

Package ‘D2MCS’

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Type Package

Title Data Driving Multiple Classifier System

Version 1.0.1

Description Provides a novel framework to able to automatically develop and deploy an accurate Multiple Classifier System based on the feature-clustering distribution achieved from an input dataset. 'D2MCS' was developed focused on four main aspects: (i) the ability to determine an effective method to evaluate the independence of features, (ii) the identification of the optimal number of feature clusters, (iii) the training and tuning of ML models and (iv) the execution of voting schemes to combine the outputs of each classifier comprising the Multiple Classifier System.

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BugReports <https://github.com/drordas/D2MCS/issues>

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Accuracy	<i>Computes the Accuracy measure.</i>
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Description

Computes the ratio of number of correct predictions to the total number of input samples.

Details

$$Accuracy = (NumberCorrectPredictions)/(TotalNumberofPredictions)$$

Super class

[D2MCS::MeasureFunction](#) -> Accuracy

Methods

Public methods:

- [Accuracy\\$new\(\)](#)
- [Accuracy\\$compute\(\)](#)
- [Accuracy\\$clone\(\)](#)

Method `new()`: Method for initializing the object arguments during runtime.

Usage:

```
Accuracy$new(performance.output = NULL)
```

Arguments:

`performance.output` An optional [ConfMatrix](#) used as basis to compute the performance.

Method `compute()`: The function computes the **Accuracy** achieved by the M.L. model.

Usage:

```
Accuracy$compute(performance.output = NULL)
```

Arguments:

`performance.output` An optional [ConfMatrix](#) parameter to define the type of object used as basis to compute the **Accuracy** measure.

Details: This function is automatically invoke by the [ClassificationOutput](#) object.

Returns: A [numeric](#) vector of size 1 or [NULL](#) if an error occurred.

Method `clone()`: The objects of this class are cloneable with this method.

Usage:

```
Accuracy$clone(deep = FALSE)
```

Arguments:

`deep` Whether to make a deep clone.

See Also

[MeasureFunction](#), [ClassificationOutput](#), [ConfMatrix](#).

BinaryPlot

Plotting feature clusters following bi-class problem.

Description

The [BinaryPlot](#) implements a basic plot for bi-class problem.

Super class

[D2MCS::GenericPlot](#) -> [BinaryPlot](#)

Methods

Public methods:

- [BinaryPlot\\$new\(\)](#)
- [BinaryPlot\\$plot\(\)](#)
- [BinaryPlot\\$clone\(\)](#)

Method `new()`: Empty function used to initialize the object arguments in runtime.

Usage:

```
BinaryPlot$new()
```

Method `plot()`: Plots feature-clustering data from a bi-class problem.

Usage:

```
BinaryPlot$plot(summary)
```

Arguments:

summary A [data.frame](#) comprising the elements to be plotted.

Method `clone()`: The objects of this class are cloneable with this method.

Usage:

```
BinaryPlot$clone(deep = FALSE)
```

Arguments:

deep Whether to make a deep clone.

See Also

[GenericPlot](#)

ChiSquareHeuristic *Feature-clustering based on ChiSquare method.*

Description

Performs feature-clustering based on ChiSquare method.

Super class

[D2MCS::GenericHeuristic](#) -> ChiSquareHeuristic

Methods

Public methods:

- [ChiSquareHeuristic\\$new\(\)](#)
- [ChiSquareHeuristic\\$heuristic\(\)](#)
- [ChiSquareHeuristic\\$clone\(\)](#)

Method `new()`: Empty function used to initialize the object arguments in runtime.

Usage:

```
ChiSquareHeuristic$new()
```

Method `heuristic()`: Functions responsible of performing the ChiSquare feature-clustering operation.

Usage:

```
ChiSquareHeuristic$heuristic(col1, col2, column.names = NULL)
```

Arguments:

`col1` A [numeric](#) vector or matrix required to perform the clustering operation.

`col2` A [numeric](#) vector or matrix to perform the clustering operation.

`column.names` An optional [character](#) vector with the names of both columns.

Returns: A [numeric](#) vector of length 1 or [NA](#) if an error occurs.

Method `clone()`: The objects of this class are cloneable with this method.

Usage:

```
ChiSquareHeuristic$clone(deep = FALSE)
```

Arguments:

`deep` Whether to make a deep clone.

See Also

[Dataset](#), [chisq.test](#)

ClassificationOutput *D2MCS Classification Output.*

Description

Allows computing the classification performance values achieved by D2MCS. The class is automatically created when [D2MCS](#) classification method is invoked.

Methods

Public methods:

- [ClassificationOutput\\$new\(\)](#)
- [ClassificationOutput\\$getMetrics\(\)](#)
- [ClassificationOutput\\$getPositiveClass\(\)](#)
- [ClassificationOutput\\$getModelInfo\(\)](#)
- [ClassificationOutput\\$getPerformances\(\)](#)
- [ClassificationOutput\\$savePerformances\(\)](#)
- [ClassificationOutput\\$plotPerformances\(\)](#)
- [ClassificationOutput\\$getPredictions\(\)](#)
- [ClassificationOutput\\$savePredictions\(\)](#)
- [ClassificationOutput\\$clone\(\)](#)

Method `new()`: Method for initializing the object arguments during runtime.

Usage:

```
ClassificationOutput$new(voting.schemes, models)
```

Arguments:

`voting.schemes` A [list](#) containing the voting schemes used (inherited from [VotingStrategy](#)).
`models` A [list](#) containing the used [Model](#) during classification stage.

Method `getMetrics()`: The function returns the measures used during training stage.

Usage:

```
ClassificationOutput$getMetrics()
```

Returns: A [character](#) vector or `NULL` if training was not performed.

Method `getPositiveClass()`: The function gets the name of the positive class used for training/classification.

Usage:

```
ClassificationOutput$getPositiveClass()
```

Returns: A [character](#) vector of size 1.

Method `getModelInfo()`: The function compiled all the information concerning to the M.L. models used during training/classification.

Usage:

```
ClassificationOutput$getModelInfo(metrics = NULL)
```

Arguments:

`metrics` A [character](#) vector defining the metrics used during training/classification.

Returns: A [list](#) with the information of each M.L. model.

Method `getPerformances()`: The function is used to compute the performance of D2MCS.

Usage:

```
ClassificationOutput$getPerformances(
  test.set,
  measures,
  voting.names = NULL,
  metric.names = NULL,
  cutoff.values = NULL
)
```

Arguments:

`test.set` A **Subset** object used to compute the performance.

`measures` A **character** vector with the measures to be used to compute performance value (inherited from **MeasureFunction**).

`voting.names` A **character** vector with the name of the voting schemes to analyze the performance. If not defined, all the voting schemes used during classification stage will be taken into account.

`metric.names` A **character** containing the measures used during training stage. If not defined, all training metrics used during classification will be taken into account.

`cutoff.values` A **character** vector defining the minimum probability used to perform a positive classification. If is not defined, all cutoffs used during classification stage will be taken into account.

`dir.path` A **character** vector with location where the plot will be saved.

Returns: A **list** of performance values.

Method `savePerformances()`: The function is used to save the computed predictions into a CSV file.

Usage:

```
ClassificationOutput$savePerformances(
  dir.path,
  test.set,
  measures,
  voting.names = NULL,
  metric.names = NULL,
  cutoff.values = NULL
)
```

Arguments:

`dir.path` A **character** vector with location where the plot will be saved.

`test.set` A **Subset** object used to compute the performance.

`measures` A **character** vector with the measures to be used to compute performance value (inherited from **MeasureFunction**).

`voting.names` A **character** vector with the name of the voting schemes to analyze the performance. If not defined, all the voting schemes used during classification stage will be taken into account.

`metric.names` A **character** containing the measures used during training stage. If not defined, all training metrics used during classification will be taken into account.

`cutoff.values` A **character** vector defining the minimum probability used to perform a positive classification. If is not defined, all cutoffs used during classification stage will be taken into account.

Method plotPerformances(): The function allows to graphically visualize the computed performance.

Usage:

```
ClassificationOutput$plotPerformances(  
  dir.path,  
  test.set,  
  measures,  
  voting.names = NULL,  
  metric.names = NULL,  
  cutoff.values = NULL  
)
```

Arguments:

dir.path A **character** vector with location where the plot will be saved.

test.set A **Subset** object used to compute the performance.

measures A **character** vector with the measures to be used to compute performance value (inherited from **MeasureFunction**).

voting.names A **character** vector with the name of the voting schemes to analyze the performance. If not defined, all the voting schemes used during classification stage will be taken into account.

metric.names A **character** containing the measures used during training stage. If not defined, all training metrics used during classification will be taken into account.

cutoff.values A **character** vector defining the minimum probability used to perform a positive classification. If is not defined, all cutoffs used during classification stage will be taken into account.

Method getPredictions(): The function is used to obtain the computed predictions.

Usage:

```
ClassificationOutput$getPredictions(  
  voting.names = NULL,  
  metric.names = NULL,  
  cutoff.values = NULL,  
  type = NULL,  
  target = NULL,  
  filter = FALSE  
)
```

Arguments:

voting.names A **character** vector with the name of the voting schemes to analyze the performance. If not defined, all the voting schemes used during classification stage will be taken into account.

metric.names A **character** containing the measures used during training stage. If not defined, all training metrics used during classification will be taken into account.

cutoff.values A **character** vector defining the minimum probability used to perform a positive classification. If is not defined, all cutoffs used during classification stage will be taken into account.

type A **character** to define which type of predictions should be returned. If not defined all type of probabilities will be returned. Conversely if "prob" or "raw" is defined then computed 'probabilistic' or 'class' values are returned.

target A [character](#) defining the value of the positive class.

filter A [logical](#) value used to specify if only predictions matching the target value should be returned or not. If [TRUE](#) the function returns only the predictions matching the target value. Conversely if [FALSE](#) (by default) the function returns all the predictions.

Returns: A [PredictionOutput](#) object.

Method `savePredictions()`: The function saves the predictions into a CSV file.

Usage:

```
ClassificationOutput$savePredictions(
  dir.path,
  voting.names = NULL,
  metric.names = NULL,
  cutoff.values = NULL,
  type = NULL,
  target = NULL,
  filter = FALSE
)
```

Arguments:

dir.path A [character](#) vector with location defining the location of the CSV file.

voting.names A [character](#) vector with the name of the voting schemes to analyze the performance. If not defined, all the voting schemes used during classification stage will be taken into account.

metric.names A [character](#) containing the measures used during training stage. If not defined, all training metrics used during classification will be taken into account.

cutoff.values A [character](#) vector defining the minimum probability used to perform a positive classification. If is not defined, all cutoffs used during classification stage will be taken into account.

type A [character](#) to define which type of predictions should be returned. If not defined all type of probabilities will be returned. Conversely if "prob" or "raw" is defined then computed 'probabilistic' or 'class' values are returned.

target A [character](#) defining the value of the positive class.

filter A [logical](#) value used to specify if only predictions matching the target value should be returned or not. If [TRUE](#) the function returns only the predictions matching the target value. Conversely if [FALSE](#) (by default) the function returns all the predictions.

