

Package ‘conclust’

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Type Package

Title Pairwise Constraints Clustering

Version 1.1

Date 2016-08-15

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Description There are 4 main functions in this package: ckmeans(), lcvqe(), mpckm() and ccls(). They take an unlabeled dataset and two lists of must-link and cannot-link constraints as input and produce a clustering as output.

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conclust-package *Pairwise Constraints Clustering*

Description

There are 4 main functions in this package: ckmeans(), lcvqe(), mpckm() and ccls(). They take an unlabeled dataset and two lists of must-link and cannot-link constraints as input and produce a clustering as output.

Details

The DESCRIPTION file:

```
Package:      conclust
Type:        Package
Title:       Pairwise Constraints Clustering
Version:     1.1
Date:       2016-08-15
Author:      Tran Khanh Hiep, Nguyen Minh Duc
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License:     GPL-3
```

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lcvqe	LCVQE algorithm
mpckm	MPC K-means algorithm

There are 4 main functions in this package: ckmeans(), lcvqe(), mpckm() and ccls(). They take an unlabeled dataset and two lists of must-link and cannot-link constraints as input and produce a clustering as output.

Author(s)

Tran Khanh Hiep, Nguyen Minh Duc

Maintainer: Tran Khanh Hiep <hieptkse03059@fpt.edu.vn>

References

Wagstaff, Cardie, Rogers, Schrodl (2001), Constrained K-means Clustering with Background Knowledge Bilenko, Basu, Mooney (2004), Integrating Constraints and Metric Learning in Semi-Supervised Clustering Dan Pelleg, Dorit Baras (2007), K-means with large and noisy constraint sets

See Also

Wagstaff, Cardie, Rogers, Schrodl (2001), Constrained K-means Clustering with Background Knowledge Bilenko, Basu, Mooney (2004), Integrating Constraints and Metric Learning in Semi-Supervised Clustering Dan Pelleg, Dorit Baras (2007), K-means with large and noisy constraint sets

Examples

```
data = matrix(c(0, 1, 1, 0, 0, 0, 1, 1), nrow = 4)
mustLink = matrix(c(1, 2), nrow = 1)
cantLink = matrix(c(1, 4), nrow = 1)
k = 2
```

```
pred = ckmeans(data, k, mustLink, cantLink)
pred
pred = mpckm(data, k, mustLink, cantLink)
pred
pred = lcvqe(data, k, mustLink, cantLink)
pred
pred = ccls(data, k, mustLink, cantLink)
pred
```

ccls*Pairwise Constrained Clustering by Local Search*

Description

This function takes an unlabeled dataset and two lists of must-link and cannot-link constraints as input and produce a clustering as output.

Usage

```
ccls(data, k = -1, mustLink, cantLink, maxIter = 1, tabuIter = 100, tabuLength = 20)
```

Arguments

<code>data</code>	The unlabeled dataset.
<code>k</code>	Number of clusters.
<code>mustLink</code>	A list of must-link constraints
<code>cantLink</code>	A list of cannot-link constraints
<code>maxIter</code>	Number of iteration
<code>tabuIter</code>	Number of iteration in Tabu search
<code>tabuLength</code>	The number of elements in the Tabu list

Details

This algorithm minimizes the clustering cost function using Tabu search.

Value

A vector that represents the labels (clusters) of the data points

Note

This is the first algorithm for pairwise constrained clustering by local search.

Author(s)

Tran Khanh Hiep Nguyen Minh Duc

References

Tran Khanh Hiep, Nguyen Minh Duc, Bui Quoc Trung (2016), Pairwise Constrained Clustering by Local Search.

See Also

Tran Khanh Hiep, Nguyen Minh Duc, Bui Quoc Trung (2016), Pairwise Constrained Clustering by Local Search.

