

# Package ‘qVarSel’

February 20, 2015

**Type** Package

**Title** Variables Selection for Clustering and Classification

**Version** 1.0

**Date** 2014-05-27

**Author** Stefano Benati

**Maintainer** Stefano Benati <stefano.benati@unitn.it>

**Description** For a given data matrix A and cluster centers/prototypes collected in the matrix P, the functions described here select a subset of statistic variables Q that mostly explains/justifies P as prototypes. The functions are useful to reduce the data dimension for classification and to discard masking variables for clustering.

**License** GPL-2

**Depends** lpSolveAPI

**Suggests** clusterGeneration, mclust

**Imports** Rcpp (>= 0.11.0)

**LinkingTo** Rcpp

**NeedsCompilation** yes

**Repository** CRAN

**Date/Publication** 2014-06-12 16:42:34

## R topics documented:

qVarSel-package . . . . .	2
PrtDist . . . . .	3
qVarSelH . . . . .	5
qVarSelLP . . . . .	6
<b>Index</b>	<b>9</b>

**Description**

For a given data matrix  $A$  and cluster centers/prototypes collected in the matrix  $P$ , the functions described here select a subset of variables  $Q$  that mostly explains/justifies  $P$  as prototypes. The functions are useful to reduce the dimension of the data for classification and to discard masking variables for clustering.

**Details**

Package: qVarSel  
Type: Package  
Version: 1.0  
Date: 2014-05-27  
License: gpl-2

The package is useful to reduce the variable dimension for clustering. The example below shows the sequence of the operations. First, k-means can be applied to the whole data sets, to calculate prototypes  $P$ . Then, distances between units  $U$  and  $P$  are calculated and stored in a matrix  $D$ . Then, apply package subroutine `q-VarSelH` to select the most important variables. Apply EM optimization on data  $D$  for full clustering parameters estimation.

**Author(s)**

Stefano Benati

Maintainer: Stefano Benati <stefano.benati@unitn.it>

**References**

S. Benati, S. Garcia Quiles, J. Puerto "Optimization Methods to Select Variables for Clustering", Working Paper, Universidad de Sevilla, 2014

**Examples**

```
# Generate random cluster with masking variables

require(clusterGeneration)
tmp1 <- genRandomClust(numClust = 4, sepVal = 0.2, clustszind = 2,
                      rangeN = c( 100, 150 ),
                      numNonNoisy = 5, numNoisy = 5, numReplicate = 1,
                      fileName = "chk1")
a <- tmp1$datList$chk1_1
ass <- tmp1$memList$chk1_1
```

```

numunits <- length(ass)
noiseindex <- tmp1$noisyList$chk1_1
a <- scale(a) #Standardzation for columns

# calculate data prototypes using k-means

sl2 <- kmeans(a, 4, iter.max = 200,
              nstart = 10, algorithm = "L")
prototype = sl2$centers

# calculate distances between observations and prototypes
# Remark: d is a 3-dimensions matrix

d = PrtDist(a, prototype)

# Select 5 most representative variables, use 200 iterations

lsH <- qVarSelH(d, 5, maxit = 200)

# reduce the dimension of a

sq = 1:(dim(a)[2])
vrb = sq[lsH$x > 0.01]
a_reduced = a[ ,vrb]

# use the EM methodology for clustering on the reduced data

require(mclust)
sl1 <- Mclust(a_reduced, G = 4, modelName = "VVV")

```

---

PrtDist

*Calculation of the distances between units and centers*


---

### Description

Given a data set A, with  $a[i,k]$  be the measure of variable k on unit i, and a prototype set P, with  $p[j,k]$  be the measure of variable k on prototype j, the function calculate  $d[i,j,k]$ , the i,j distance according variable k

### Usage

```
PrtDist(a,
        p)
```

### Arguments

a	Matrix with n rows (units) and m columns (variables)
p	Matrix with g rows (units) and m columns (variables)

**Details**

$d[i,j,k]$  is the squared distance:  $d[i,j,k] = (a[i,k] - p[j,k])^2$

**Value**

d: The 3-dimensional matrix of i,j,k distances

**Note**

The function has been written to simplify the code examples. It has been written as a R script with minimal vectorization, therefore it is not computationally much efficient. Moreover  $d(i,j,k)$  is the square of differences and users may prefer to employ other dissimilarity measures. In that case, they should better write their own function.

**Author(s)**

Stefano Benati

**References**

S. Benati, S. Garcia Quiles, J. Puerto "Optimization Methods to Select Variables for Clustering", Working Paper, Universidad de Sevilla, 2014

**Examples**

```
## Generate random 2 cluster with 20 masking variables
## and 10 true variables

require(clusterGeneration)
tmp1 <- genRandomClust(numClust = 2, sepVal = 0.2, clustszind = 2,
                      rangeN = c( 100, 150 ),
                      numNonNoisy = 10, numNoisy = 20, numReplicate = 1,
                      fileName = "chk1")
a <- tmp1$datList$chk1_1
a <- scale(a) # Standardize for column

## Calculate two prototypes, using kmeans
y <- kmeans(a, 2, iter.max = 200, nstart = 10)
p = y$centers

## Calculate dist:
d <- PrtDist(a, p)
```

**Description**

The function implements the q-Vars heuristic described in the reference below. Given a 3-dimension matrix  $D$ , with  $d[i,j,k]$  being the distance between statistic unit  $i$  and prototype  $j$  measured through variable  $k$ , the function calculates the set of variables of cardinality  $q$  that mostly explains the prototypes.