Method `clone()`: The objects of this class are cloneable with this method.

Usage:

```
ClassificationOutput$clone(deep = FALSE)
```

Arguments:

deep Whether to make a deep clone.

See Also

[D2MCS](#)

ClassMajorityVoting *Implementation of Majority Voting voting.*

Description

Implementation of the parliamentary 'majority voting' procedure. The majority class value is defined as final class. All class values have the same importance.

Super class

`D2MCS::SimpleVoting` -> `ClassMajorityVoting`

Methods

Public methods:

- `ClassMajorityVoting$new()`
- `ClassMajorityVoting$getMajorityClass()`
- `ClassMajorityVoting$getClassTie()`
- `ClassMajorityVoting$execute()`
- `ClassMajorityVoting$clone()`

Method `new()`: Method for initializing the object arguments during runtime.

Usage:

```
ClassMajorityVoting$new(cutoff = 0.5, class.tie = NULL, majority.class = NULL)
```

Arguments:

`cutoff` A **character** vector defining the minimum probability used to perform a positive classification. If is not defined, 0.5 will be used as default value.

`class.tie` A **character** used to define the target class value used when a tie is found. If **NULL** positive class value will be assigned.

`majority.class` A **character** defining the value of the majority class. If **NULL** will be used same value as training stage.

Method `getMajorityClass()`: The function returns the value of the majority class.

Usage:

```
ClassMajorityVoting$getMajorityClass()
```

Returns: A **character** vector of length 1 with the name of the majority class.

Method `getClassTie()`: The function gets the class value assigned to solve ties.

Usage:

```
ClassMajorityVoting$getClassTie()
```

Returns: A **character** vector of length 1.

Method `execute()`: The function implements the majority voting procedure.

Usage:

```
ClassMajorityVoting$execute(predictions, verbose = FALSE)
```

Arguments:

predictions A [ClusterPredictions](#) object containing all the predictions achieved for each cluster.

verbose A [logical](#) value to specify if more verbosity is needed.

Method clone(): The objects of this class are cloneable with this method.

Usage:

```
ClassMajorityVoting$clone(deep = FALSE)
```

Arguments:

deep Whether to make a deep clone.

See Also

[D2MCS](#), [ClassMajorityVoting](#), [ClassWeightedVoting](#), [ProbAverageVoting](#), [ProbAverageWeightedVoting](#), [ProbBasedMethodology](#)

ClassWeightedVoting *Implementation Weighted Voting scheme.*

Description

A new implementation of [ClassMajorityVoting](#) where each class value has different values (weights).

Super class

[D2MCS::SimpleVoting](#) -> [ClassWeightedVoting](#)

Methods**Public methods:**

- [ClassWeightedVoting\\$new\(\)](#)
- [ClassWeightedVoting\\$getWeights\(\)](#)
- [ClassWeightedVoting\\$setWeights\(\)](#)
- [ClassWeightedVoting\\$execute\(\)](#)
- [ClassWeightedVoting\\$clone\(\)](#)

Method new(): Method for initializing the object arguments during runtime.

Usage:

```
ClassWeightedVoting$new(cutoff = 0.5, weights = NULL)
```

Arguments:

cutoff A [character](#) vector defining the minimum probability used to perform a positive classification. If is not defined, 0.5 will be used as default value.

weights A [numeric](#) vector with the weights of each cluster. If [NULL](#) performance achieved during training will be used as default.

Method `getWeights()`: The function returns the weights used to perform the voting scheme.

Usage:

```
ClassWeightedVoting$getWeights()
```

Returns: A [numeric](#) vector.

Method `setWeights()`: The function allows changing the value of the weights.

Usage:

```
ClassWeightedVoting$setWeights(weights)
```

Arguments:

weights A [numeric](#) vector containing the new weights.

Method `execute()`: The function implements the cluster-weighted majority voting procedure.

Usage:

```
ClassWeightedVoting$execute(predictions, verbose = FALSE)
```

Arguments:

predictions A [ClusterPredictions](#) object containing all the predictions achieved for each cluster.

verbose A [logical](#) value to specify if more verbosity is needed.

Method `clone()`: The objects of this class are cloneable with this method.

Usage:

```
ClassWeightedVoting$clone(deep = FALSE)
```

Arguments:

deep Whether to make a deep clone.

See Also

[D2MCS](#), [ClassMajorityVoting](#), [ClassWeightedVoting](#), [ProbAverageVoting](#), [ProbAverageWeightedVoting](#), [ProbBasedMethodology](#)

ClusterPredictions *Manages the predictions achieved on a cluster.*

Description

Stores the predictions achieved by the best M.L. of each cluster.

Methods

Public methods:

- `ClusterPredictions$new()`
- `ClusterPredictions$add()`
- `ClusterPredictions$get()`
- `ClusterPredictions$getAll()`
- `ClusterPredictions$size()`
- `ClusterPredictions$getPositiveClass()`
- `ClusterPredictions$getClassValues()`
- `ClusterPredictions$clone()`

Method `new()`: Method for initializing the object arguments during runtime.

Usage:

```
ClusterPredictions$new(class.values, positive.class)
```

Arguments:

`class.values` A [character](#) vector containing the values of the target class.

`positive.class` A [character](#) with the value of the positive class.

Method `add()`: The function is used to add the prediction achieved by a specific M.L. model.

Usage:

```
ClusterPredictions$add(prediction)
```

Arguments:

`prediction` A [Prediction](#) object containing the computed predictions.

Method `get()`: The function returns the predictions placed at specific position.

Usage:

```
ClusterPredictions$get(position)
```

Arguments:

`position` A [numeric](#) value indicating the position of the predictions to be obtained.

Returns: A [Prediction](#) object.

Method `getAll()`: The function returns all the predictions.

Usage:

```
ClusterPredictions$getAll()
```

Returns: A [list](#) containing all computed predictions.

Method `size()`: The function returns the number of computed predictions.

Usage:

```
ClusterPredictions$size()
```

Returns: A [numeric](#) value.

Method `getPositiveClass()`: The function gets the value of the positive class.

Usage:

```
ClusterPredictions$getPositiveClass()
```

Returns: A [character](#) vector of size 1.

Method `getClassValues()`: The function returns all the values of the target class.

Usage:

```
ClusterPredictions$getClassValues()
```

Returns: A [character](#) vector containing all target values.

Method `clone()`: The objects of this class are cloneable with this method.

Usage:

```
ClusterPredictions$clone(deep = FALSE)
```

Arguments:

`deep` Whether to make a deep clone.

See Also

[D2MCS](#), [ClassificationOutput](#), [Prediction](#)

CombinedMetrics	<i>Abstract class to compute the class prediction based on combination between metrics.</i>
-----------------	---

Description

Abstract class used as a template to define new customized strategies to combine the class predictions made by different metrics.

Methods

Public methods:

- [CombinedMetrics\\$new\(\)](#)
- [CombinedMetrics\\$getRequiredMetrics\(\)](#)
- [CombinedMetrics\\$getFinalPrediction\(\)](#)
- [CombinedMetrics\\$clone\(\)](#)

Method `new()`: Method for initializing the object arguments during runtime.

Usage:

```
CombinedMetrics$new(required.metrics)
```

Arguments:

`required.metrics` A [character](#) vector of length greater than 2 with the name of the required metrics.

Method `getRequiredMetrics()`: The function returns the required metrics that will participate in the combined metric process.

Usage:

```
CombinedMetrics$getRequiredMetrics()
```

Returns: A [character](#) vector of length greater than 2 with the name of the required metrics.

Method `getFinalPrediction()`: Function used to implement the strategy to obtain the final prediction based on different metrics.

Usage:

```
CombinedMetrics$getFinalPrediction(
  raw.pred,
  prob.pred,
  positive.class,
  negative.class
)
```

Arguments:

`raw.pred` A [character](#) list of length greater than 2 with the class value of the predictions made by the metrics.

`prob.pred` A [numeric](#) list of length greater than 2 with the probability of the predictions made by the metrics.

`positive.class` A [character](#) with the value of the positive class.

`negative.class` A [character](#) with the value of the negative class.

Returns: A [logical](#) value indicating if the instance is predicted as positive class or not.

Method `clone()`: The objects of this class are cloneable with this method.

Usage:

```
CombinedMetrics$clone(deep = FALSE)
```

Arguments:

`deep` Whether to make a deep clone.

See Also

[CombinedVoting](#)

CombinedVoting

Implementation of Combined Voting.

Description

Calculates the final prediction by performing the result of the predictions of different metrics obtained through a [SimpleVoting](#) class.

Super class

[D2MCS::VotingStrategy](#) -> CombinedVoting

Methods

Public methods:

- [CombinedVoting\\$new\(\)](#)
- [CombinedVoting\\$getCombinedMetrics\(\)](#)
- [CombinedVoting\\$getMethodology\(\)](#)
- [CombinedVoting\\$getFinalPred\(\)](#)
- [CombinedVoting\\$execute\(\)](#)
- [CombinedVoting\\$clone\(\)](#)

Method [new\(\)](#): Method for initializing the object arguments during runtime.

Usage:

```
CombinedVoting$new(voting.schemes, combined.metrics, methodology, metrics)
```

Arguments:

`voting.schemes` A [list](#) of elements inherited from [SimpleVoting](#).

`combined.metrics` An object defining the metrics used to combine the voting schemes. The object must inherit from [CombinedMetrics](#) class.

`methodology` An object specifying the methodology used to execute the combined voting. Object inherited from [Methodology](#) object

`metrics` A [character](#) vector with the name of the metrics used to perform the combined voting operations. Metrics should be previously defined during training stage.

Method [getCombinedMetrics\(\)](#): The function returns the metrics used to combine the metrics results.

Usage:

```
CombinedVoting$getCombinedMetrics()
```

Returns: An object inherited from [CombinedMetrics](#) class.

Method [getMethodology\(\)](#): The function gets the methodology used to execute the combined votings.

Usage:

```
CombinedVoting$getMethodology()
```

Returns: An object inherited from [Methodology](#) class.

Method [getFinalPred\(\)](#): The function returns the predictions obtained after executing the combined-voting methodology.

Usage:

```
CombinedVoting$getFinalPred(type = NULL, target = NULL, filter = NULL)
```

Arguments:

`type` A [character](#) to define which type of predictions should be returned. If not defined all type of probabilities will be returned. Conversely if "prob" or "raw" is defined then computed 'probabilistic' or 'class' values are returned.

