Value

A bdm data mapping instance. This bdm instance is the starting object of the mapping protocol: a list to which new elements are added at each step of the mapping protocol.

Examples

```
# --- load example dataset
bdm.example()
## Not run:
m \le - bdm.init(ex$data, ppx = 250, labels = ex$labels)
```
End(Not run)

bdm.knp *k-ary Neighborhood Preservation*

Description

A measure of matching between HD and LD neighborhoods ('Multi-scale similarities in stochastic neighbour embedding: Reducing dimensionality while preserving both local and global structure', Lee et. al 2015).

```
bdm.knp(data, bdm, k.max = NULL, sampling = 0.9, threads = 4, mpi.cl = NULL)
```
Arguments

Value

A copy of the input bdm instance with new element bdm\$knP. #'

Examples

```
# --- load example dataset
bdm.example()
## Not run:
# --- compte the kNP
m <- bdm.knp(ex$data, ex$map, threads = 4)
# --- plot the kNP
bdm.knp.plot(m)
```
End(Not run)

bdm.knp.plot *k-ary Neighborhood Preservation plot*

Description

Log and linear plots of the k-ary Neighborhood Preservation

Usage

```
bdm.knp.plot(bdm, ppxfrmt = 0)
```


bdm.labels 11

Examples

```
# --- load example dataset
bdm.example()
## Not run:
# --- compte the kNP
m <- bdm.knp(ex$data, ex$map, threads = 4)
# --- plot the kNP
bdm.knp.plot(m, ppxfrmt = 0)
## End(Not run)
```
bdm.labels *Get data-point clustering labels.*

Description

Given that clusters are computed at grid-cell level, this function returns the clustering label for each data-point.

Usage

```
bdm.labels(bdm, merged = F, layer = 1)
```
Arguments

Value

A vector of data-point clustering labels.

Examples

bdm.example() m.labels <- bdm.labels(ex\$map)

Description

Performs a recursive merging of clusters based on minimum loss of signal-to-noise-ratio (S2NR) until reaching the desired number of clusters. The S2NR is the explained/unexplained variance ratio measured in the high dimensional space based on the given low dimensional clustering.

Usage

```
bdm.merge.s2nr(
  data,
 bdm,
  k = 10,
 plot.merge = T,
  ret.merge = F,
  info = T,
  layer = 1,
  ...
)
```
Arguments

Details

See details in bdm.optk.s2nr().

bdm.mpi.start 13

Value

None if ret.merge = FALSE. Else, a copy of the input bdm instance with new element bdm\$merge.

Examples

```
bdm.example()
m.labels <- bdm.labels(ex$map)
```
bdm.mpi.start *Initialize parallel computing environment.*

Description

Initialize parallel computing environment.

Usage

```
bdm.mpi.start(threads)
```
Arguments

Value

cl A cluster instance (as created by the snow::makeCluster() function).

bdm.mpi.stop *Stops MPI parallel computing environment.*

Description

Stops MPI parallel computing environment.

Usage

bdm.mpi.stop(cl)

Arguments

cl A cluster instance (as created by the bdm.mpi.start() function).

Description

Starts the multi-core t-SNE (mtSNE) algorithm.

Usage

```
bdm.mtsne(
  data,
  is.distance = F,
  is.sparse = F,
  ppx = 100,
  theta = 0.5,
  iters = 250,
  mpi.c1 = NULL,threads = 4,
  infoRate = 25
)
```
Arguments

Value

A bdm data mapping instance.

bdm.optk.plot 15

Examples

```
# --- load example dataset
bdm.example()
## Not run:
# --- perform mtSNE
m \le - bdm.mtsne(ex$data, ex$map, ppx = 250, iters = 250, threads = 4)
# --- plot the Cost function
bdm.cost(m)
# --- plot mtSNE output (use bdm.ptsne.plot() function)
bdm.ptsne.plot(m)
```
End(Not run)

bdm.optk.plot *Plots the signal-to-noise-ratio as a function of the number of clusters.*

Description

The function bdm.optk.sn2r() computes the S2NR that results from recursively merging clusters and, by deafult, makes a plot of these values. For large datasets this computation can take a while, so we can save this result by setting optk.ret = TRUE. If this result is saved, we can plot it again at any time using this funcion.

Usage

bdm.optk.plot(bdm)

Arguments

bdm A *bdm* instance as generated by bdm.init().

Value

None.

Examples

```
bdm.example()
m <- bdm.optk.s2nr(ex$data, ex$map, ret.optk = TRUE)
bdm.optk.plot(m)
```


Description

Performs a recursive merging of clusters based on minimum loss of signal-to-noise-ratio (S2NR). The S2NR is the explained/unexplained variance ratio measured in the high dimensional space based on the given low dimensional clustering. Merging is applied recursively until reaching a configuration of only 2 clusters and the S2NR is measured at each step.