Examples

```
data = matrix(c(0, 1, 1, 0, 0, 0, 1, 1), nrow = 4)
mustLink = matrix(c(1, 2), nrow = 1)
cantLink = matrix(c(1, 4), nrow = 1)
k = 2
pred = ckmeans(data, k, mustLink, cantLink)
pred
```

ckmeans

COP K-means algorithm

Description

This function takes an unlabeled dataset and two lists of must-link and cannot-link constraints as input and produce a clustering as output.

Usage

```
ckmeans(data, k, mustLink, cantLink, maxIter = 100)
```

Arguments

data	The unlabeled dataset.
k	Number of clusters.
mustLink	A list of must-link constraints
cantLink	A list of cannot-link constraints
maxIter	Number of iteration

Details

This algorithm produces a clustering that satisfies all given constraints.

Value

A vector that represents the labels (clusters) of the data points

Note

The constraints should be consistent in order for the algorithm to work.

Author(s)

Tran Khanh Hiep Nguyen Minh Duc

References

Wagstaff, Cardie, Rogers, Schrodl (2001), Constrained K-means Clustering with Background Knowledge

See Also

Wagstaff, Cardie, Rogers, Schrodl (2001), Constrained K-means Clustering with Background Knowledge

Examples

```
data = matrix(c(0, 1, 1, 0, 0, 0, 1, 1), nrow = 4)
mustLink = matrix(c(1, 2), nrow = 1)
cantLink = matrix(c(1, 4), nrow = 1)
k = 2
pred = ckmeans(data, k, mustLink, cantLink)
pred
```

lcvqe

LCVQE algorithm

Description

This function takes an unlabeled dataset and two lists of must-link and cannot-link constraints as input and produce a clustering as output.

Usage

```
lcvqe(data, k, mustLink, cantLink, maxIter = 10)
```

Arguments

data	The unlabeled dataset.
k	Number of clusters.
mustLink	A list of must-link constraints
cantLink	A list of cannot-link constraints
maxIter	Number of iteration

Details

This algorithm finds a clustering that satisfies as many constraints as possible

Value

A vector that represents the labels (clusters) of the data points

Note

This algorithm can handle noisy constraints.

Author(s)

Tran Khanh Hiep Nguyen Minh Duc

References

Dan Pelleg, Dorit Baras (2007), K-means with large and noisy constraint sets

See Also

Dan Pelleg, Dorit Baras (2007), K-means with large and noisy constraint sets

Examples

```
data = matrix(c(0, 1, 1, 0, 0, 0, 1, 1), nrow = 4)
mustLink = matrix(c(1, 2), nrow = 1)
cantLink = matrix(c(1, 4), nrow = 1)
k = 2
pred = lcvqe(data, k, mustLink, cantLink)
pred
```

mpckm

MPC K-means algorithm

Description

This function takes an unlabeled dataset and two lists of must-link and cannot-link constraints as input and produce a clustering as output.

Usage

```
mpckm(data, k, mustLink, cantLink, maxIter = 10)
```

Arguments

data	The unlabeled dataset.
k	Number of clusters.
mustLink	A list of must-link constraints
cantLink	A list of cannot-link constraints
maxIter	Number of iteration

Details

This algorithm finds a clustering that satisfies as many constraints as possible

Value

A vector that represents the labels (clusters) of the data points

Note

This is one of the best algorithm for clustering with constraints.

Author(s)

Tran Khanh Hiep Nguyen Minh Duc

References

Bilenko, Basu, Mooney (2004), Integrating Constraints and Metric Learning in Semi-Supervised Clustering

See Also

Bilenko, Basu, Mooney (2004), Integrating Constraints and Metric Learning in Semi-Supervised Clustering

Examples

```
data = matrix(c(0, 1, 1, 0, 0, 0, 1, 1), nrow = 4)
mustLink = matrix(c(1, 2), nrow = 1)
cantLink = matrix(c(1, 4), nrow = 1)
k = 2
pred = mpckm(data, k, mustLink, cantLink)
pred
```

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