`target` A [character](#) defining the value of the positive class.

filter A [logical](#) value used to specify if only predictions matching the target value should be returned or not. If [TRUE](#) the function returns only the predictions matching the target value. Conversely if [FALSE](#) (by default) the function returns all the predictions.

Returns: A [data.frame](#) with the computed predictions.

Method `execute()`: The function implements the combined voting scheme.

Usage:

```
CombinedVoting$execute(predictions, verbose = FALSE)
```

Arguments:

`predictions` A [ClusterPredictions](#) object containing the predictions computed for each cluster.

`verbose` A [logical](#) value to specify if more verbosity is needed.

Method `clone()`: The objects of this class are cloneable with this method.

Usage:

```
CombinedVoting$clone(deep = FALSE)
```

Arguments:

`deep` Whether to make a deep clone.

See Also

[D2MCS](#), [ClassMajorityVoting](#), [ClassWeightedVoting](#), [ProbAverageVoting](#), [ProbAverageWeightedVoting](#), [ProbBasedMethodology](#), [SimpleVoting](#)

ConfMatrix

Confusion matrix wrapper.

Description

Creates a [R6](#) confusion matrix from the [confusionMatrix](#) caret package.

Methods

Public methods:

- [ConfMatrix\\$new\(\)](#)
- [ConfMatrix\\$getConfusionMatrix\(\)](#)
- [ConfMatrix\\$getTP\(\)](#)
- [ConfMatrix\\$getTN\(\)](#)
- [ConfMatrix\\$getFN\(\)](#)
- [ConfMatrix\\$getFP\(\)](#)
- [ConfMatrix\\$clone\(\)](#)

Method `new()`: Method to create a confusion matrix object from a caret [confusionMatrix](#)

Usage:

```
ConfMatrix$new(confMatrix)
```

Arguments:

confMatrix A caret [confusionMatrix](#) argument.

Method `getConfusionMatrix()`: The function obtains the [confusionMatrix](#) following the same structured as defined in the caret package

Usage:

```
ConfMatrix$getConfusionMatrix()
```

Returns: A [confusionMatrix](#) object.

Method `getTP()`: The function is used to compute the number of True Positive values achieved.

Usage:

```
ConfMatrix$getTP()
```

Returns: A [numeric](#) vector of size 1.

Method `getTN()`: The function computes the True Negative values.

Usage:

```
ConfMatrix$getTN()
```

Returns: A [numeric](#) vector of size 1.

Method `getFN()`: The function returns the number of Type II errors (False Negative).

Usage:

```
ConfMatrix$getFN()
```

Returns: A [numeric](#) vector of size 1.

Method `getFP()`: The function returns the number of Type I errors (False Negative).

Usage:

```
ConfMatrix$getFP()
```

Returns: A [numeric](#) vector of size 1.

Method `clone()`: The objects of this class are cloneable with this method.

Usage:

```
ConfMatrix$clone(deep = FALSE)
```

Arguments:

deep Whether to make a deep clone.

See Also

[D2MCS](#), [MeasureFunction](#), [ClassificationOutput](#)

Description

The class is responsible of managing the whole process. Concretely builds the M.L. models (optimizes models hyperparameters), selects the best M.L. model for each cluster and executes the classification stage.

Methods**Public methods:**

- [D2MCS\\$new\(\)](#)
- [D2MCS\\$train\(\)](#)
- [D2MCS\\$classify\(\)](#)
- [D2MCS\\$getAvailableModels\(\)](#)
- [D2MCS\\$clone\(\)](#)

Method `new()`: The function is used to initialize all parameters needed to build a Multiple Classifier System.

Usage:

```
D2MCS$new(
  dir.path,
  num.cores = NULL,
  socket.type = "PSOCK",
  outfile = NULL,
  serialize = FALSE
)
```

Arguments:

`dir.path` A [character](#) defining location where the trained models should be saved.

`num.cores` An optional [numeric](#) value specifying the number of CPU cores used for training the models (only if parallelization is allowed). If not defined (`num.cores - 2`) cores will be used.

`socket.type` A [character](#) value defining the type of socket used to communicate the workers. The default type, "PSOCK", calls `makePSOCKcluster`. Type "FORK" calls `makeForkCluster`. For more information see [makeCluster](#)

`outfile` Where to direct the stdout and stderr connection output from the workers. "" indicates no redirection (which may only be useful for workers on the local machine). Defaults to `'/dev/null'`

`serialize` A [logical](#) value. If `TRUE` (default) serialization will use XDR: where large amounts of data are to be transferred and all the nodes are little-endian, communication may be substantially faster if this is set to false.

Method `train()`: The function is responsible of performing the M.L. model training stage.

Usage:

```
D2MCS$train(
  train.set,
  train.function,
  num.clusters = NULL,
  model.recipe = DefaultModelFit$new(),
  ex.classifiers = c(),
  ig.classifiers = c(),
  metrics = NULL,
  saveAllModels = FALSE
)
```

Arguments:

`train.set` A [Trainset](#) object used as training input for the M.L. models

`train.function` A [TrainFunction](#) defining the training configuration options.

`num.clusters` An [numeric](#) value used to define the number of clusters from the [Trainset](#) that should be utilized during the training stage. If not defined all clusters will be taken into account for training.

`model.recipe` An unprepared recipe object inherited from [GenericModelFit](#) class.

`ex.classifiers` A [character](#) vector containing the name of the M.L. models used in training stage. See [getModelInfo](#) and <https://topepo.github.io/caret/available-models.html> for more information about all the available models.

`ig.classifiers` A [character](#) vector containing the name of the M.L. that should be ignored when performing the training stage. See [getModelInfo](#) and <https://topepo.github.io/caret/available-models.html> for more information about all the available models.

`metrics` A [character](#) vector containing the metrics used to perform the M.L. model hyperparameter optimization during the training stage. See [SummaryFunction](#), [UseProbability](#) and [NoProbability](#) for more information.

`saveAllModels` A [logical](#) parameter. A [TRUE](#) saves all trained models while A [FALSE](#) saves only the M.L. model achieving the best performance on each cluster.

Returns: A [TrainOutput](#) object containing all the information computed during the training stage.

Method `classify()`: The function is responsible for executing the classification stage.

Usage:

```
D2MCS$classify(train.output, subset, voting.types, positive.class = NULL)
```

Arguments:

`train.output` The [TrainOutput](#) object computed in the train stage.

`subset` A [Subset](#) containing the data to be classified.

`voting.types` A [list](#) containing [SingleVoting](#) or [CombinedVoting](#) objects.

`positive.class` An optional [character](#) parameter used to define the positive class value.

Returns: A [ClassificationOutput](#) with all the values computed during classification stage.

Method `getAvailableModels()`: The function obtains all the available M.L. models.

Usage:

```
D2MCS$getAvailableModels()
```

Returns: A [data.frame](#) containing the information of the available M.L. models.

Method `clone()`: The objects of this class are cloneable with this method.

Usage:

```
D2MCS$clone(deep = FALSE)
```

Arguments:

`deep` Whether to make a deep clone.

See Also

[Dataset](#), [Subset](#), [Trainset](#)

Examples

```
# Specify the random number generation
set.seed(1234)

## Create Dataset Handler object.
loader <- DatasetLoader$new()

## Load 'hcc-data-complete-balanced.csv' dataset file.
data <- loader$load(filepath = system.file(file.path("examples",
                                                    "hcc-data-complete-balanced.csv"),
                                           package = "D2MCS"),
                    header = TRUE, normalize.names = TRUE)

## Get column names
data$getColumnNames()

## Split data into 4 partitions keeping balance ratio of 'Class' column.
data$createPartitions(num.folds = 4, class.balance = "Class")

## Create a subset comprising the first 2 partitions for clustering purposes.
cluster.subset <- data$createSubset(num.folds = c(1, 2), class.index = "Class",
                                   positive.class = "1")

## Create a subset comprising second and third partitions for training purposes.
train.subset <- data$createSubset(num.folds = c(2, 3), class.index = "Class",
                                  positive.class = "1")

## Create a subset comprising last partitions for testing purposes.
test.subset <- data$createSubset(num.folds = 4, class.index = "Class",
                                 positive.class = "1")

## Distribute the features into clusters using MCC heuristic.
distribution <- SimpleStrategy$new(subset = cluster.subset,
                                   heuristic = MCCHeuristic$new())
distribution$execute()

## Get the best achieved distribution
```

```

distribution$getBestClusterDistribution()

## Create a train set from the computed clustering distribution
train.set <- distribution$createTrain(subset = train.subset)

## Not run:

## Initialization of D2MCS configuration parameters.
## - Defining training operation.
##   + 10-fold cross-validation
##   + Use only 1 CPU core.
##   + Seed was set to ensure straightforward reproducibility of experiments.
trFunction <- TwoClass$new(method = "cv", number = 10, savePredictions = "final",
                           classProbs = TRUE, allowParallel = TRUE,
                           verboseIter = FALSE, seed = 1234)

#' ## - Specify the models to be trained
ex.classifiers <- c("ranger", "lda", "lda2")

## Initialize D2MCS
#' d2mcs <- D2MCS$new(dir.path = tempdir(),
                     num.cores = 1)

## Execute training stage for using 'MCC' and 'PPV' measures to optimize model hyperparameters.
trained.models <- d2mcs$train(train.set = train.set,
                              train.function = trFunction,
                              ex.classifiers = ex.classifiers,
                              metrics = c("MCC", "PPV"))

## Execute classification stage using two different voting schemes
predictions <- d2mcs$classify(train.output = trained.models,
                              subset = test.subset,
                              voting.types = c(
                                SingleVoting$new(voting.schemes = c(ClassMajorityVoting$new(),
                                                                    ClassWeightedVoting$new()),
                                                    metrics = c("MCC", "PPV"))))

## Compute the performance of each voting scheme using PPV and MMC measures.
predictions$getPerformances(test.subset, measures = list(MCC$new(), PPV$new()))

## Execute classification stage using multiple voting schemes (simple and combined)
predictions <- d2mcs$classify(train.output = trained.models,
                              subset = test.subset,
                              voting.types = c(
                                SingleVoting$new(voting.schemes = c(ClassMajorityVoting$new(),
                                                                    ClassWeightedVoting$new()),
                                                    metrics = c("MCC", "PPV")),
                                CombinedVoting$new(voting.schemes = ClassMajorityVoting$new(),
                                                    combined.metrics = MinimizeFP$new(),
                                                    methodology = ProbBasedMethodology$new(),
                                                    metrics = c("MCC", "PPV"))))

## Compute the performance of each voting scheme using PPV and MMC measures.

```

```

predictions$getPerformances(test.subset, measures = list(MCC$new(), PPV$new()))

## End(Not run)

```

Dataset

Simple Dataset handler.

