Package 'SelvarMix'

September 20, 2015

Type Package

Title Regularization for Variable Selection in Model-Based Clustering and Discriminant Analysis

Version 1.1

Date 2015-09-20

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Description Performs a regularization approach to variable selection in the model-based clustering and classification frameworks.
First, the variables are arranged in order with a lasso-like procedure.
Second, the method of Maugis, Celeux, and Martin-Magniette (2009, 2011) is adapted to define the role of variables in the two frameworks.

License GPL (>= 3)

Imports Rcpp (>= 0.11.1), glasso, parallel, Rmixmod, methods

LinkingTo Rcpp, RcppArmadillo

NeedsCompilation yes

Repository CRAN

Date/Publication 2015-09-20 22:51:05

R topics documented:

`SelvarMix-package` *Regularization for variable selection in model-based clustering and discriminant analysis*

Description

SelvarMix is a package where a regularization approach of variable selection is considered in model-based clustering and discriminant analysis frameworks. First, this procedure consists of ranking the variables with a lasso-like procedure. Second, the method of Maugis et al (2009, 2011) is adapted to define the role of variables in the two frameworks. SelvarMix provides a faster variable selection algorithm than the backward stepwise or forward stepwise algorithms of Maugis et al (2009), allowing us to study high-dimensional datasets.

Details

Package:	SelvarMix
Type:	Package
Version:	1.0
Date:	2014-04-03
License:	GPL-3 + file LICENSE
LazyLoad:	yes

The general purpose of the package is to perform variable selection in model-based clustering and discriminant analysis. It focus on model-based clustering, where the clusters are assumed to arise from Gaussian distributions. The most achieved model in model-based clustering has been proposed by Maugis et al (2009). This so-called $SRUW$ modeling considers three roles of variables: one variable my belong to the relevant clustering set S, the redundant variable set U or the independent variable set W. Moreover, the redundant variables may be explained by a subset R of the relevant variables S. In order to avoid the slow of this algorithm when data with numerous variables are studied, the SelvarMix procedure is proposed. It proceeds in two steps: First, the variables are ranked using a lasso-like procedure analogous to the one of Zhou et al (2009); second, the $SRUW$ procedure is run on this ranked set of variables.

Author(s)

Author: Mohammed Sedki, Gilles Celeux and Cathy Maugis-Rabusseau

References

Maugis, C., Celeux, G., and Martin-Magniette, M. L., 2009. "Variable selection in model-based clustering: A general variable role modeling". Computational Statistics and Data Analysis, vol. 53/11, pp. 3872-3882.

Maugis, C., Celeux, G., and Martin-Magniette, M. L., 2011. "Variable selection in model-based discriminant analysis". Journal of Multivariate Analysis, vol. 102, pp. 1374-1387.

Zhou, H., Pan, W., and Shen, X., 2009. "Penalized model-based clustering with unconstrained covariance matrices". Electronic Journal of Statistics, vol. 3, pp.1473-1496.

Sedki, M., Celeux, G., Maugis-Rabusseau, C., 2014. "SelvarMix: A R package for variable selection in model-based clustering and discriminant analysis with a regularization approach". Inria Research Report available at http://hal.inria.fr/hal-01053784

Examples

```
## Not run:
## Simulated data  example as shown in Maugis et al. (2009) (correlated scenario 2)
## n = 2000 observations, p = 14 variables
require(Rmixmod)
require(glasso)
data(scenarioCor)
data.cor <- scenarioCor[,1:14]
labels.cor <-scenarioCor[,15]


lambda <- seq(20,  100, by = 10)
rho <- seq(1, 2, length=2)
hybrid.size <- 3
models <- mixmodGaussianModel(family = "spherical", equal.proportions = TRUE)
regModel <- c("LI","LB","LC")
indepModel <- c("LI","LB")

## variable selection in model-based clustering
nbCluster <-  c(3,4)
criterion <- "BIC"
simulate.cl  <- SelvarClustLasso(data.cor, nbCluster, lambda, rho, hybrid.size,
                                 criterion, models, regModel, indepModel)



## variables selection in discriminant analysis
## training sample : n = 1900, p = 14 variables
data.learn <- scenarioCor[1:1900,1:14]
labels.learn <-scenarioCor[1:1900,15]

## testing sample : n = 100, p = 14 variables
data.test <- scenarioCor[1901:2000,1:14]
labels.test <-scenarioCor[1901:2000,15]

lambda <- seq(20,  50, length = 10)

simulate.da <- SelvarLearnLasso(data.learn, labels.learn, lambda, rho, hybrid.size,
                                models, regModel, indepModel, data.test, labels.test)

## End(Not run)
```

scenarioCor *Simulated quantitative data according SRUW modeling*

Description

The dataset consists of 2000 data points in R^{14}. On the subset of relevant clustering variables $S = \{1, 2\}$, data are distributed from a mixture of four equiprobable spherical Gaussian distributions with means $(0, 0), (4, 0)(0, 2)$ and $(4, 2)$. The subset of redundant variables is $U = \{3 - 11\}$ that are explained by the subset of predictor variables $R = \{1, 2\}$. The last three variables are independent $W = \{11, 12, 13\}$.

