

Package: biClassify (via r-universe)

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Type Package

Title Binary Classification Using Extensions of Discriminant Analysis

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Description Implements methods for sample size reduction within Linear and Quadratic Discriminant Analysis in Lapanowski and Gaynanova (2020) <[arXiv:2005.03858](#)>. Also includes methods for non-linear discriminant analysis with simultaneous sparse feature selection in Lapanowski and Gaynanova (2019) PMLR 89:1704-1713.

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Imports Rcpp (>= 1.0.1), Matrix, stats, fields, MASS, datasets, mvtnorm, expm, DAAG

Depends R (>= 2.10)

LinkingTo Rcpp, RcppArmadillo

Suggests testthat, knitr, rmarkdown

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Contents

KOS	2
KOS_Data	4
LDA	4

LDA_Data	7
QDA	8
QDA_Data	10
SelectParams	11

Index	13
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KOS	<i>Function which generates feature weights, discriminant vector, and class predictions.</i>
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Description

Returns a (m x 1) vector of predicted group membership (either 1 or 2) for each data point in X. Uses Data and Cat to train the classifier.

Usage

```
KOS(TestData = NULL, TrainData, TrainCat, Method = "Full",
     Mode = "Automatic", m1 = NULL, m2 = NULL, Sigma = NULL,
     Gamma = NULL, Lambda = NULL, Epsilon = 1e-05)
```

Arguments

TestData	(m x p) Matrix of unlabelled data with numeric features to be classified. Cannot have missing values.
TrainData	(n x p) Matrix of training data with numeric features. Cannot have missing values.
TrainCat	(n x 1) Vector of class membership corresponding to Data. Values must be either 1 or 2.
Method	A string of characters which determines which version of KOS to use. Must be either "Full" or "Subsampled". Default is "Full".
Mode	A string of characters which determines how the reduced sample paramters will be inputted for each method. Must be either "Research", "Interactive", or "Automatic". Default is "Automatic".
m1	The number of class 1 compressed samples to be generated. Must be a positive integer.
m2	The number of class 2 compressed samples to be generated. Must be a positive integer.
Sigma	Scalar Gaussian kernel parameter. Default set to NULL and is automatically generated if user-specified value not provided. Must be > 0. User-specified parameters must satisfy hierarchical ordering.
Gamma	Scalar ridge parameter used in kernel optimal scoring. Default set to NULL and is automatically generated if user-specified value not provided. Must be > 0. User-specified parameters must satisfy hierarchical ordering.

Lambda	Scalar sparsity parameter on weight vector. Default set to NULL and is automatically generated by the function if user-specified value not provided. Must be ≥ 0 . When $\text{Lambda} = 0$, SparseKOS defaults to kernel optimal scoring of [Lapanowski and Gaynanova, preprint] without sparse feature selection. User-specified parameters must satisfy hierarchical ordering.
Epsilon	Numerical stability constant with default value $1e-05$. Must be > 0 and is typically chosen to be small.

Details

Function which handles classification. Generates feature weight vector and discriminant coefficients vector in sparse kernel optimal scoring. If a matrix X is provided, the function classifies each data point using the generated feature weight vector and discriminant vector. Will use user-supplied parameters Sigma , Gamma , and Lambda if any are given. If any are missing, the function will run `SelectParams` to generate the other parameters. User-specified values must satisfy hierarchical ordering.

Value

A list of

Predictions	$(m \times 1)$ Vector of predicted class labels for the data points in <code>TestData</code> . Only included in non-null value of X is provided.
Weights	$(p \times 1)$ Vector of feature weights.
Dvec	$(n \times 1)$ Discriminant coefficients vector.

References

Lapanowski, Alexander F., and Gaynanova, Irina. "Sparse feature selection in kernel discriminant analysis via optimal scoring", *Artificial Intelligence and Statistics*, 2019.

Examples

```
Sigma <- 1.325386 #Set parameter values equal to result of SelectParam.
Gamma <- 0.07531579 #Speeds up example.
Lambda <- 0.002855275

TrainData <- KOS_Data$TrainData
TrainCat <- KOS_Data$TrainCat
TestData <- KOS_Data$TestData
TestCat <- KOS_Data$TestCat

KOS(TestData = TestData,
     TrainData = TrainData,
     TrainCat = TrainCat ,
     Sigma = Sigma ,
     Gamma = Gamma ,
     Lambda = Lambda)
```

KOS_Data	<i>A list consisting of Training and Test data along with corresponding class labels.</i>
----------	---

Description

A list consisting of Training and Test data along with corresponding class labels.