Description

Creates a valid simple dataset object.

Methods

Public methods:

- [Dataset\\$new\(\)](#)
- [Dataset\\$getColumnNames\(\)](#)
- [Dataset\\$getDataset\(\)](#)
- [Dataset\\$getNcol\(\)](#)
- [Dataset\\$getNrow\(\)](#)
- [Dataset\\$getRemovedColumns\(\)](#)
- [Dataset\\$cleanData\(\)](#)
- [Dataset\\$removeColumns\(\)](#)
- [Dataset\\$createPartitions\(\)](#)
- [Dataset\\$createSubset\(\)](#)
- [Dataset\\$createTrain\(\)](#)

Method `new()`: Method for initializing the object arguments during runtime.

Usage:

```

Dataset$new(
  filepath,
  header = TRUE,
  sep = ",",
  skip = 0,
  normalize.names = FALSE,
  string.as.factor = FALSE,
  ignore.columns = NULL
)

```

Arguments:

`filepath` The name of the file which the data are to be read from. Each row of the table appears as one line of the file. If it does not contain an `_absolute_` path, the file name is `_relative_` to the current working directory, `'getwd()'`.

`header` A **logical** value indicating whether the file contains the names of the variables as its first line. If missing, the value is determined from the file format: 'header' is set to 'TRUE' if and only if the first row contains one fewer field than the number of columns.

`sep` The field separator character. Values on each line of the file are separated by this character.

`skip` Defines the number of header lines should be skipped.

`normalize.names` A **logical** value indicating whether the columns names should be automatically renamed to ensure R compatibility.

`string.as.factor` A **logical** value indicating if character columns should be converted to factors (default = FALSE).

`ignore.columns` Specify the columns from the input file that should be ignored.

Method `getColumnNames()`: Get the name of the columns comprising the dataset.

Usage:

```
Dataset$getColumnNames()
```

Returns: A **character** vector with the name of each column.

Method `getDataset()`: Gets the full dataset.

Usage:

```
Dataset$getDataset()
```

Returns: A **data.frame** with all the loaded information.

Method `getNcol()`: Obtains the number of columns present in the dataset.

Usage:

```
Dataset$getNcol()
```

Returns: An **integer** of length 1 or **NULL**

Method `getNrow()`: Obtains the number of rows present in the dataset.

Usage:

```
Dataset$getNrow()
```

Returns: An **integer** of length 1 or **NULL**

Method `getRemovedColumns()`: Get the columns removed or ignored.

Usage:

```
Dataset$getRemovedColumns()
```

Returns: A **list** containing the name of the removed columns.

Method `cleanData()`: Removes **data.frame** columns matching some criterion.

Usage:

```
Dataset$cleanData(remove.funcs = NULL, remove.na = TRUE, remove.const = FALSE)
```

Arguments:

`remove.funcs` A vector of functions use to define which columns must be removed.

`remove.na` A **logical** value indicating whether **NA** values should be removed.

`remove.const` A **logical** value used to indicate if constant values should be removed.

Method `removeColumns()`: Applies `cleanData` function over an specific set of columns.

Usage:

```
Dataset$removeColumns(
  columns,
  remove.funcs = NULL,
  remove.na = FALSE,
  remove.const = FALSE
)
```

Arguments:

`columns` Set of columns (**numeric** or **character**) where removal operation should be applied.

`remove.funcs` A vector of functions use to define which columns must be removed.

`remove.na` A **logical** value indicating whether **NA** values should be removed.

`remove.const` A **logical** value used to indicate if constant values should be removed.

Method `createPartitions()`: Creates a k-folds partition from the initial dataset.

Usage:

```
Dataset$createPartitions(
  num.folds = NULL,
  percent.folds = NULL,
  class.balance = NULL
)
```

Arguments:

`num.folds` A **numeric** for the number of folds (partitions)

`percent.folds` A **numeric** vector with the percentage of instances containing each fold.

`class.balance` A **logical** value indicating if class balance should be kept.

Method `createSubset()`: Creates a **Subset** for testing or classification purposes. A target class should be provided for testing purposes.

Usage:

```
Dataset$createSubset(
  num.folds = NULL,
  opts = list(remove.na = TRUE, remove.const = FALSE),
  class.index = NULL,
  positive.class = NULL
)
```

Arguments:

`num.folds` A **numeric** defining the number of folds that should we used to build the **Subset**.

`opts` A list with optional parameters. Valid arguments are `remove.na` (removes columns with **NA** values) and `remove.const` (ignore columns with constant values).

`class.index` A **numeric** value identifying the column representing the target class

`positive.class` Defines the positive class value.

Returns: A **Subset** object.

Method `createTrain()`: Creates a set for training purposes. A class should be defined to guarantee full-compatibility with supervised models.

Usage:

```
Dataset$createTrain(
  class.index,
  positive.class,
  num.folds = NULL,
  opts = list(remove.na = TRUE, remove.const = FALSE)
)
```

Arguments:

`class.index` A **numeric** value identifying the column representing the target class

`positive.class` Defines the positive class value.

`num.folds` A **numeric** defining the number of folds that should we used to build the **Subset**.

`opts` A list with optional parameters. Valid arguments are `remove.na` (removes columns with **NA** values) and `remove.const` (ignore columns with constant values).

Returns: A **Trainset** object.

See Also

[HDDataset](#)

DatasetLoader

Dataset creation.

Description

Wrapper class able to automatically create a **Dataset**, **HDDataset** according to the input data.

Methods**Public methods:**

- [DatasetLoader\\$new\(\)](#)
- [DatasetLoader\\$load\(\)](#)

Method `new()`: Empty function used to initialize the object arguments in runtime.

Usage:

```
DatasetLoader$new()
```

Method `load()`: Stores the input source into a **Dataset** or **HDDataset** type object.

Usage:

```
DatasetLoader$load(
  filepath,
  header = TRUE,
  sep = ",",
  skip.lines = 0,
  normalize.names = FALSE,
  string.as.factor = FALSE,
  ignore.columns = NULL
)
```

Arguments:

`filepath` The name of the file which the data are to be read from. Each row of the table appears as one line of the file. If it does not contain an `_absolute_` path, the file name is `_relative_` to the current working directory, `'getwd()'`.

`header` A [logical](#) value indicating whether the file contains the names of the variables as its first line. If missing, the value is determined from the file format: `'header'` is set to `'TRUE'` if and only if the first row contains one fewer field than the number of columns.

`sep` The field separator character. Values on each line of the file are separated by this character.

`skip.lines` Defines the number of header lines should be skipped.

`normalize.names` A [logical](#) value indicating whether the columns names should be automatically renamed to ensure R compatibility.

`string.as.factor` A [logical](#) value indicating if character columns should be converted to factors (default = FALSE).

`ignore.columns` Specify the columns from the input file that should be ignored.

Returns: A [Dataset](#) or [HDDataset](#) object.

See Also

[Dataset](#), [HDDataset](#)

Examples

```
## Not run:
# Create Dataset Handler object.
loader <- DatasetLoader$new()

# Load input file.
data <- loader$load(filepath = system.file(file.path("examples",
                                                "hcc-data-complete-balanced.csv"),
                                                package = "D2MCS"),
                    header = T, normalize.names = T)

## End(Not run)
```

DefaultModelFit

Default model fitting implementation.

Description

Creates a default [recipe](#) and [formula](#) objects used in model training stage.

Super class

[D2MCS::GenericModelFit](#) -> DefaultModelFit

Methods

Public methods:

- [DefaultModelFit\\$new\(\)](#)
- [DefaultModelFit\\$createFormula\(\)](#)
- [DefaultModelFit\\$createRecipe\(\)](#)
- [DefaultModelFit\\$clone\(\)](#)

Method `new()`: Method for initializing the object arguments during runtime.

Usage:

```
DefaultModelFit$new()
```

Method `createFormula()`: The function is responsible of creating a [formula](#) for M.L. model.

Usage:

```
DefaultModelFit$createFormula(instances, class.name, simplify = FALSE)
```

Arguments:

`instances` A [data.frame](#) containing the instances used to create the recipe.

`class.name` A [character](#) vector representing the name of the target class.

`simplify` A [logical](#) argument defining whether the formula should be generated as simple as possible.

Returns: A [formula](#) object.

Method `createRecipe()`: The function is responsible of creating a [recipe](#) with five operations over the data: [step_zv](#), [step_nzv](#), [step_corr](#), [step_center](#), [step_scale](#)

Usage:

```
DefaultModelFit$createRecipe(instances, class.name)
```

Arguments:

`instances` A [data.frame](#) containing the instances used to create the recipe.

`class.name` A [character](#) vector representing the name of the target class.

Details: This function is automatically invoked by [D2MCS](#) during model training stage.

Returns: An object of class [recipe](#).

Method `clone()`: The objects of this class are cloneable with this method.

Usage:

```
DefaultModelFit$clone(deep = FALSE)
```

Arguments:

`deep` Whether to make a deep clone.

See Also

[GenericModelFit](#), [train](#)

 DependencyBasedStrategy

Clustering strategy based on dependency between features.

Description

Features are distributed according to their independence values. This strategy is divided into two steps. The first phase focuses on forming groups with those features most dependent on each other. This step also identifies those that are independent from all the others in the group. The second step is to try out different numbers of clusters until you find the one you think is best. These clusters are formed by inserting in all the independent characteristics identified previously and trying to distribute the features of the groups formed in the previous step in separate clusters. In this way, it seeks to ensure that the features are as independent as possible from those found in the same cluster.

Details

The strategy is suitable only for binary and real features. Other features are automatically grouped into a specific cluster named as 'unclustered'. This class requires the [StrategyConfiguration](#) type object implements the following methods:

- `getBinaryCutoff()`: The function is used to define the interval to consider the dependency between binary features.
- `getRealCutoff()`: The function allows defining the cutoff to consider the dependency between real features.
- `tiebreak(feature, clus.candidates, fea.dep.dist.clus, corpus, heuristic, class, class.name)`: The function solves the ties between two (or more) features.
- `qualityOfCluster(clusters, metrics)`: The function determines the quality of a cluster
- `isImprovingClustering(clusters.delta)`: The function indicates if clustering is getting better as the number of them increases.

An example of implementation with the description of each parameter is the [DependencyBasedStrategyConfiguration](#) class.

Super class

[D2MCS::GenericClusteringStrategy](#) -> DependencyBasedStrategy

Methods

Public methods:

- [DependencyBasedStrategy\\$new\(\)](#)
- [DependencyBasedStrategy\\$execute\(\)](#)
- [DependencyBasedStrategy\\$getDistribution\(\)](#)
- [DependencyBasedStrategy\\$createTrain\(\)](#)
- [DependencyBasedStrategy\\$plot\(\)](#)
- [DependencyBasedStrategy\\$saveCSV\(\)](#)

- [DependencyBasedStrategy\\$clone\(\)](#)

Method new(): Method for initializing the object parameters during runtime.

