

# Package: GridOnClusters (via r-universe)

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**Type** Package

**Title** Cluster-Preserving Multivariate Joint Grid Discretization

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**Description** Discretize multivariate continuous data using a grid that captures the joint distribution via preserving clusters in the original data (Wang et al. 2020) <[doi:10.1145/3388440.3412415](https://doi.org/10.1145/3388440.3412415)>. Joint grid discretization is applicable as a data transformation step to prepare data for model-free inference of association, function, or causality.

**Imports** Rcpp, Ckmeans.1d.dp, cluster, fossil, dqrng, mclust, Rdpack, plotrix

**Suggests** FunChisq, knitr, testthat (>= 3.0.0), rmarkdown

**RdMacros** Rdpack

**License** LGPL (>= 3)

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## Contents

cluster . . . . .	2
discretize.jointly . . . . .	2
plot.GridOnClusters . . . . .	5
plotGOCpatterns . . . . .	5

<b>Index</b>	<b>7</b>
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cluster	<i>Cluster Multivariate Data</i>
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### Description

The function obtains clusters from data using the given number of clusters, which may be a range.

### Usage

```
cluster(data, k, method)
```

### Arguments

data	input continuous multivariate data
k	the number(s) of clusters
method	the method for clustering

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discretize.jointly	<i>Discretize Multivariate Continuous Data by a Cluster-Preserving Grid</i>
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### Description

Discretize multivariate continuous data using a grid that captures the joint distribution via preserving clusters in the original data

### Usage

```
discretize.jointly(
  data,
  k = c(2:10),
  min_level = 1,
  cluster_method = c("Ball+BIC", "kmeans+silhouette", "PAM"),
  grid_method = c("Sort+split", "MultiChannel.WUC"),
  cluster_label = NULL
)
```

**Arguments**

<code>data</code>	a matrix containing two or more continuous variables. Columns are variables, rows are observations.
<code>k</code>	either an integer, a vector of integers, or <code>Inf</code> , specifying different ways to find clusters in data. The default is a vector containing integers from 2 to 10. If <code>'k'</code> is a single number, data will be grouped into exactly <code>'k'</code> clusters. If <code>'k'</code> is an integer vector, an optimal <code>'k'</code> is chosen from among the integers, that maximizes the average silhouette width. If <code>'k'</code> is set to <code>Inf</code> , an optimal <code>k</code> is chosen among 2 to <code>nrow(data)</code> . If <code>cluster_label</code> is specified, <code>k</code> is ignored.
<code>min_level</code>	integer or vector, signifying the minimum number of levels along each dimension. If a vector of size <code>ncol(data)</code> , then each element will be mapped 1:1 to each dimension in order. If an integer, then all dimensions will have the same minimum number of levels.
<code>cluster_method</code>	the clustering method to be used. Ignored if cluster labels are given <code>"kmeans+silhouette"</code> will use k-means to cluster data and the average Silhouette score to select the number of clusters <code>k</code> . <code>"Ball+BIC"</code> will use <code>Mclust</code> ( <code>modelName = "VII"</code> ) to cluster data and BIC score to select the number of cluster <code>k</code> .
<code>grid_method</code>	the discretization method to be used. <code>"Sort+split"</code> will sort the cluster by cluster mean in each dimension and then split consecutive pairs only if the sum of the error rate of each cluster is less than or equal to 50 in a certain dimension. The maximum number of lines is the number of clusters minus one. <code>"MultiChannel.WUC"</code> will split each dimension by weighted with-in cluster sum of squared distances by <code>"Ckmeans.1d.dp::MultiChannel.WUC"</code> . Applied in each projection on each dimension. The channel of each point is defined by its multivariate cluster label.
<code>cluster_label</code>	a vector of user-specified cluster labels for each observation in data. The user is free to choose any clustering. If unspecified, k-means clustering is used by default.

**Details**

The function implements algorithms described in (Wang et al. 2020).

**Value**

A list that contains four items:

<code>D</code>	a matrix that contains the discretized version of the original data. Discretized values are one(1)-based.
<code>grid</code>	a list of vectors containing decision boundaries for each variable/dimension.
<code>clabels</code>	a vector containing cluster labels for each observation in data.
<code>csimilarity</code>	a similarity score between clusters from joint discretization <code>D</code> and cluster labels <code>clabels</code> . The score is the adjusted Rand index.

**Author(s)**

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## References

Wang J, Kumar S, Song M (2020). “Joint Grid Discretization for Biological Pattern Discovery.” In *Proceedings of the 11th ACM International Conference on Bioinformatics, Computational Biology and Health Informatics*. ISBN 9781450379649, doi:10.1145/3388440.3412415.

## See Also

See [Ckmeans.1d.dp](#) for discretizing univariate continuous data.

## Examples

```
# using a specified k
x = rnorm(100)
y = sin(x)
z = cos(x)
data = cbind(x, y, z)
discretized_data = discretize.jointly(data, k=5)$D

# using a range of k
x = rnorm(100)
y = log1p(abs(x))
z = tan(x)
data = cbind(x, y, z)
discretized_data = discretize.jointly(data, k=c(3:10))$D

# using k = Inf
x = c()
y = c()
mns = seq(0,1200,100)
for(i in 1:12){
  x = c(x,runif(n=20, min=mns[i], max=mns[i]+20))
  y = c(y,runif(n=20, min=mns[i], max=mns[i]+20))
}
data = cbind(x, y)
discretized_data = discretize.jointly(data, k=Inf)$D

# using an alternate clustering method to k-means
library(cluster)
x = rnorm(100)
y = log1p(abs(x))
z = sin(x)
data = cbind(x, y, z)

# pre-cluster the data using partition around medoids (PAM)
cluster_label = pam(x=data, diss = FALSE, metric = "euclidean", k = 5)$clustering
discretized_data = discretize.jointly(data, cluster_label = cluster_label)$D
```

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plot.GridOnClusters     *Plotting the continuous data along with cluster-preserving Grid*

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### Description

Plots examples of jointly discretizing continuous data based on grids that preserve clusters in the original data.

### Usage

```
## S3 method for class 'GridOnClusters'
plot(
  x,
  xlab = NULL,
  ylab = NULL,
  main = NULL,
  main.table = NULL,
  sub = NULL,
  pch = 19,
  ...
)
```

### Arguments

x	the result generated by discretize.jointly
xlab	the horizontal axis label
ylab	the vertical axis label
main	the title of the clustering scatter plots
main.table	the title of the discretized data plots
sub	the subtitle
pch	the symbol for points on the scatter plots
...	additional graphical parameters

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plotGOCpatterns     *(OBOSOLETE) Plotting the continuous data along with cluster-preserving Grid*

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### Description

Plots examples of jointly discretizing continuous data based on grids that preserve clusters in the original data.

**Usage**

```
plotGOCpatterns(data, res)
```

**Arguments**

data	the input continuous data matrix
res	the result generated by <code>discretize.jointly</code>

# Index

Ckmeans.1d.dp, [4](#)  
cluster, [2](#)

discretize.jointly, [2](#)

plot.GridOnClusters, [5](#)  
plotGOCpatterns, [5](#)