Usage

KOS_Data

Format

A list consisting of:

TrainData (179 x 4) Matrix of training data features. the first two features satisfy $\sqrt{x_{i1}^2 + x_{i2}^2} > 2/3$ if the *i*th sample is in class 1. Otherwise, they satisfy $\sqrt{x_{i1}^2 + x_{i2}^2} < 2/3 - 1/10$ if the *i*th sample is in class 2. The third and fourth features are generated as independent $N(0, 1/2)$ noise.

TestData (94 x 4) Matrix of test data features. the first two features satisfy $\sqrt{x_{i1}^2 + x_{i2}^2} > 2/3$ if the *i*th sample is in class 1. Otherwise, they satisfy $\sqrt{x_{i1}^2 + x_{i2}^2} < 2/3 - 1/10$ if the *i*th sample is in class 2. The third and fourth features are generated as independent $N(0, 1/2)$ noise.

CatTrain (179 x 1) Vector of class labels for the training data.

CatTest (94 x 1) Vector of class labels for the test data. ...

Source

Simulation model 1 from [Lapanowski and Gaynanova, preprint].

References

Lapanowski, Alexander F., and Gaynanova, Irina. "Sparse Feature Selection in Kernel Discriminant Analysis via Optimal Scoring", preprint.

Description

A wrapper function for the various LDA implementations available in this package.

Generates class predictions for TestData.

Usage

```
LDA(TrainData, TrainCat, TestData, Method = "Full", Mode = "Automatic",
    m1 = NULL, m2 = NULL, m = NULL, s = NULL, gamma = 1e-05,
    type = "Rademacher")
```

Arguments

TrainData	A (n x p) numeric matrix without missing values consisting of n training samples each with p features.
TrainCat	A vector of length n consisting of group labels of the n training samples in TrainData. Must consist of 1s and 2s.
TestData	A (m x p) numeric matrix without missing values consisting of m training samples each with p features. The number of features must equal the number of features in TrainData.
Method	A string of characters which determines which version of LDA to use. Must be either "Full", "Compressed", "Subsampled", "Projected", or "fastRandomFisher". Default is "Full".
Mode	A string of characters which determines how the reduced sample parameters will be inputted for each method. Must be either "Research", "Interactive", or "Automatic". Default is "Automatic".
m1	The number of class 1 compressed samples to be generated. Must be a positive integer.
m2	The number of class 2 compressed samples to be generated. Must be a positive integer.
m	The number of total compressed samples to be generated. Must be a positive integer.
s	The sparsity level used in compression. Must satisfy $0 < s < 1$.
gamma	A numeric value for the stabilization amount $\gamma * I$ added to the covariance matrix used in the LDA decision rule. Default amount is $1E-5$. Cannot be negative.
type	A string of characters determining the type of compression matrix used. The accepted values are Rademacher, Gaussian, and Count.

Details

Function which handles all implementations of LDA.

Value

A list containing

Predictions	(m x 1) Vector of predicted class labels for the data points in TestData.
Dvec	(px1) Discriminant vector used to predict the class labels.

References

Lapanowski, Alexander F., and Gaynanova, Irina. “Compressing large sample data for discriminant analysis” arXiv preprint arXiv:2005.03858 (2020).

Ye, Haishan, Yujun Li, Cheng Chen, and Zhihua Zhang. “Fast Fisher discriminant analysis with randomized algorithms.” *Pattern Recognition* 72 (2017): 82-92.