Usage:

```
DependencyBasedStrategy$new(
  subset,
  heuristic,
  configuration = DependencyBasedStrategyConfiguration$new()
)
```

Arguments:

subset The [Subset](#) used to apply the feature-clustering strategy.

heuristic The heuristic used to compute the relevance of each feature. Must inherit from [GenericHeuristic](#) abstract class.

configuration optional parameter to customize configuration parameters for the strategy. Must inherited from [StrategyConfiguration](#) abstract class.

Method execute(): Function responsible of performing the dependency-based feature clustering strategy over the defined [Subset](#).

Usage:

```
DependencyBasedStrategy$execute(verbose = TRUE)
```

Arguments:

verbose A [logical](#) value to specify if more verbosity is needed.

Method getDistribution(): Function used to obtain a specific cluster distribution.

Usage:

```
DependencyBasedStrategy$getDistribution(
  num.clusters = NULL,
  num.groups = NULL,
  include.unclustered = FALSE
)
```

Arguments:

num.clusters A [numeric](#) value to select the number of clusters (define the distribution).

num.groups A single or [numeric](#) vector value to identify a specific group that forms the clustering distribution.

include.unclustered A [logical](#) value to determine if unclustered features should be included.

Returns: A [list](#) with the features comprising an specific clustering distribution.

Method createTrain(): The function is used to create a [Trainset](#) object from a specific clustering distribution.

Usage:

```
DependencyBasedStrategy$createTrain(
  subset,
  num.clusters = NULL,
  num.groups = NULL,
  include.unclustered = FALSE
)
```

Arguments:

`subset` The [Subset](#) object used as a basis to create the train set (see [Trainset](#) class).
`num.clusters` A [numeric](#) value to select the number of clusters (define the distribution).
`num.groups` A single or [numeric](#) vector value to identify a specific group that forms the clustering distribution.
`include.unclustered` A [logical](#) value to determine if unclustered features should be included.

Details: If `num.clusters` and `num.groups` are not defined, best clustering distribution is used to create the train set.

Method `plot()`: The function is responsible for creating a plot to visualize the clustering distribution.

Usage:

```
DependencyBasedStrategy$plot(dir.path = NULL, file.name = NULL)
```

Arguments:

`dir.path` An optional argument to define the name of the directory where the exported plot will be saved. If not defined, the file path will be automatically assigned to the current working directory, `'getwd()'`.
`file.name` A character to define the name of the PDF file where the plot is exported.

Method `saveCSV()`: The function is used to save the clustering distribution to a CSV file.

Usage:

```
DependencyBasedStrategy$saveCSV(  
  dir.path = NULL,  
  name = NULL,  
  num.clusters = NULL  
)
```

Arguments:

`dir.path` The name of the directory to save the CSV file.
`name` Defines the name of the CSV file.
`num.clusters` An optional parameter to select the number of clusters to be saved. If not defined, all cluster distributions will be saved.

Method `clone()`: The objects of this class are cloneable with this method.

Usage:

```
DependencyBasedStrategy$clone(deep = FALSE)
```

Arguments:

`deep` Whether to make a deep clone.

See Also

[GenericClusteringStrategy](#), [StrategyConfiguration](#), [DependencyBasedStrategyConfiguration](#)

DependencyBasedStrategyConfiguration

Custom Strategy Configuration handler for the DependencyBased-Strategy strategy.

Description

Define the default configuration parameters for the [DependencyBasedStrategy](#) strategy.

Super class

[D2MCS::StrategyConfiguration](#) -> DependencyBasedStrategyConfiguration

Methods

Public methods:

- [DependencyBasedStrategyConfiguration\\$new\(\)](#)
- [DependencyBasedStrategyConfiguration\\$minNumClusters\(\)](#)
- [DependencyBasedStrategyConfiguration\\$maxNumClusters\(\)](#)
- [DependencyBasedStrategyConfiguration\\$getBinaryCutoff\(\)](#)
- [DependencyBasedStrategyConfiguration\\$getRealCutoff\(\)](#)
- [DependencyBasedStrategyConfiguration\\$setBinaryCutoff\(\)](#)
- [DependencyBasedStrategyConfiguration\\$setRealCutoff\(\)](#)
- [DependencyBasedStrategyConfiguration\\$tiebreak\(\)](#)
- [DependencyBasedStrategyConfiguration\\$qualityOfCluster\(\)](#)
- [DependencyBasedStrategyConfiguration\\$isImprovingClustering\(\)](#)
- [DependencyBasedStrategyConfiguration\\$clone\(\)](#)

Method `new()`: Method for initializing the object arguments during runtime.

Usage:

```
DependencyBasedStrategyConfiguration$new(
  binaryCutoff = 0.6,
  realCutoff = 0.6,
  tiebreakMethod = "lfdc",
  metric = "dep.tar"
)
```

Arguments:

`binaryCutoff` The [numeric](#) value of binary cutoff.

`realCutoff` The [numeric](#) value of real cutoff.

`tiebreakMethod` The [character](#) value of tie-break method. The two tiebreak methods available are "lfdc" (less dependence cluster with the features) and "ltdc" (less dependence cluster with the target). These methods are used to add the features in the candidate feature clusters.

metric The [character](#) value of the metric to apply the mean to obtain the quality of a cluster. The two metrics available are "dep.tar" (Dependence of cluster features on the target) and "dep.fea" (Dependence between cluster features).

Method `minNumClusters()`: Function used to return the minimum number of clusters distributions used. By default the minimum is set in 2.

Usage:

```
DependencyBasedStrategyConfiguration$minNumClusters(...)
```

Arguments:

... Further arguments passed down to `minNumClusters` function.

Returns: A [numeric](#) vector of length 1.

Method `maxNumClusters()`: The function is responsible of returning the maximum number of cluster distributions used. By default the maximum number is set in 50.

Usage:

```
DependencyBasedStrategyConfiguration$maxNumClusters(...)
```

Arguments:

... Further arguments passed down to `maxNumClusters` function.

Returns: A [numeric](#) vector of length 1.

Method `getBinaryCutoff()`: Gets the cutoff to consider the dependency between binary features.

Usage:

```
DependencyBasedStrategyConfiguration$getBinaryCutoff()
```

Returns: The [numeric](#) value of binary cutoff.

Method `getRealCutoff()`: Gets the cutoff to consider the dependency between real features.

Usage:

```
DependencyBasedStrategyConfiguration$getRealCutoff()
```

Returns: The [numeric](#) value of real cutoff.

Method `setBinaryCutoff()`: Sets the cutoff to consider the dependency between binary features.

Usage:

```
DependencyBasedStrategyConfiguration$setBinaryCutoff(cutoff)
```

Arguments:

`cutoff` The new [numeric](#) value of binary cutoff.

Method `setRealCutoff()`: Sets the cutoff to consider the dependency between real features.

Usage:

```
DependencyBasedStrategyConfiguration$setRealCutoff(cutoff)
```

Arguments:

`cutoff` The new [numeric](#) value of real cutoff.

Method `tiebreak()`: The function solves the ties between two (or more) features.

Usage:

```
DependencyBasedStrategyConfiguration$tiebreak(
  feature,
  clus.candidates,
  fea.dep.dist.clus,
  corpus,
  heuristic,
  class,
  class.name
)
```

Arguments:

`feature` A [character](#) containing the name of the feature

`clus.candidates` A single or [numeric](#) vector value to identify the candidate groups to insert the feature.

`fea.dep.dist.clus` A [list](#) containing the groups chosen for the features.

`corpus` A [data.frame](#) containing the features of the initial data.

`heuristic` The heuristic used to compute the relevance of each feature. Must inherit from [GenericHeuristic](#) abstract class.

`class` A [character](#) vector containing all the values of the target class.

`class.name` A [character](#) value representing the name of the target class.

Method `qualityOfCluster()`: The function determines the quality of a cluster.

Usage:

```
DependencyBasedStrategyConfiguration$qualityOfCluster(clusters, metrics)
```

Arguments:

`clusters` A [list](#) with the feature distribution of each cluster.

`metrics` A numeric [list](#) with the metrics associated to the cluster (dependency between all features and dependency between the features and the class).

Returns: A [numeric](#) vector of length 1.

Method `isImprovingClustering()`: The function indicates if clustering is getting better as the number of them increases.

Usage:

```
DependencyBasedStrategyConfiguration$isImprovingClustering(clusters.delta)
```

Arguments:

`clusters.delta` A [numeric](#) vector value with the quality values of the built clusters.

Returns: A [numeric](#) vector of length 1.

Method `clone()`: The objects of this class are cloneable with this method.

Usage:

```
DependencyBasedStrategyConfiguration$clone(deep = FALSE)
```

Arguments:

`deep` Whether to make a deep clone.

See Also

[StrategyConfiguration](#), [DependencyBasedStrategy](#)

FisherTestHeuristic *Feature-clustering based on Fisher's Exact Test.*

Description

Performs feature-clustering based on Fisher's exact test for testing the null of independence of rows and columns in a contingency table with fixed marginals.

Super class

[D2MCS::GenericHeuristic](#) -> FisherTestHeuristic

Methods**Public methods:**

- [FisherTestHeuristic\\$new\(\)](#)
- [FisherTestHeuristic\\$heuristic\(\)](#)
- [FisherTestHeuristic\\$clone\(\)](#)

Method `new()`: Empty function used to initialize the object arguments in runtime.

Usage:

```
FisherTestHeuristic$new()
```

Method `heuristic()`: Performs the Fisher's exact test for testing the null of independence between two columns (`col1` and `col2`).

Usage:

```
FisherTestHeuristic$heuristic(col1, col2, column.names = NULL)
```

Arguments:

`col1` A [numeric](#) vector or matrix required to perform the clustering operation.

`col2` A [numeric](#) vector or matrix to perform the clustering operation.

`column.names` An optional [character](#) vector with the names of both columns.

Returns: A [numeric](#) vector of length 1 or [NA](#) if an error occurs.

Method `clone()`: The objects of this class are cloneable with this method.

Usage:

```
FisherTestHeuristic$clone(deep = FALSE)
```

Arguments:

`deep` Whether to make a deep clone.

See Also

[Dataset](#), [fisher.test](#)

FN *Computes the False Negative errors.*

Description

Computes the ratio of number of Type II errors achieved by the final M.L. model.

Super class

[D2MCS::MeasureFunction](#) -> FN

Methods

Public methods:

- [FN\\$new\(\)](#)
- [FN\\$compute\(\)](#)
- [FN\\$clone\(\)](#)

Method `new()`: Method for initializing the object arguments during runtime.