**Usage**

```
qVarSelH(d,
         q,
         maxit = 100)
```

**Arguments**

<code>d</code>	A numeric 3-dimensional matrix where elements $d(i,j,k)$ are the distances between observation $i$ and cluster center/prototype $j$ , that are measured through variable $k$ .
<code>q</code>	A positive scalar, that is the number of variables to select
<code>maxit</code>	A positive scalar, that is the maximum number of iteration allowed

**Details**

The heuristic repeatedly selects a set of variables and then allocates units to prototypes, while a local optimum is reached. Random restart is used to continue the search until the maximum number of iteration is reached.

**Value**

<code>obj</code>	The value of the objective function
<code>x</code>	A 0-1 vector describing wheter variable $k$ is selected: If $x[k] = 1$ then $k$ is selected
<code>ass</code>	A vector of assignment of units to clusters: if $ass[i] = j$ then unit $i$ is assigned to the cluster represented by center/prototype $j$
<code>bestit</code>	The iteration in which the optimal solution is found

**Note**

The methodology is heuristic and some steps are random. It may be the case that different runs provide different solutions.

**Author(s)**

Stefano Benati

## References

S. Benati, S. Garcia Quiles, J. Puerto "Optimization Methods to Select Variables for Clustering", Working Paper, Universidad de Sevilla, 2014

## See Also

qVarSelLP

## Examples

```
## Generate random 2 cluster with 20 masking variables
## and 10 true variables

require(clusterGeneration)
tmp1 <- genRandomClust(numClust = 2, sepVal = 0.2, clustszind = 2,
                      rangeN = c( 100, 150 ),
                      numNonNoisy = 10, numNoisy = 20, numReplicate = 1,
                      fileName = "chk1")
a <- tmp1$datList$chk1_1
a <- scale(a) # Standardize for column

## Calculate two prototype, using kmeans
y <- kmeans(a, 2, iter.max = 200, nstart = 10)
p = y$centers

## Calculate dist:
d <- PrtDist(a, p)

## Calculate Best 10 variables:
lsH <- qVarSelH(d, 10, maxit = 200)
```

---

qVarSelLP

*A Mixed Integer Linear Programming Formulation for the Variable Selection Problem*

---

## Description

The function solve the mixed integer linear programming formulation of the variable selection problem.

## Usage

```
qVarSelLP(d,
          q,
          binary = FALSE,
          write = FALSE)
```

**Arguments**

d	A 3-dimensional distance matrix, in which $d[i,j,k]$ is the distance between unit $i$ and prototype $j$ , according to variable $k$ .
q	The number of variables to select.
binary	Set this value to TRUE if you wish to solve the problem with integer variables, or set it to FALSE if you just want to solve the continuous relaxation
write	Set this value to TRUE if you want that the optimization problem is exported in a file called <code>qdistsel.lp</code>

**Details**

The function solves the linear problem through the lpSolve solver available through the package lpSolveAPI. The linear programming formulation is the implementation of model F3 described in the paper below (without the median variables).

**Value**

status	The result of the optimization as output of the function <code>solve()</code> of library lpSolveAPI
obj	The value of the objective function
x	The value of the problem variables corresponding to the variable selection: $x[j] = 1$ means that variable $j$ has been selected, 0 otherwise. If the continuous relaxation has been solved, the vector can contain fractional variables (most likely meaningless).

**Note**

The computational time to solve an integer programming problem can easily become exponential, therefore be careful when set variable "binary" to TRUE, as you could wait days even to get the solution of a small scale problem. Even though the continuous version can contain fractional variables, comparing the objective functions of subroutines `qVarSelH` and `qVarSelLP` is a certificate of the solution quality.

**Author(s)**

Stefano Benati

**References**

S. Benati, S. Garcia Quiles, "A p-median model with distance selection", Working Paper, Universidad Carlos III de Madrid, 2012

**See Also**

lpSolveAPI

**Examples**

```
## Generate random cluster

a <- rbind(cbind(rnorm(5, 0, 1), rnorm(5, 0, 3), rnorm(5, 0, 5)),
          cbind(rnorm(5, 5, 1), rnorm(5, 5, 3), rnorm(5, 5, 5) ))

## calculate data prototypes using k-means

sl2 <- kmeans(a, 2, iter.max = 100, nstart = 2)
p = sl2$centers

## calculate distances between observations and prototypes
## Remark: d is a 3-dimensions matrix

d = PrtDist(a, p)

## Select 2 most representative variables, use heuristic

lsH <- qVarSelH(d, 2, maxit = 200)

## Select 2 variables, use linear relaxation

require(lpSolveAPI)
lsC <- qVarSelLP(d, 2)

## check optimality

if (abs(lsH$obj - lsC$obj) < 0.001)
  message = "Heuristic Solution is Optimal"
```



# Index

\*Topic **classif**

PrtDist, [3](#)  
qVarSel-package, [2](#)  
qVarSelH, [5](#)  
qVarSelLP, [6](#)

\*Topic **cluster**

PrtDist, [3](#)  
qVarSel-package, [2](#)  
qVarSelH, [5](#)  
qVarSelLP, [6](#)

\*Topic **optimize**

PrtDist, [3](#)  
qVarSel-package, [2](#)  
qVarSelH, [5](#)  
qVarSelLP, [6](#)

PrtDist, [3](#)

qVarSel (qVarSel-package), [2](#)  
qVarSel-package, [2](#)  
qVarSelH, [5](#)  
qVarSelLP, [6](#)