

# Package ‘PredPsych’

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**Type** Package

**Title** Generic Package for Predictive Approaches in Psychology

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**Description** The Functions for Predictive Approaches in Psychology.

**License** GPL-3

**LazyData** TRUE

**Depends** R (>= 3.1.0)

**Imports** plyr, ggplot2, caret, rpart, e1071, mclust, MASS, party,  
randomForest

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**Suggests** knitr, rmarkdown

**VignetteBuilder** knitr

**Repository** CRAN

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 classifyFun

*Generic Classification Analyses*


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### Description

function for performing generic classification Analysis

### Usage

```
classifyFun(Data, classCol, selectedCols, ranges = NULL, tune = FALSE,
  cost = 1, gamma = 0.5, classifierName = "svm",
  genclassifier = Classifier.svm, silent = FALSE, SetSeed = TRUE, ...)
```

### Arguments

Data	(dataframe) dataframe of the data
classCol	(numeric) column number that contains the variable to be predicted
selectedCols	(optional) (numeric) all the columns of data that would be used either as predictor or as feature
ranges	(optional) (list) ranges for tuning support vector machine
tune	(optional) (logical) whether tuning of svm parameters should be performed or not
cost	(optional) (numeric) regularization parameter of svm
gamma	(optional) (numeric) rbf kernel parameter
classifierName	(optional) (string) name of the classifier to be used
genclassifier	(optional) (function or string) a classifier function or a name (e.g. Classifier.svm)
silent	(optional) (logical) whether to print messages on mean accuracy or not
SetSeed	(optional) (logical) Whether to setseed or not. use SetSeed to seed the random number generator to get consistent results; set false only for permutation tests
...	(optional) additional arguments for the function

### Details

This function implements Classification Analysis. Classification Analysis is a supervised machine learning approach that attempts to identify holistic patters in the data and assign to it classes (classification). Given a set of features, a classification analysis automatically learns intrinsic patterns in the data to be able to predict respective classes. If the data features are informative about the classes, a high classification score would be achieved.

### Value

Outputs Crossvalidation accuracy acc and Test accuracy accTest

### Author(s)

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**Examples**

```
#classification analysis with SVM
Results <- classifyFun(Data = KinData,classCol = 1,
selectedCols = c(1,2,12,22,32,42,52,62,72,82,92,102,112))
# output
# [1] "Begining k-fold Classification"
# [1] "Mean CV Accuracy 0.66"
# [1] "Mean Test Accuracy 0.62"
```

ClassPerm

*Permutation Analysis for classification***Description**

simple function to create permutation testing of a classifier

**Usage**

```
ClassPerm(Data, classCol, selectedCols, classifierFun, nSims = 1000,
plot = TRUE, ...)
```

**Arguments**

Data	(dataframe) dataframe of the data
classCol	(numeric) column number that contains the variable to be predicted
selectedCols	(optional) (numeric) all the columns of data that would be used either as predictor or as feature
classifierFun	(optional) (function) classifier function
nSims	(optional) (numeric) number of simulations
plot	(optional) (logical) whether to plot null accuracy distribution
...	(optional) additional arguments for the function

**Details**

The function implements Permutation tests for classification. Permutation tests are a set of non-parametric methods for hypothesis testing without assuming a particular distribution (Good, 2005). In case of classification analysis, this requires shuffling the labels of the dataset (i.e. randomly shuffling classes/conditions between observations) and calculating accuracies obtained.

**Value**

Returns actualAcc of the classification analysis, p-value from permutation testing, nullAcc distribution of the permutation figure containing null distribution

**Author(s)**

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## Examples

```
# perform a permutation testing for 10% of the kinematics movement data
PermutationResult <- ClassPerm(Data = KinData, classCol = 1,
  selectedCols = c(1,2,12,22,32,42,52,62,72,82,92,102,112), nSims = 1000)
```

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DimensionRed

*Generic Dimensionality Reduction Function*

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## Description

A simple function to perform dimensionality reduction

## Usage

```
DimensionRed(Data, method = "MDS", selectedCols, outcome = NA,
  plot = FALSE, ...)
```

## Arguments

Data	(dataframe) a data frame with variable/feature columns
method	(optional) (character) Dimensionality reduction method to be used
selectedCols	(optional)(numeric) which columns should be treated as data(features/columns) (defaults to all columns)
outcome	(optional)(vector) optional vector for visualising plots
plot	(optional)(logical) To plot or not to plot
...	(optional) additional arguments for the function

## Details

Dimensionality Reduction is the process of reducing the dimensions of the dataset. Multivariate data, even though are useful in getting an overall understanding of the underlying phenomena, do not permit easy interpretability. Moreover, variables in such data often are correlated with each other. For these reasons, it might be imperative to reduce the dimensions of the data. Various models have been developed for such dimensionality reduction. Of these, MDS and PCA has been demonstrated in the current implementation.