Usage:

```
FN$new(performance.output = NULL)
```

Arguments:

`performance.output` An optional [ConfMatrix](#) parameter to define the type of object used to compute the **FN** measure.

Method `compute()`: The function computes the **FN** achieved by the M.L. model.

Usage:

```
FN$compute(performance.output = NULL)
```

Arguments:

`performance.output` An optional [ConfMatrix](#) parameter to define the type of object used as basis to compute the **FN** measure

Details: This function is automatically invoked by the [ClassificationOutput](#) framework.

Returns: A [numeric](#) vector of size 1 or **NULL** if an error occurred.

Method `clone()`: The objects of this class are cloneable with this method.

Usage:

```
FN$clone(deep = FALSE)
```

Arguments:

`deep` Whether to make a deep clone.

See Also

[MeasureFunction](#), [ClassificationOutput](#), [ConfMatrix](#)

FP

Computes the False Positive value.

Description

This is the number of individuals with a negative condition for which the test result is positive. The value entered here must be non-negative.

Super class

[D2MCS::MeasureFunction](#) -> FP

Methods

Public methods:

- [FP\\$new\(\)](#)
- [FP\\$compute\(\)](#)
- [FP\\$clone\(\)](#)

Method `new()`: Method for initializing the object arguments during runtime.

Usage:

`FP$new(performance.output = NULL)`

Arguments:

`performance.output` An optional [ConfMatrix](#) parameter used as basis to define the type of compute the FP measure.

Method `compute()`: The function computes the **FP** achieved by the M.L. model.

Usage:

`FP$compute(performance.output = NULL)`

Arguments:

`performance.output` An optional [ConfMatrix](#) parameter to define the type of object used as basis to compute the FP measure.

Details: This function is automatically invoked by the [ClassificationOutput](#) object.

Returns: A [numeric](#) vector of size 1 or [NULL](#) if an error occurred.

Method `clone()`: The objects of this class are cloneable with this method.

Usage:

`FP$clone(deep = FALSE)`

Arguments:

`deep` Whether to make a deep clone.

See Also

[MeasureFunction](#), [ClassificationOutput](#), [ConfMatrix](#)

GainRatioHeuristic *Feature-clustering based on GainRatio methodology.*

Description

Performs the feature-clustering using entropy-based filters.

Super class

[D2MCS::GenericHeuristic](#) -> GainRatioHeuristic

Methods

Public methods:

- [GainRatioHeuristic\\$new\(\)](#)
- [GainRatioHeuristic\\$heuristic\(\)](#)
- [GainRatioHeuristic\\$clone\(\)](#)

Method `new()`: Empty function used to initialize the object arguments in runtime.

Usage:

```
GainRatioHeuristic$new()
```

Method `heuristic()`: The algorithms find weights of discrete attributes basing on their correlation with continuous class attribute.

Usage:

```
GainRatioHeuristic$heuristic(col1, col2, column.names = NULL)
```

Arguments:

`col1` A [numeric](#) vector or matrix required to perform the clustering operation.

`col2` A [numeric](#) vector or matrix to perform the clustering operation.

`column.names` An optional [character](#) vector with the names of both columns.

Returns: A [numeric](#) vector of length 1 or [NA](#) if an error occurs.

Method `clone()`: The objects of this class are cloneable with this method.

Usage:

```
GainRatioHeuristic$clone(deep = FALSE)
```

Arguments:

`deep` Whether to make a deep clone.

See Also

[Dataset](#), [gain.ratio](#)

GenericClusteringStrategy

Abstract Feature Clustering Strategy class.

Description

Abstract class used as a template to ensure the proper definition of new customized clustering strategies.

Details

The [GenericClusteringStrategy](#) is an archetype class so it cannot be instantiated.

Methods

Public methods:

- [GenericClusteringStrategy\\$new\(\)](#)
- [GenericClusteringStrategy\\$getDescription\(\)](#)
- [GenericClusteringStrategy\\$getHeuristic\(\)](#)
- [GenericClusteringStrategy\\$getConfiguration\(\)](#)
- [GenericClusteringStrategy\\$getBestClusterDistribution\(\)](#)
- [GenericClusteringStrategy\\$getUnclustered\(\)](#)
- [GenericClusteringStrategy\\$execute\(\)](#)
- [GenericClusteringStrategy\\$getDistribution\(\)](#)
- [GenericClusteringStrategy\\$createTrain\(\)](#)
- [GenericClusteringStrategy\\$plot\(\)](#)
- [GenericClusteringStrategy\\$saveCSV\(\)](#)
- [GenericClusteringStrategy\\$clone\(\)](#)

Method [new\(\)](#): A function responsible for creating a [GenericClusteringStrategy](#) object.

Usage:

```
GenericClusteringStrategy$new(subset, heuristic, description, configuration)
```

Arguments:

subset A [Subset](#) object to perform the clustering strategy.

heuristic The heuristic to be applied. Must inherit from [GenericHeuristic](#) class.

description A [character](#) vector describing the strategy operation.

configuration Optional customized configuration parameters for the strategy. Must inherited from [StrategyConfiguration](#) abstract class.

Method [getDescription\(\)](#): The function is used to obtain the description of the strategy.

Usage:

```
GenericClusteringStrategy$getDescription()
```

Returns: A [character](#) vector of [NULL](#) if not defined.

Method `getHeuristic()`: The function returns the heuristic applied for the clustering strategy.

Usage:

```
GenericClusteringStrategy$getHeuristic()
```

Returns: An object inherited from `GenericClusteringStrategy` class.

Method `getConfiguration()`: The function returns the configuration parameters used to perform the clustering strategy.

Usage:

```
GenericClusteringStrategy$getConfiguration()
```

Returns: An object inherited from `StrategyConfiguration` class.

Method `getBestClusterDistribution()`: The function obtains the best clustering distribution.

Usage:

```
GenericClusteringStrategy$getBestClusterDistribution()
```

Returns: A [list](#) of clusters. Each list element represents a feature group.

Method `getUnclustered()`: The function is used to return the features that cannot be clustered due to incompatibilities with the used heuristic.

Usage:

```
GenericClusteringStrategy$getUnclustered()
```

Returns: A [character](#) vector containing the unclassified features.

Method `execute()`: Abstract function responsible of performing the clustering strategy over the defined [Subset](#).

Usage:

```
GenericClusteringStrategy$execute(verbose, ...)
```

Arguments:

`verbose` A [logical](#) value to specify if more verbosity is needed.

`...` Further arguments passed down to execute function.

Method `getDistribution()`: Abstract function used to obtain the set of features following an specific clustering distribution.

Usage:

```
GenericClusteringStrategy$getDistribution(  
  num.clusters = NULL,  
  num.groups = NULL,  
  include.unclustered = FALSE  
)
```

Arguments:

`num.clusters` A [numeric](#) value to select the number of clusters (define the distribution).

`num.groups` A single or [numeric](#) vector value to identify a specific group that forms the clustering distribution.

`include.unclustered` A [logical](#) value to determine if unclustered features should be included.

Returns: A [list](#) with the features comprising an specific clustering distribution.

Method `createTrain()`: Abstract function in charge of creating a [Trainset](#) object for training purposes.

Usage:

```
GenericClusteringStrategy$createTrain(
  subset,
  num.cluster = NULL,
  num.groups = NULL,
  include.unclustered = FALSE
)
```

Arguments:

`subset` A [Subset](#) object used as a basis to create the [Trainset](#)

`num.cluster` A [numeric](#) value to select the number of clusters (define the distribution).

`num.groups` A single or [numeric](#) vector value to identify a specific group that forms the clustering distribution.

`include.unclustered` A [logical](#) value to determine if unclustered features should be included.

Method `plot()`: Abstract function responsible of creating a plot to visualize the clustering distribution.

Usage:

```
GenericClusteringStrategy$plot(dir.path = NULL, file.name = NULL, ...)
```

Arguments:

`dir.path` An optional [character](#) argument to define the name of the directory where the exported plot will be saved. If not defined, the file path will be automatically assigned to the current working directory, `'getwd()'`.

`file.name` The name of the PDF file where the plot is exported.

`...` Further arguments passed down to execute function.

Method `saveCSV()`: Abstract function to save the clustering distribution to a CSV file.

Usage:

```
GenericClusteringStrategy$saveCSV(dir.path, name, num.clusters = NULL)
```

Arguments:

`dir.path` The name of the directory to save the CSV file.

`name` Defines the name of the CSV file.

`num.clusters` An optional parameter to select the number of clusters to be saved. If not defined, all clusters will be saved.

Method `clone()`: The objects of this class are cloneable with this method.

Usage:

```
GenericClusteringStrategy$clone(deep = FALSE)
```

Arguments:

`deep` Whether to make a deep clone.

See Also

[Subset](#), [GenericHeuristic](#)

GenericHeuristic *Abstract Feature Clustering heuristic object.*

Description

Abstract class used as a template to define new customized clustering heuristics.

Details

The [GenericHeuristic](#) is an archetype class so it cannot be instantiated.

Methods

Public methods:

- [GenericHeuristic\\$new\(\)](#)
- [GenericHeuristic\\$heuristic\(\)](#)
- [GenericHeuristic\\$clone\(\)](#)

Method `new()`: Empty function used to initialize the object arguments in runtime.

Usage:

```
GenericHeuristic$new()
```

Method `heuristic()`: Function used to implement the clustering heuristic.

Usage:

```
GenericHeuristic$heuristic(col1, col2, column.names = NULL, ...)
```

Arguments:

`col1` A [numeric](#) vector or matrix required to perform the clustering operation.

`col2` A [numeric](#) vector or matrix to perform the clustering operation.

`column.names` An optional [character](#) vector with the names of both columns

`...` Further arguments passed down to `heuristic` function.

Returns: A [numeric](#) vector of length 1.

Method `clone()`: The objects of this class are cloneable with this method.

Usage:

```
GenericHeuristic$clone(deep = FALSE)
```

Arguments:

`deep` Whether to make a deep clone.

See Also

[Dataset](#)

GenericModelFit

Abstract class for defining model fitting method.

Description

Template to create a [recipe](#) or [formula](#) objects used in model training stage.

Methods

Public methods:

- [GenericModelFit\\$new\(\)](#)
- [GenericModelFit\\$createFormula\(\)](#)
- [GenericModelFit\\$createRecipe\(\)](#)
- [GenericModelFit\\$clone\(\)](#)

Method `new()`: Method for initializing the object arguments during runtime.

Usage:

```
GenericModelFit$new()
```

Method `createFormula()`: The function is responsible of creating a [formula](#) for M.L. model.

Usage:

```
GenericModelFit$createFormula(instances, class.name, simplify = TRUE)
```

Arguments:

`instances` A [data.frame](#) containing the instances used to create the recipe.

`class.name` A [character](#) vector representing the name of the target class.