Format

A data matrix with 2000 observations on 14 variables and the last column contains the labels.

`scenarioCor[,1:14]` a numeric matrix containing the observations

`scenarioCor[,15]` an integer vector containing the labels

Details

The subset U of redundant variables is simulated as follows :

$x^U = (0, 0, 0.4, 0.8, ..., 2) + x^S b + \varepsilon$, with $\varepsilon \sim N(0_9, \Omega)$

The subset W of independent variables is simulated as follows :

$x^W \sim N((3.2, 3.6, 4), I_3)$

For more details on the regression coefficients b and the covariance matrix Ω see Maugis et al.(2009).

References

Maugis, C., Celeux, G., and Martin-Magniette, M. L., 2009. "Variable selection in model-based clustering: A general variable role modeling". Computational Statistics and Data Analysis, vol. 53/11, pp. 3872-3882.

Examples

```
data(scenarioCor)
```

`SelvarClustLasso` *Regularization for variable selection in model-based clustering*

Description

This function implements the variable selection in model-based clustering using a lasso ranking on the variables as described in Sedki et al (2014). The variable ranking step uses the penalized EM algorithm of Zhou et al (2009).

Usage

```
SelvarClustLasso(data, nbCluster, lambda, rho, hybrid.size, criterion,
                 models, regModel, indepModel, nbCores)
```

Arguments

`data`	matrix containing quantitative data. Rows correspond to observations and columns correspond to variables
`nbCluster`	numeric listing of the number of clusters (must be positive integers)
`lambda`	numeric listing of the tuning parameter for ℓ_1 mean penalty
`rho`	numeric listing of the tuning parameter for ℓ_1 precision matrix penalty
`hybrid.size`	optional parameter make less strength the hybrid forward and backward algorithms to select S and W sets
`criterion`	list of character defining the criterion to select the best model. The best model is the one with the highest criterion value. Possible values: "BIC", "ICL", c("BIC", "ICL"). Default is "BIC"
`models`	a Rmixmod [`Model`] object defining the list of models to run. The models Gaussian_pk_L_C, Gaussian_pk_Lk_C, Gaussian_pk_L_Ck, and Gaussian_pk_Lk_Ck are called by default (see mixmodGaussianModel() in Rmixmod package to specify other models)
`regModel`	list of character defining the covariance matrix form for the linear regression of U on the R set of variables. Possible values: "LI" for spherical form, "LB" for diagonal form and "LC" for general form. Possible values: "LI", "LB", "LC", c("LI", "LB"), c("LI", "LC"), c("LB", "LC") and c("LI", "LB", "LC"). Default is c("LI", "LB", "LC")
`indepModel`	list of character defining the covariance matrix form for independent variables W. Possible values: "LI" for spherical form and "LB" for diagonal form. Possible values: "LI", "LB", c("LI", "LB"). Default is c("LI", LB")
`nbCores`	number of CPUs to be used when parallel computing is utilized (default is 2)

Value

for each criterion BIC or ICL

S	The selected set of relevant clustering variables
R	The selected subset of regressors
U	The selected set of redundant variables
W	The selected set of independent variables
criterionValue	The criterion value for the selected model
nbCluster	The selected number of clusters
model	The selected Gaussian mixture form
regModel	The selected covariance form for the regression
indepModel	The selected covariance form for the independent gaussian distribution
proba	Matrix containing the conditional probabilities of belonging to each cluster for all observations
partition	Vector of length n containing the cluster assignments of the n observations according to the Maximum-a-Posteriori rule

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References

Zhou, H., Pan, W., and Shen, X., 2009. "Penalized model-based clustering with unconstrained covariance matrices". Electronic Journal of Statistics, vol. 3, pp.1473-1496.

Maugis, C., Celeux, G., and Martin-Magniette, M. L., 2009. "Variable selection in model-based clustering: A general variable role modeling". Computational Statistics and Data Analysis, vol. 53/11, pp. 3872-3882.