Usage

```
bdm.optk.s2nr(data, bdm, info = T, plot.optk = T, ret.optk = F, layer = 1)
```
Arguments

Details

The underlying idea is that neigbouring clusters in the embedding correspond to close clusters in the high dimensional space, i.e. this merging heuristic is based on the spatial distribution of clusters. For each cluster (child cluster) we choose the neighboring cluster with steepest gradient along their common border (father cluster). Thus, we get a set of pairs of clusters (child/father) to be potentially merged. Given this set of candidates, the merging is performed recursively choosing, at each step, the pair of child/father clusters that results in a minimum loss of S2NR. Typically some clusters dominate over all of their neighboring clusters. These clusters have no father. Thus, once all posible mergings have been performed we reach a blocked state where only the dominant clusters remain. This situation identifies a hierarchy level in the clustering. When this situation is reached, the algorithm starts a new merging round, identifying the child/father relations at that level of the hierarchy. The process stops when only two clusters remain. Usually, the clustering hierarchy is clearly depicted by singular points in the S2NR function. This is a hint that the low dimensional clustering configuration is an image of a hierarchycal configuration in the high dimensional space. See bdm.optk.plot().

bdm.pakde 17

Value

None if ret.optk = FALSE. Else, a copy of the input bdm instance with new element bdm\$optk (a matrix).

Examples

```
# --- load mapped dataset
bdm.example()
# --- compute optimal number of clusters and attach the computation
bdm.optk.s2nr(ex$map, data = ex$data, plot.optk = TRUE, ret.optk = FALSE)
```
bdm.pakde *Perplexity-adaptive kernel density estimation*

Description

Starts the paKDE algorithm (second step of the mapping protocol).

Usage

```
bdm.pakde(
 bdm,
 ppx = 100,
 g = 200,
 g. exp = 3,
 mpi.c1 = NULL,threads = 2,
  layer = 1)
```


Details

When computing the paKDE the embedding area is discretized as a grid of size $g * g$ cells. In order to avoid border effects, the limits of the grid are expanded by default so as to enclose at least the 0.9986 of the cumulative distribution function (3σ) of the kernels of the most extreme mapped points in each direction.

The presence of outliers in the embedding can lead to undesired expansion of the grid limits. We can overcome this using lower values of g.exp. By setting $g_{\text{c}} exp = 0$ the grid limits will be equal to the range of the embedding.

The values $g_{\text{e}} exp = c(1, 2, 3, 4, 5, 6)$ enclose cdf values of 0.8413, 0.9772, 0.9986, 0.99996, 0.99999, 1.0 respectively.

Value

A copy of the input bdm instance with new element bdm\$pakde (paKDE output). bdm\$pakde[[layer]]\$layer = 'NC' stands for not computed layers.

Examples

```
# --- load mapped dataset
bdm.example()
# --- run paKDE
## Not run:
m <- bdm.pakde(ex$map, ppx = 200, g = 200, g.exp = 3, threads = 4)
# --- plot paKDE output
bdm.pakde.plot(m)
## End(Not run)
```
bdm.pakde.plot *Plot paKDE (density landscape)*

Description

Plot paKDE (density landscape)

Usage

```
bdm.pakde.plot(bdm, pakde.pltt = NULL, pakde.lvls = 16, layer = 1)
```


bdm.pMap 19

Value

None.

Examples

```
bdm.example()
m <- bdm.pakde.plot(ex$map)
```
bdm.pMap *Precision map (quantile map of betas)*

Description

Precision map (quantile map of betas)

Usage

```
bdm.pMap(
 bdm,
 pMap.levels = 8,
 pMap.cex = 0.1,
 pMap.bg = "#000000",
 colorbar = T
)
```
Arguments

Value

None.

Examples

```
bdm.example()
bdm.pMap(ex$map)
```


Description

Starts the parallelized t-SNE algorithm (pt-SNE). This is the first step of the mapping protocol.