`simplify` A [logical](#) argument defining whether the formula should be generated as simple as possible.

Returns: A [formula](#) object.

Method `createRecipe()`: The function is responsible of creating a [recipe](#) for M.L. model.

Usage:

```
GenericModelFit$createRecipe(instances, class.name)
```

Arguments:

`instances` A [data.frame](#) containing the instances used to create the recipe.

`class.name` A [character](#) vector representing the name of the target class.

Returns: A object of class [recipe](#).

Method `clone()`: The objects of this class are cloneable with this method.

Usage:

```
GenericModelFit$clone(deep = FALSE)
```

Arguments:

`deep` Whether to make a deep clone.

See Also

[DefaultModelFit](#), [train](#)

GenericPlot

Pseudo-abstract class for creating feature clustering plots.

Description

The [GenericPlot](#) implements a basic plot.

Methods

Public methods:

- [GenericPlot\\$new\(\)](#)
- [GenericPlot\\$plot\(\)](#)
- [GenericPlot\\$clone\(\)](#)

Method `new()`: Empty function used to initialize the object arguments in runtime.

Usage:

```
GenericPlot$new()
```

Method `plot()`: Implements a generic plot to visualize basic feature-clustering data.

Usage:

```
GenericPlot$plot(summary)
```

Arguments:

`summary` A [data.frame](#) comprising the elements to be plotted.

Method `clone()`: The objects of this class are cloneable with this method.

Usage:

```
GenericPlot$clone(deep = FALSE)
```

Arguments:

`deep` Whether to make a deep clone.

See Also

[BinaryPlot](#)

HDDataset

*High Dimensional Dataset handler.***Description**

Creates a high dimensional dataset object. Only the required instances are loaded in memory to avoid unnecessary of resources and memory.

Methods**Public methods:**

- [HDDataset\\$new\(\)](#)
- [HDDataset\\$getColumnNameNames\(\)](#)
- [HDDataset\\$getNcol\(\)](#)
- [HDDataset\\$createSubset\(\)](#)

Method `new()`: Method for initializing the object arguments during runtime.

Usage:

```
HDDataset$new(
  filepath,
  header = TRUE,
  sep = ",",
  skip = 0,
  normalize.names = FALSE,
  ignore.columns = NULL
)
```

Arguments:

`filepath` The name of the file which the data are to be read from. Each row of the table appears as one line of the file. If it does not contain an `_absolute_ path`, the file name is `_relative_ to the current working directory, 'getwd()'`.

`header` A **logical** value indicating whether the file contains the names of the variables as its first line. If missing, the value is determined from the file format: 'header' is set to 'TRUE' if and only if the first row contains one fewer field than the number of columns.

`sep` The field separator character. Values on each line of the file are separated by this character.

`skip` Defines the number of header lines should be skipped.

`normalize.names` A **logical** value indicating whether the columns names should be automatically renamed to ensure R compatibility.

`ignore.columns` Specify the columns from the input file that should be ignored.

Method `getColumnNameNames()`: Gets the name of the columns comprising the dataset

Usage:

```
HDDataset$getColumnNameNames()
```

Returns: A **character** vector with the name of each column.

Method `getNcol()`: Obtains the number of columns present in the dataset.

Usage:

```
HDDataset$getNcol()
```

Returns: An [integer](#) of length 1 or `NULL`

Method `createSubset()`: Creates a blinded [HDSubset](#) for classification purposes.

Usage:

```
HDDataset$createSubset(column.id = FALSE, chunk.size = 1e+05)
```

Arguments:

`column.id` An [integer](#) or [character](#) indicating the column (number or name respectively) identifier. Default `NULL` value is valid ignores defining a identification column.

`chunk.size` an [integer](#) value indicating the size of chunks taken over each iteration.

Returns: A [HDSubset](#) object.

See Also

[Dataset](#), [HDSubset](#), [DatasetLoader](#)

HDSubset

High Dimensional Subset handler.

Description

Creates a high dimensional subset from a [HDDataset](#) object. Only the required instances are loaded in memory to avoid unnecessary use of resources and memory.

Details

Use [HDDataset](#) to ensure the creation of a valid [HDSubset](#) object.

Methods

Public methods:

- [HDSubset\\$new\(\)](#)
- [HDSubset\\$getColumnNames\(\)](#)
- [HDSubset\\$getNcol\(\)](#)
- [HDSubset\\$getID\(\)](#)
- [HDSubset\\$getIterator\(\)](#)
- [HDSubset\\$isBlinded\(\)](#)
- [HDSubset\\$clone\(\)](#)

Method `new()`: Method for initializing the object arguments during runtime.

Usage:

```
HDSubset$new(
  file.path,
  feature.names,
  feature.id,
  start.at = 0,
  sep = ",",
  chunk.size
)
```

Arguments:

`file.path` The name of the file which the data are to be read from. Each row of the table appears as one line of the file. If it does not contain an `_absolute_path`, the file name is `_relative_` to the current working directory, `'getwd()'`.

`feature.names` A [character](#) vector specifying the name of the features that should be included in the [HDDataset](#) object.

`feature.id` An [integer](#) or [character](#) indicating the column (number or name respectively) identifier. Default [NULL](#) value is valid ignores defining a identification column.

`start.at` A [numeric](#) value to identify the reading start position.

`sep` the field separator character. Values on each line of the file are separated by this character.

`chunk.size` an [integer](#) value indicating the size of chunks taken over each iteration. By default `chunk.size` is defined as 10000.

Method `getColumnNames()`: Gets the name of the columns comprising the subset.

Usage:

```
HDSubset$getColumnNames()
```

Returns: A [character](#) vector containing the name of each column.

Method `getNcol()`: Obtains the number of columns present in the dataset.

Usage:

```
HDSubset$getNcol()
```

Returns: A [numeric](#) value or 0 if is empty.

Method `getID()`: Obtains the column identifier.

Usage:

```
HDSubset$getID()
```

Returns: A [character](#) vector of size 1.

Method `getIterator()`: Creates the [FIterator](#) object.

Usage:

```
HDSubset$getIterator(chunk.size = private$chunk.size, verbose = FALSE)
```

Arguments:

`chunk.size` An [integer](#) value indicating the size of chunks taken over each iteration. By default `chunk.size` is defined as 10000.

`verbose` A [logical](#) value to specify if more verbosity is needed.

Returns: A [FIterator](#) object to transverse through [HDSubset](#) instances

Method `isBlinded()`: Checks if the subset contains a target class.

Usage:

`HDSubset$isBlinded()`

Returns: A **logical** to specify if the subset contains a target class or not.

Method `clone()`: The objects of this class are cloneable with this method.

Usage:

`HDSubset$clone(deep = FALSE)`

Arguments:

`deep` Whether to make a deep clone.

See Also

[HDDataset](#), [DatasetLoader](#)

InformationGainHeuristic

Feature-clustering based on InformationGain methodology.

Description

Performs the feature-clustering using entropy-based filters.

Super class

[D2MCS::GenericHeuristic](#) -> InformationGainHeuristic

Methods

Public methods:

- [InformationGainHeuristic\\$new\(\)](#)
- [InformationGainHeuristic\\$heuristic\(\)](#)
- [InformationGainHeuristic\\$clone\(\)](#)

Method `new()`: Empty function used to initialize the object arguments in runtime.

Usage:

`InformationGainHeuristic$new()`

Method `heuristic()`: The algorithm find weights of discrete attributes basing on their correlation with continuous class attribute. Particularly Information Gain uses $H(\text{Class}) + H(\text{Attribute}) - H(\text{Class}, \text{Attribute})$

Usage:

`InformationGainHeuristic$heuristic(col1, col2, column.names = NULL)`

Arguments:

col1 A **numeric** vector or matrix required to perform the clustering operation.
 col2 A **numeric** vector or matrix to perform the clustering operation.
 column.names an optional **character** vector with the names of both columns.
Returns: A **numeric** vector of length 1 or **NA** if an error occurs.

Method clone(): The objects of this class are cloneable with this method.

Usage:

```
InformationGainHeuristic$clone(deep = FALSE)
```

Arguments:

deep Whether to make a deep clone.

See Also

[Dataset](#), [information.gain](#)

Kappa

Computes the Kappa Cohen value.

Description

Cohen's Kappa measures the agreement between two raters who each classify N items into C mutually exclusive categories.

Details

κ is equivalent to $(p_o - p_e)/(1 - p_e) = 1 - (1 - p_o)/(1 - p_e)$

Super class

[D2MCS::MeasureFunction](#) -> Kappa

Methods

Public methods:

- [Kappa\\$new\(\)](#)
- [Kappa\\$compute\(\)](#)
- [Kappa\\$clone\(\)](#)

Method new(): Method for initializing the object arguments during runtime.

Usage:

```
Kappa$new(performance.output = NULL)
```

Arguments:

performance.output An optional [ConfMatrix](#) used as basis to compute the performance.

Method `compute()`: The function computes the **Kappa** achieved by the M.L. model.

Usage:

```
Kappa$compute(performance.output = NULL)
```

Arguments:

`performance.output` An optional [ConfMatrix](#) parameter to define the type of object used as basis to compute the Kappa measure.

Details: This function is automatically invoked by the [ClassificationOutput](#) object.

Returns: A [numeric](#) vector of size 1 or [NULL](#) if an error occurred.

Method `clone()`: The objects of this class are cloneable with this method.

Usage:

```
Kappa$clone(deep = FALSE)
```

Arguments:

`deep` Whether to make a deep clone.

See Also

[MeasureFunction](#), [ClassificationOutput](#), [ConfMatrix](#)

KendallHeuristic

Feature-clustering based on Kendall Correlation Test.

Description

Performs the feature-clustering using Kendall correlation tests.

Details

The method estimate the association between paired samples and compute a test of the value being zero. They use different measures of association, all in the range [-1, 1] with 0 indicating no association. Method valid only for bi-class problems.

Super class

[D2MCS::GenericHeuristic](#) -> KendallHeuristic

Methods

Public methods:

- [KendallHeuristic\\$new\(\)](#)
- [KendallHeuristic\\$heuristic\(\)](#)
- [KendallHeuristic\\$clone\(\)](#)

Method `new()`: Empty function used to initialize the object arguments in runtime.

Usage:

KendallHeuristic\$new()

Method heuristic(): Test for association between paired samples using Kendall's tau value.

Usage:

KendallHeuristic\$heuristic(col1, col2, column.names = NULL)

Arguments:

col1 A **numeric** vector or matrix required to perform the clustering operation.

col2 A **numeric** vector or matrix to perform the clustering operation.

column.names An optional **character** vector with the names of both columns.

Returns: a **numeric** vector of length 1 or **NA** if an error occurs.

Method clone(): The objects of this class are cloneable with this method.