Sedki, M., Celeux, G., Maugis-Rabusseau, C., 2014. "SelvarMix: A R package for variable selection in model-based clustering and discriminant analysis with a regularization approach". Inria Research Report available at http://hal.inria.fr/hal-01053784

See Also

SelvarLearnLasso SortvarClust SortvarLearn scenarioCor

Examples

```
## Not run:
## Simulated data  example as shown in Maugis et al. (2009)
## n = 2000 observations, p = 14 variables
require(Rmixmod)
require(glasso)
data(scenarioCor)
data.cor <- scenarioCor[,1:14]
```

```
lambda <- seq(20,  100, by = 10)
rho <- seq(1, 2, length=2)
hybrid.size <- 3
nbCluster <-  c(3,4)
criterion <- "BIC"
models <- mixmodGaussianModel(family = "spherical", equal.proportions = TRUE)
regModel <- c("LI","LB","LC")
indepModel <- c("LI","LB")


simulate.cl <- SelvarClustLasso(data.cor, nbCluster, lambda, rho, hybrid.size,
                                criterion, models, regModel, indepModel)


## End(Not run)
```

`SelvarLearnLasso` *Regularization for variable selection in discriminant analysis*

Description

This function implements the variable selection in discriminant analysis using a lasso ranking on the variables as described in Sedki et al (2014). The variable ranking step uses the penalized EM algorithm of Zhou et al (2009) (adapted in Sedki et al (2014) for the discriminant analysis settings). A testing sample can be used to compute the averaged classification error rate.

Usage

```
SelvarLearnLasso(data, knownlabels, lambda, rho, hybrid.size,  models,
                 regModel, indepModel, dataTest, labelsTest, nbCores)
```

Arguments

`data`	matrix containing quantitative data. Rows correspond to observations and columns correspond to variables
`knownlabels`	an integer vector or a factor of size number of observations. Each cell corresponds to a cluster affectation
`lambda`	numeric listing of tuning parameter for ℓ_1 mean penalty
`rho`	numeric listing of tuning parameter for ℓ_1 precision matrix penalty
`hybrid.size`	optional parameter make less strength the hybrid forward and backward algorithms to select S and W sets
`models`	a Rmixmod [`Model`] object defining the list of models to run. The models Gaussian_pk_L_C, Gaussian_pk_Lk_C, Gaussian_pk_L_Ck, and Gaussian_pk_Lk_Ck are called by default (see mixmodGaussianModel() in Rmixmod package to specify other models)

regModel	list of character defining the covariance matrix form for the linear regression of U on the R set of variable. Possible values: "LI" for spherical form, "LB" for diagonal form and "LC" for general form. Possible values: "LI", "LB", "LC", c("LI", "LB") , c("LI", "LC"), c("LB", "LC") and c("LI", "LB", "LC"). Default is c("LI", "LB", "LC")
indepModel	list of character defining the covariance matrix form for independent variables W. Possible values: "LI" for spherical form and "LB" for diagonal form. Possible values: "LI", "LB", c("LI", "LB"). Default is c("LI", LB")
dataTest	matrix containing quantitative testing data. Rows correspond to observations and columns correspond to variables
labelsTest	an integer vector or a factor of size number of testing observations. Each cell corresponds to a cluster affectation
nbCores	number of CPUs to be used when parallel computing is utilized (default is 2)

Value

S	The selected set of relevant clustering variables
R	The selected subset of regressors
U	The selected set of redundant variables
W	The selected set of independent variables
criterionValue	The criterion value for the selected model
nbCluster	The selected number of clusters
model	The selected covariance model
regModel	The selected covariance form for the regression
indepModel	The selected covariance form for the independent variables
proba	Optional : matrix containing the conditional probabilities of belonging to each cluster for the testing observations
partition	Optional: vector containing the cluster assignments of the testing observations according to the Maximum-a-Posteriori rule
error	Optional : error rate done by the predicted partition (obtained using Maximum-A-Posteriori rule)

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References

Zhou, H., Pan, W., and Shen, X., 2009. "Penalized model-based clustering with unconstrained covariance matrices". Electronic Journal of Statistics, vol. 3, pp.1473-1496.

Maugis, C., Celeux, G., and Martin-Magniette, M. L., 2009. "Variable selection in model-based clustering: A general variable role modeling". Computational Statistics and Data Analysis, vol. 53/11, pp. 3872-3882.

Sedki, M., Celeux, G., Maugis-Rabusseau, C., 2014. "SelvarMix: A R package for variable selection in model-based clustering and discriminant analysis with a regularization approach". Inria Research Report available at http://hal.inria.fr/hal-01053784