Examples

```
TrainData <- LDA_Data$TrainData
TrainCat <- LDA_Data$TrainCat
TestData <- LDA_Data$TestData
plot(TrainData[,2]~TrainData[,1], col = c("blue", "orange")[as.factor(TrainCat)])
```

```
#----- Full LDA -----
```

```
LDA(TrainData = TrainData,
    TrainCat = TrainCat,
    TestData = TestData,
    Method = "Full",
    gamma = 1E-5)
```

```
#----- Compressed LDA -----
```

```
m1 <- 700
m2 <- 300
s <- 0.01
LDA(TrainData = TrainData,
    TrainCat = TrainCat,
    TestData = TestData,
    Method = "Compressed",
    Mode = "Research",
    m1 = m1,
    m2 = m2,
    s = s,
    gamma = 1E-5)
```

```
LDA(TrainData = TrainData,
    TrainCat = TrainCat,
    TestData = TestData,
    Method = "Compressed",
    Mode = "Automatic",
    gamma = 1E-5)
```

```
#----- Sub-sampled LDA -----
```

```
m1 <- 700
m2 <- 300
LDA(TrainData = TrainData,
    TrainCat = TrainCat,
    TestData = TestData,
    Method = "Subsampled",
    Mode = "Research",
    m1 = m1,
    m2 = m2,
```

```
gamma = 1E-5)

LDA(TrainData = TrainData,
    TrainCat = TrainCat,
    TestData = TestData,
    Method = "Subsampled",
    Mode = "Automatic",
    gamma = 1E-5)

#----- Projected LDA -----
m1 <- 700
m2 <- 300
s <- 0.01
LDA(TrainData = TrainData,
    TrainCat = TrainCat,
    TestData = TestData,
    Method = "Projected",
    Mode = "Research",
    m1 = m1,
    m2 = m2,
    s = s,
    gamma = 1E-5)

LDA(TrainData = TrainData,
    TrainCat = TrainCat,
    TestData = TestData,
    Method = "Projected",
    Mode = "Automatic",
    gamma = 1E-5)

#----- Fast Random Fisher -----
m <- 1000
s <- 0.01
LDA(TrainData = TrainData,
    TrainCat = TrainCat,
    TestData = TestData,
    Method = "fastRandomFisher",
    Mode = "Research",
    m = m,
    s = s,
    gamma = 1E-5)

LDA(TrainData = TrainData,
    TrainCat = TrainCat,
    TestData = TestData,
    Method = "fastRandomFisher",
    Mode = "Automatic",
    gamma = 1E-5)
```

LDA_Data

A list consisting of Training and Test data along with corresponding class labels.

Description

A list consisting of Training and Test data along with corresponding class labels.

Usage

LDA_Data

Format

A list consisting of:

TrainData (10000 x 10) Matrix of independent normally-distributed training samples conditioned on class membership. There are 7000 samples belonging to class 1, and 3000 samples belonging to class 2. The class 1 mean vector is the vector of length 10 consisting only of -2. Likewise, the class 2 mean vector is the vector of length 10 consisting only of 2. The shared covariance matrix has (i,j) entry $(0.5)^{|i-j|}$.

TestData (1000 x 10) Matrix of independent test data features with the same distributions and class proportions as TrainData.

Train (10000 x 1) Vector of class labels for the samples in TrainData.

TestCat (1000 x 1) Vector of class labels for the samples in TestData. ...

References

Lapanowski, Alexander F., and Gaynanova, Irina. "Compressing large-sample data for discriminant analysis", preprint.

QDA

Quadratic Discriminant Analysis (QDA)

Description

A wrapper function for the various QDA implementations available in this package.

Generates class predictions for TestData.

Usage

```
QDA(TrainData, TrainCat, TestData, Method = "Full", Mode = "Automatic",
    m1 = NULL, m2 = NULL, m = NULL, s = NULL, gamma = 1e-05)
```

Arguments

TrainData A (n x p) numeric matrix without missing values consisting of n training samples each with p features.

TrainCat A vector of length n consisting of group labels of the n training samples in TrainData. Must consist of 1s and 2s.

TestData	A (m x p) numeric matrix without missing values consisting of m training samples each with p features. The number of features must equal the number of features in TrainData.
Method	A string of characters which determines which version of QDA to use. Must be either "Full", "Compressed", or "Subsampled".
Mode	A string of characters which determines how the reduced sample parameters will be inputted for each method. Must be either "Research", "Interactive", or "Automatic". Default is "Automatic".
m1	The number of class 1 compressed samples to be generated. Must be a positive integer.
m2	The number of class 2 compressed samples to be generated. Must be a positive integer.
m	The number of total compressed samples to be generated. Must be a positive integer.
s	The sparsity level used in compression. Must satisfy $0 < s < 1$.
gamma	A numeric value for the stabilization amount $\gamma * I$ added to the covariance matrix used in the LDA decision rule. Default amount is $1E-5$. Cannot be negative.

Details

Function which handles all implementations of LDA.

Value

Predictions (m x 1) Vector of predicted class labels for the data points in TestData.

References

Lapanowski, Alexander F., and Gaynanova, Irina. "Compressing large sample data for discriminant analysis" arXiv preprint arXiv:2005.03858 (2020).