## Value

Data frame with Results

## Author(s)

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## Examples

```
# reducing dimension of Grip aperture from 10 to 2
GripAperture <- DimensionRed(KinData,selectedCols = 12:21,
  outcome = KinData[, "Object.Size"], plot = TRUE)
```

DTModel

*Generic Decision Tree Function***Description**

A simple function to create Decision Trees

**Usage**

```
DTModel(Data, classCol, selectedCols, tree, ...)
```

**Arguments**

Data	(dataframe) a data frame with regressors and response
classCol	(numeric) which column should be used as response col
selectedCols	(optional)(numeric) which columns should be treated as data(features + response) (defaults to all columns)
tree	which decision tree model to implement; One of the following values: <ul style="list-style-type: none"> <li>• CART = Classification And Regression Tree;</li> <li>• CARTNAHF = Crossvalidated Half Model CART Tree removing missing values;</li> <li>• CARTHF = Crossvalidated Half Model CART Tree With missing values;</li> <li>• CF = Conditional inference framework Tree;</li> <li>• RF = Random Forest Tree;</li> </ul>
...	(optional) additional arguments for the function

**Details**

The function implements the Decision Tree models (DT models). DT models fall under the general "Tree based methods" involving generation of a recursive binary tree (Hastie et al., 2009). In terms of input, DT models can handle both continuous and categorical variables as well as missing data. From the input data, DT models build a set of logical "if ..then" rules that permit accurate prediction of the input cases.

Unlike regression methods like GLMs, Decision Trees are more flexible and can model nonlinear interactions.

**Value**

model result for the input tree Results

**Author(s)**

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**Examples**

```
# generate a cart model for 10% of the data with cross-validation
model <- DTModel(Data = KinData[,c(1,2,12,22,32,42,52,62,72,82,92,102,112)],
  classCol=1, tree='CARTHF')
```

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fscore	<i>f-score</i>
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## Description

A simple function to generate F-scores (Fisher scores) for ranking features

## Usage

```
fscore(Data, classCol, featureCol)
```

## Arguments

Data	(dataframe) Data dataframe
classCol	(numeric) column with different classes
featureCol	(numeric) all the columns that contain features

## Details

The function implements F-score for feature selection. F-score provides a measure of how well a single feature at a time can discriminate between different classes. The higher the F-score, the better the discriminatory power of that feature

## Value

named numeric f-scores

## Author(s)

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## Examples

```
# calculate f-scores for 10% of movement  
fscore(KinData, classCol = 1, featureCol = c(2,12,22,32,42,52,62,72,82,92,102,112))
```

KinData

*Kinematics Dataset A dataset containing part of the motion capture dataset freely available in the publication (Ansuini et al., 2015). The dataset was obtained by recording 15 naive participants performing reach-to-grasp movements towards two differently sized objects: a small object (i.e., hazelnut) and a large object (i.e., grapefruit). The variables are as follows:*

## Description

- Object Size : Size of the to-be-grasped object (1 = small, 2 = large)
- Wrist\_Velocity\_01 .. Wrist\_Height\_10: module of the velocity of the wrist marker (mm/sec) from 10% (\_01) to 100% (\_10) of the movement
- Grip\_Aperture\_01 .. Grip\_Aperture\_10 Distance between the marker placed on thumb tip and that placed on the tip of the index finger (mm) from 10% (\_01) to 100% (\_10) of the movement
- Wrist\_Height\_01 .. Wrist\_Height\_10 z-component of the wrist marker (mm) from 10% (\_01) to 100% (\_10) of the movement
- x\_index\_01 .. x\_index\_10 : x-coordinates for the index with respect to F-local (mm) from 10% (\_01) to 100% (\_10) of the movement
- y\_index\_01 .. y\_index\_10 : y-coordinates for the index with respect to F-local (mm) from 10% (\_01) to 100% (\_10) of the movement
- z\_index\_01 .. z\_index\_10 : z-coordinates for the index with respect to F-local (mm) from 10% (\_01) to 100% (\_10) of the movement
- x\_thumb\_01 .. x\_thumb\_10 : x-coordinates for the thumb with respect to F-local (mm) from 10% (\_01) to 100% (\_10) of the movement
- y\_thumb\_01 .. y\_thumb\_10 : y-coordinates for the thumb with respect to F-local (mm) from 10% (\_01) to 100% (\_10) of the movement
- z\_thumb\_01 .. z\_thumb\_10 : z-coordinates for the thumb with respect to F-local (mm) from 10% (\_01) to 100% (\_10) of the movement
- x\_finger\_plane\_01 .. x\_finger\_plane\_10 x-components of the thumb-index plane from 10% (\_01) to 100% (\_10) of the movement
- y\_finger\_plane\_01 .. y\_finger\_plane\_10 y-components of the thumb-index plane from 10% (\_01) to 100% (\_10) of the movement
- z\_finger\_plane\_01 .. z\_finger\_plane\_10 z-components of the thumb-index plane from 10% (\_01) to 100% (\_10) of the movement