Usage

```
bdm.ptsne(
  data,
 bdm,
  theta = 0.5,
 Y.init = NULL,
 mpi.cl = NULL,
  threads = 4,
 layers = 2,
  info = 0)
```
Arguments

Value

A bdm data mapping instance.

bdm.ptsne.plot 21

Examples

```
# --- load example dataset
bdm.example()
# --- perform ptSNE
## Not run:
# --- run ptSNE
m <- bdm.ptsne(ex$data, ex$map, threads = 10, layers = 2)
# --- plot the Cost function
bdm.cost(m)
# --- plot ptSNE output
bdm.ptsne.plot(m, class.lbls = ex$labels)
```

```
## End(Not run)
```
bdm.ptsne.plot *Plot ptSNE (low-dimensional embedding)*

Description

Plot ptSNE (low-dimensional embedding)

Usage

```
bdm.ptsne.plot(
 bdm,
 ptsne.cex = 0.5,
 ptsne.bg = "#FFFFFF",
 class.lbls = NULL,
  class.pltt = NULL,
  layer = 1)
```


Value

None.

Examples

```
bdm.example()
m <- bdm.ptsne.plot(ex$map, class.lbls = ex$labels)
```
bdm.qMap *ptSNE quantile-maps*

Description

Maps quantitative variables onto the embedding space.

Usage

```
bdm.qMap(
 bdm,
  data,
  labels = NULL,
  subset = NULL,qMap.levels = 8,
 qMap.cex = 0.3,
  qMap.bg = "#FFFFFF",
  class.pltt = NULL,
 qtitle = NULL,
 cex.main = 1,
  colorbar = T,
  layer = 1\mathcal{L}
```


bdm.restart 23

Details

This is not a heat-map but a quantile-map plot. This function splits the range of each variable into as many quantiles as specified by levels so that the color gradient will hardly ever correspond to a constant numeric gradient. Thus, the mapping will show more evenly distributed colors though at the expense of possibly exaggerating artifacts. For variables with very extrem distributions, it will be impossible to find as many quantiles as desired and the distribution of colors will not be so homogeneous.

Value

None.

Examples

```
bdm.example()
bdm.qMap(ex$map, ex$data)
# --- show only components (1, 2, 4, 8) of the GMM
bdm.qMap(ex$map, ex$data, subset = which(ex$map$lbls %in% c(1, 4, 8, 16)))
```
bdm.restart *Restart pt-SNE*

Description

Restarts the ptSNE algorithm (runs more epochs).

```
bdm.restart(
  data,
  bdm,
  epochs = NULL,
  iters = NULL,
 mpi.cl = NULL,
  threads = NULL,
  layers = NULL,
  info = 0
)
```
Arguments

Value

A bdm data mapping instance.

Examples

```
# --- load example dataset
bdm.example()
## Not run:
# --- restart ptSNE
m <- bdm.restart(ex$data, ex$map, epochs = 50)
```
End(Not run)

bdm.wtt *Watertrack transform (WTT)*

Description

Starts the WTT algorithm (third setp of the mapping protocol).

Usage

bdm.wtt(bdm, layer = 1)

bdm.wtt.plot 25

Details

This function requires the up-stream step bdm.pakde().

Value

A bdm data mapping instance.

Examples

```
# --- load mapped dataset
bdm.example()
# --- perform WTT
m <- bdm.wtt(ex$map)
# --- plot WTT output
bdm.wtt.plot(m)
```
bdm.wtt.plot *Plot WTT (clustering)*

Description

Plot WTT (clustering)

Usage

```
bdm.wtt.plot(
  bdm,
  pakde.pltt = NULL,
  pakde.lvls = 16,
  wtt.lwd = 1,
  plot.peaks = T,
  labels.cex = 1,
  layer = 1\mathcal{L}
```


26 bdm.wtt.plot

Value

None.

Examples

```
bdm.example()
m <- bdm.wtt.plot(ex$map)
```
Index

bdm.boxp, [2](#page-1-0) bdm.cost, [3](#page-2-0) bdm.dMap, [4](#page-3-0) bdm.dMap.plot, [5](#page-4-0) bdm.example, [7](#page-6-0) bdm.hlCorr, [7](#page-6-0) bdm.init, [8](#page-7-0) bdm.knp, [9](#page-8-0) bdm.knp.plot, [10](#page-9-0) bdm.labels, [11](#page-10-0) bdm.merge.s2nr, [12](#page-11-0) bdm.mpi.start, [13](#page-12-0) bdm.mpi.stop, [13](#page-12-0) bdm.mtsne, [14](#page-13-0) bdm.optk.plot, [15](#page-14-0) bdm.optk.s2nr, [16](#page-15-0) bdm.pakde, [17](#page-16-0) bdm.pakde.plot, [18](#page-17-0) bdm.pMap, [19](#page-18-0) bdm.ptsne, [20](#page-19-0) bdm.ptsne.plot, [21](#page-20-0) bdm.qMap, [22](#page-21-0) bdm.restart, [23](#page-22-0) bdm.wtt, [24](#page-23-0) bdm.wtt.plot, [25](#page-24-0)