Examples

```
TrainData <- QDA_Data$TrainData
TrainCat <- QDA_Data$TrainCat
TestData <- QDA_Data$TestData
plot(TrainData[,2]~TrainData[,1], col = c("blue", "orange")[as.factor(TrainCat)])

#----- Full QDA -----
QDA(TrainData = TrainData,
    TrainCat = TrainCat,
    TestData = TestData,
    Method = "Full",
    gamma = 1E-5)

#----- Compressed QDA -----
m1 <- 700
```

```
m2 <- 300
s <- 0.01
QDA(TrainData = TrainData,
    TrainCat = TrainCat,
    TestData = TestData,
    Method = "Compressed",
    Mode = "Research",
    m1 = m1,
    m2 = m2,
    s = s,
    gamma = 1E-5)

QDA(TrainData = TrainData,
    TrainCat = TrainCat,
    TestData = TestData,
    Method = "Compressed",
    Mode = "Automatic",
    gamma = 1E-5)

#----- Sub-sampled QDA -----
m1 <- 700
m2 <- 300
QDA(TrainData = TrainData,
    TrainCat = TrainCat,
    TestData = TestData,
    Method = "Subsampled",
    Mode = "Research",
    m1 = m1,
    m2 = m2,
    gamma = 1E-5)

QDA(TrainData = TrainData,
    TrainCat = TrainCat,
    TestData = TestData,
    Method = "Subsampled",
    Mode = "Automatic",
    gamma = 1E-5)
```

QDA_Data

A list consisting of Training and Test data along with corresponding class labels.

Description

A list consisting of Training and Test data along with corresponding class labels.

Usage

QDA_Data

Format

A list consisting of:

TrainData (10000 x 10) Matrix of independent normally-distributed training samples conditioned on class membership. There are 7000 samples belonging to class 1, and 3000 samples belonging to class 2. The class 1 mean vector is the vector of length 10 consisting only of -2. Likewise, the class 2 mean vector is the vector of length 10 consisting only of 2. The class 1 covariance matrix has (i,j) entry $(0.5)^{|i-j|}$. The class 2 covariance matrix has (i,j) entry $(-0.5)^{|i-j|}$.

TestData (1000 x 10) Matrix of independent test data features with the same distributions and class proportions as TrainData.

Train (10000 x 1) Vector of class labels for the samples in TrainData.

TestCat (1000 x 1) Vector of class labels for the samples in TestData. ...

References

Lapanowski, Alexander F., and Gaynanova, Irina. "Compressing large-sample data for discriminant analysis", preprint.

SelectParams	<i>Generates parameters.</i>
--------------	------------------------------

Description

Generates parameters to be used in sparse kernel optimal scoring.

Usage

```
SelectParams(TrainData, TrainCat, Sigma = NULL, Gamma = NULL,
  Epsilon = 1e-05)
```

Arguments

TrainData	(n x p) Matrix of training data with numeric features. Cannot have missing values.
TrainCat	(n x 1) Vector of class membership. Values must be either 1 or 2.
Sigma	Scalar Gaussian kernel parameter. Default set to NULL and is automatically generated if user-specified value not provided. Must be > 0. User-specified parameters must satisfy hierarchical ordering.
Gamma	Scalar ridge parameter used in kernel optimal scoring. Default set to NULL and is automatically generated if user-specified value not provided. Must be > 0. User-specified parameters must satisfy hierarchical ordering.
Epsilon	Numerical stability constant with default value 1e-05. Must be > 0 and is typically chosen to be small.

Details

Generates the gaussian kernel, ridge, and sparsity parameters for use in sparse kernel optimal scoring using the methods presented in [Lapanowski and Gaynanova, preprint]. The Gaussian kernel parameter is generated using five-fold cross-validation of the misclassification error rate across the .05, .1, .2, .3, .5 quantiles of squared-distances between groups. The ridge parameter is generated using a stabilization technique developed in Lapanowski and Gaynanova (2019). The sparsity parameter is generated by five-fold cross-validation over a logarithmic grid of 20 values in an automatically-generated interval.

Value

A list of

Sigma	Gaussian kernel parameter.
Gamma	Ridge Parameter.
Lambda	Sparsity parameter.

References

Lancewicki, Tomer. "Regularization of the kernel matrix via covariance matrix shrinkage estimation." arXiv preprint arXiv:1707.06156 (2017).

Lapanowski, Alexander F., and Gaynanova, Irina. "Sparse feature selection in kernel discriminant analysis via optimal scoring", Artificial Intelligence and Statistics, 2019.

Examples

```
Sigma <- 1.325386 #Set parameter values equal to result of SelectParam.
Gamma <- 0.07531579 #Speeds up example

TrainData <- KOS_Data$TrainData
TrainCat <- KOS_Data$TrainCat

SelectParams(TrainData = TrainData ,
             TrainCat = TrainCat,
             Sigma = Sigma,
             Gamma = Gamma)
```

Index

* datasets

KOS_Data, [4](#)

LDA_Data, [8](#)

QDA_Data, [10](#)

KOS, [2](#)

KOS_Data, [4](#)

LDA, [4](#)

LDA_Data, [7](#)

QDA, [8](#)

QDA_Data, [10](#)

SelectParams, [11](#)