## Usage

```
data(KinData)
```

## Format

A data frame with 848 rows and 121 variables

## LinearDA

*Cross-validated Linear Discriminant Analysis***Description**

A simple function to perform cross-validated Linear Discriminant Analysis

**Usage**

```
LinearDA(Data, classCol, selectedCols, CV = FALSE, cvFraction = 0.8,
  extendedResults = FALSE, SetSeed = TRUE, cvType = "createDataPartition",
  k = 10, ...)
```

**Arguments**

Data	(dataframe) Data dataframe
classCol	(numeric) column number that contains the variable to be predicted
selectedCols	(optional) (numeric) all the columns of data that would be used either as predictor or as feature
CV	(optional) (logical) perform Cross validation of training dataset? If TRUE, posterior probabilities are present with the model
cvFraction	(optional) (numeric) Fraction of data to keep for training data
extendedResults	(optional) (logical) Return extended results with model?
SetSeed	(optional) (logical) Whether to setseed or not. use SetSeed to seed the random number generator to get consistent results; set false only for permutation tests
cvType	(optional) (string) type of cross validation to perform if cvType = 'createDataPartition' a portion of data (cvFraction) is used, For cvType = 'Folds', a n-fold cross validation is performed.
k	(optional) (numeric) the number of folds to use in case cvType = 'Folds'
...	(optional) additional arguments for the function

**Details**

The function implements Linear Discriminant Analysis, a simple algorithm for classification based analyses. LDA builds a model composed of a number of discriminant functions based on linear combinations of data features that provide the best discrimination between two or more conditions/classes. The aim of the statistical analysis in LDA is thus to combine the data features scores in a way that a single new composite variable, the discriminant function, is produced (for details see Fisher, 1936; Rao, 1948)).

**Value**

Depending upon extendedResults. extendedResults FALSE = Acc of discrimination () extendedResults TRUE Acc Accuracy of discrimination and fitLDA the fit cross-validated LDA model. If CV = TRUE , Posterior probabilities are generated and stored in the model



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**Examples**

```
# simple model with data partition of 80% and no extended results
LDAModel <- LinearDA(Data = KinData, classCol = 1,
  selectedCols = c(1,2,12,22,32,42,52,62,72,82,92,102,112))
#outout
#          Predicted
#Actual   1   2
#1  51  32
#2  40  45
#"The accuracy of discrimination was 0.57"

LDAModel <- LinearDA(Data = KinData, classCol = 1,
  selectedCols = c(1,2,12,22,32,42,52,62,72,82,92,102,112),
  CV=FALSE,cvFraction = 0.8,extendedResults = TRUE)
```

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ModelCluster

---

*Model based Clustering*


---

**Description**

A simple function to perform Model based cluster Analysis :

**Usage**

```
ModelCluster(Data, NewData = NULL, G, ...)
```

**Arguments**

Data	(dataframe) Data dataframe
NewData	(optional) (dataframe) New Data frame for which the class membership is requested
G	(optional) (numeric) No. of components to verify
...	(optional) additional arguments for the function

**Details**

The function implements Model based clustering in predictive framework. Model based clustering approaches provide a structured way of choosing number of clusters (C. Fraley & Raftery, 1998). Data are considered to be generated from a set of Gaussian distributions (components or clusters) i.e. as a mixture of these components (mixture models). Instead of using heuristics, model based clustering approximates Bayes factor (utilizing Bayesian information Criterion) to determine the model with the highest evidence (as provided by the data).

**Value**

class membership of the clustered NewData

**Author(s)**

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**Examples**

```
# clustering kinematics data at 10% of movement  
cluster_time <- ModelCluster(KinData[,c(2,12,22,32,42,52,62,72,82,92,102,112)],G=1:12)
```

---

PredPsych

*PredPsych.*

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**Description**

PredPsych.

**Details**

"PredPsych" is a user-friendly, R toolbox based on machine learning predictive algorithms.

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