See Also

SelvarClustLasso SortvarLearn SortvarClust scenarioCor

Examples

```
## Not run:
## Simulated data  example as shown in Sedki et al (2014)
require(Rmixmod)
require(glasso)
data(scenarioCor)

lambda <- seq(20,  50, length = 10)
rho <- seq(1, 2, length=2)
hybrid.size <- 3
models <- mixmodGaussianModel(family = "spherical", equal.proportions = TRUE)
regModel <- c("LI","LB","LC")
indepModel <- c("LI","LB")

## variables selection in discriminant analysis
## training sample : n = 1900 observations , p = 14 variables
data.learn <- scenarioCor[1:1900,1:14]
labels.learn <-scenarioCor[1:1900,15]

## testing sample : n = 100 observations, p = 14 variables
data.test <- scenarioCor[1901:2000,1:14]
labels.test <-scenarioCor[1901:2000,15]

simulate.da <- SelvarLearnLasso(data.learn, labels.learn, lambda, rho, hybrid.size,
                                models, regModel, indepModel, data.test, labels.test)

## End(Not run)
```

`SortvarClust` *Variable ranking with LASSO in model-based clustering*

Description

This function implements variable ranking procedure in model-based clustering using the penalized EM algorithm of Zhou et al (2009).

Usage

```
SortvarClust(data, nbCluster, lambda, rho, nbCores)
```

Arguments

`data`	matrix containing quantitative data. Rows correspond to observations and columns correspond to variables
`nbCluster`	numeric listing of the number of clusters (must be integers)

lambda	numeric listing of the tuning parameter for ℓ_1 mean penalty
rho	numeric listing of the tuning parameter for ℓ_1 precision matrix penalty
nbCores	number of CPUs to be used when parallel computing is utilized (default is 2)

Value

matrix with rows corresponding to variable ranking. Each row corresponds to a value nbCluster.

Author(s)

Mohammed Sedki <mohammed.sedki@u-psud.fr>

References

Zhou, H., Pan, W., and Shen, X., 2009. "Penalized model-based clustering with unconstrained covariance matrices". Electronic Journal of Statistics, vol. 3, pp.1473-1496.

Maugis, C., Celeux, G., and Martin-Magniette, M. L., 2009. "Variable selection in model-based clustering: A general variable role modeling". Computational Statistics and Data Analysis, vol. 53/11, pp. 3872-3882.

Sedki, M., Celeux, G., Maugis-Rabusseau, C., 2014. "SelvarMix: A R package for variable selection in model-based clustering and discriminant analysis with a regularization approach". Inria Research Report available at http://hal.inria.fr/hal-01053784

See Also

SortvarLearn

Examples

```
## Not run:
## Simulated data  example as shown in Sedki et al (2014)
## n = 2000 observations, p = 14 variables
require(glasso)
data(scenarioCor)
data.cor <- scenarioCor[,1:14]


lambda <- seq(20,  100, by = 10)
rho <- seq(1, 2, length=2)
nbCluster <-  c(3, 4)

## variable ranking in model-based clustering
var.ranking.cl <- SortvarClust(data.cor, nbCluster, lambda, rho)

## End(Not run)
```

SortvarLearn *Variable ranking with LASSO in discriminant analysis*

Description

This function implements variable ranking procedure in discriminant analysis using the penalized EM algorithm of Zhou et al (2009) (adapted in Sedki et al (2014) for the discriminant analysis settings).

Usage

```
SortvarLearn(data, knownlabels, lambda, rho, nbCores)
```

Arguments

data	matrix containing quantitative data. Rows correspond to observations and columns correspond to variables
knownlabels	an integer vector or a factor of size number of observations. Each cell corresponds to a cluster affectation. So the maximum value is the number of clusters.
lambda	numeric listing of tuning parameter for ℓ_1 mean penalty
rho	numeric listing of tuning parameter for ℓ_1 precision matrix penalty
nbCores	number of CPUs to be used when parallel computing is utilized (default is 2)

Value

vector of integers corresponding to variable ranking.

Author(s)

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References

Zhou, H., Pan, W., and Shen, X., 2009. "Penalized model-based clustering with unconstrained covariance matrices". Electronic Journal of Statistics, vol. 3, pp.1473-1496.

Maugis, C., Celeux, G., and Martin-Magniette, M. L., 2009. "Variable selection in model-based clustering: A general variable role modeling". Computational Statistics and Data Analysis, vol. 53/11, pp. 3872-3882.

Sedki, M., Celeux, G., Maugis-Rabusseau, C., 2014. "SelvarMix: A R package for variable selection in model-based clustering and discriminant analysis with a regularization approach". Inria Research Report available at http://hal.inria.fr/hal-01053784

See Also

SortvarClust

Examples

```
## Not run:
## Simulated data  example as shown in Sedki et al (2014)
## n = 2000 observations, p = 14 variables
require(glasso)
data(scenarioCor)
data.cor <- scenarioCor[,1:14]
labels.cor <-scenarioCor[,15]

lambda <- seq(20,  50, length = 10)
rho <- seq(1, 2, length=2)



## variable ranking in discriminant analysis
var.ranking.da <- SortvarLearn(data.cor, labels.cor, lambda, rho)

## End(Not run)
```

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