Usage:

KendallHeuristic\$clone(deep = FALSE)

Arguments:

deep Whether to make a deep clone.

See Also

[Dataset](#), [cor.test](#)

MCC

Computes the Matthews correlation coefficient.

Description

The Matthews correlation coefficient is used in machine learning as a measure of the quality of binary (two-class) classifications. It takes into account true and false positives and negatives and is generally regarded as a balanced measure which can be used even if the classes are of very different sizes. The MCC is in essence a correlation coefficient between the observed and predicted binary classifications; it returns a value between -1 and +1.

Details

$$MCC = (TP(TN - FP)FN) / (\sqrt{(TP + FP)(TP + FN)(TN + FP)(TN + FN)})$$

Super class

[D2MCS::MeasureFunction](#) -> MCC

Methods

Public methods:

- [MCC\\$new\(\)](#)
- [MCC\\$compute\(\)](#)
- [MCC\\$clone\(\)](#)

Method `new()`: Method for initializing the object arguments during runtime.

Usage:

```
MCC$new(performance.output = NULL)
```

Arguments:

`performance.output` An optional [ConfMatrix](#) parameter used as basis to compute the MCC measure.

Method `compute()`: The function computes the **MCC** achieved by the M.L. model.

Usage:

```
MCC$compute(performance.output = NULL)
```

Arguments:

`performance.output` An optional [ConfMatrix](#) parameter to define the type of object used as basis to compute the MCC measure.

Details: This function is automatically invoke by the [ClassificationOutput](#) object.

Returns: A [numeric](#) vector of size 1 or [NULL](#) if an error occurred.

Method `clone()`: The objects of this class are cloneable with this method.

Usage:

```
MCC$clone(deep = FALSE)
```

Arguments:

`deep` Whether to make a deep clone.

See Also

[MeasureFunction](#), [ClassificationOutput](#), [ConfMatrix](#)

MCCHeuristic

Feature-clustering based on Matthews Correlation Coefficient score.

Description

Performs the feature-clustering using MCC score. Valid for both bi-class and multi-class problems

Super class

[D2MCS::GenericHeuristic](#) -> MCCHeuristic

Methods

Public methods:

- [MCCHuristic\\$new\(\)](#)
- [MCCHuristic\\$heuristic\(\)](#)
- [MCCHuristic\\$clone\(\)](#)

Method `new()`: Empty function used to initialize the object arguments in runtime.

Usage:

```
MCCHuristic$new()
```

Method `heuristic()`: Calculates the Matthews correlation Coefficient (MCC) score.

Usage:

```
MCCHuristic$heuristic(col1, col2, column.names = NULL)
```

Arguments:

`col1` A [numeric](#) vector or matrix required to perform the clustering operation.

`col2` A [numeric](#) vector or matrix to perform the clustering operation.

`column.names` An optional [character](#) vector with the names of both columns.

Returns: A [numeric](#) vector of length 1 or [NA](#) if an error occurs.

Method `clone()`: The objects of this class are cloneable with this method.

Usage:

```
MCCHuristic$clone(deep = FALSE)
```

Arguments:

`deep` Whether to make a deep clone.

See Also

[Dataset](#), [mccr](#)

MeasureFunction

Archetype to define customized measures.

Description

Abstract class used as a template to define new M.L. performance measures.

Details

The [GenericHeuristic](#) is an full-abstract class so it cannot be instantiated. To ensure the proper operation, compute method is automatically invoke by [D2MCS](#) framework when needed.

Methods

Public methods:

- [MeasureFunction\\$new\(\)](#)
- [MeasureFunction\\$compute\(\)](#)
- [MeasureFunction\\$clone\(\)](#)

Method `new()`: Method for initializing the object arguments during runtime.

Usage:

```
MeasureFunction$new(performance = NULL)
```

Arguments:

`performance` An optional [ConfMatrix](#) parameter to define the type of object used to compute the measure.

Method `compute()`: The function implements the metric used to measure the performance achieved by the M.L. model.

Usage:

```
MeasureFunction$compute(performance.output = NULL)
```

Arguments:

`performance.output` An optional [ConfMatrix](#) parameter to define the type of object used to compute the measure.

Details: This function is automatically invoke by the [D2MCS](#) framework.

Returns: A [numeric](#) vector of size 1 or [NULL](#) if an error occurred.

Method `clone()`: The objects of this class are cloneable with this method.

Usage:

```
MeasureFunction$clone(deep = FALSE)
```

Arguments:

`deep` Whether to make a deep clone.

See Also

[MeasureFunction](#)

Methodology

Abstract class to compute the probability prediction based on combination between metrics.

Description

Abstract class used as a template to define new customized strategies to combine the probability predictions made by different metrics.

Methods

Public methods:

- [Methodology\\$new\(\)](#)
- [Methodology\\$getRequiredMetrics\(\)](#)
- [Methodology\\$compute\(\)](#)
- [Methodology\\$clone\(\)](#)

Method `new()`: Method for initializing the object arguments during runtime.

Usage:

```
Methodology$new(required.metrics)
```

Arguments:

`required.metrics` A [character](#) vector of length greater than 2 with the name of the required metrics.

Method `getRequiredMetrics()`: The function returns the required metrics that will participate in the methodology to compute a metric based on all of them.

Usage:

```
Methodology$getRequiredMetrics()
```

Returns: A [character](#) vector of length greater than 2 with the name of the required metrics.

Method `compute()`: Function to compute the probability of the final prediction based on different metrics.

Usage:

```
Methodology$compute(raw.pred, prob.pred, positive.class, negative.class)
```

Arguments:

`raw.pred` A [character](#) list of length greater than 2 with the class value of the predictions made by the metrics.

`prob.pred` A [numeric](#) list of length greater than 2 with the probability of the predictions made by the metrics.

`positive.class` A [character](#) with the value of the positive class.

`negative.class` A [character](#) with the value of the negative class.

Returns: A [numeric](#) value indicating the probability of the instance is predicted as positive class.

Method `clone()`: The objects of this class are cloneable with this method.

Usage:

```
Methodology$clone(deep = FALSE)
```

Arguments:

`deep` Whether to make a deep clone.

See Also

[ProbBasedMethodology](#)

MinimizeFN

Combined metric strategy to minimize FN errors.

Description

Calculates if the positive class is the predicted one in any of the metrics, otherwise, the instance is not considered to have the positive class associated.

Super class

`D2MCS::CombinedMetrics` -> MinimizeFN

Methods**Public methods:**

- `MinimizeFN$new()`
- `MinimizeFN$getFinalPrediction()`
- `MinimizeFN$clone()`

Method `new()`: Method for initializing the object arguments during runtime.

Usage:

```
MinimizeFN$new(required.metrics = c("MCC", "PPV"))
```

Arguments:

`required.metrics` A **character** vector of length 1 with the name of the required metrics.

Method `getFinalPrediction()`: Function to obtain the final prediction based on different metrics.

Usage:

```
MinimizeFN$getFinalPrediction(
  raw.pred,
  prob.pred,
  positive.class,
  negative.class
)
```

Arguments:

`raw.pred` A **character** list of length greater than 2 with the class value of the predictions made by the metrics.

`prob.pred` A **numeric** list of length greater than 2 with the probability of the predictions made by the metrics.

`positive.class` A **character** with the value of the positive class.

`negative.class` A **character** with the value of the negative class.

Returns: A **logical** value indicating if the instance is predicted as positive class or not.

Method `clone()`: The objects of this class are cloneable with this method.

Usage:

```
MinimizeFN$clone(deep = FALSE)
```

Arguments:

deep Whether to make a deep clone.

See Also

[CombinedMetrics](#)

MinimizeFP

Combined metric strategy to minimize FP errors.

Description

Calculates if the positive class is the predicted one in all metrics, otherwise, the instance is not considered to have the positive class associated.

Super class

[D2MCS::CombinedMetrics](#) -> MinimizeFP

Methods**Public methods:**

- [MinimizeFP\\$new\(\)](#)
- [MinimizeFP\\$getFinalPrediction\(\)](#)
- [MinimizeFP\\$clone\(\)](#)

Method `new()`: Method for initializing the object arguments during runtime.

Usage:

```
MinimizeFP$new(required.metrics = c("MCC", "PPV"))
```

Arguments:

`required.metrics` A [character](#) vector of length greater than 2 with the name of the required metrics.

Method `getFinalPrediction()`: Function to obtain the final prediction based on different metrics.

Usage:

```
MinimizeFP$getFinalPrediction(
  raw.pred,
  prob.pred,
  positive.class,
  negative.class
)
```

Arguments:

raw.pred A [character](#) list of length greater than 2 with the class value of the predictions made by the metrics.

prob.pred A [numeric](#) list of length greater than 2 with the probability of the predictions made by the metrics.

positive.class A [character](#) with the value of the positive class.

negative.class A [character](#) with the value of the negative class.

Returns: A [logical](#) value indicating if the instance is predicted as positive class or not.

Method clone(): The objects of this class are cloneable with this method.

Usage:

```
MinimizeFP$clone(deep = FALSE)
```

Arguments:

deep Whether to make a deep clone.

See Also

[CombinedMetrics](#)

MultinformationHeuristic

Feature-clustering based on Mutual Information Computation theory.

Description

Performs the feature-clustering using MCC score. Valid for both bi-class and multi-class problems. Only valid for bi-class problems.

Super class

[D2MCS::GenericHeuristic](#) -> MultinformationHeuristic

Methods**Public methods:**

- [MultinformationHeuristic\\$new\(\)](#)
- [MultinformationHeuristic\\$heuristic\(\)](#)
- [MultinformationHeuristic\\$clone\(\)](#)

Method new(): Empty function used to initialize the object arguments in runtime.

Usage:

```
MultinformationHeuristic$new()
```

Method heuristic(): Mutinformation takes two random variables as input and computes the mutual information in nats according to the entropy estimator method.

Usage:

```
MultinformationHeuristic$heuristic(col1, col2, column.names = NULL)
```

Arguments:

col1 A vector/factor denoting a random variable or a data.frame denoting a random vector where columns contain variables/features and rows contain outcomes/samples.

col2 An another random variable or random vector (vector/factor or data.frame).

column.names An optional [character](#) vector with the names of both columns.

Returns: Returns the mutual information $I(X;Y)$ in nats.

Method clone(): The objects of this class are cloneable with this method.

Usage:

```
MultinformationHeuristic$clone(deep = FALSE)
```

Arguments:

deep Whether to make a deep clone.

See Also

[Dataset](#), [mutinformation](#)

NoProbability

Compute performance across resamples.

Description

Computes the performance across resamples when class probabilities cannot be computed.

Super class

[D2MCS::SummaryFunction](#) -> NoProbability

Methods**Public methods:**

- [NoProbability\\$new\(\)](#)
- [NoProbability\\$execute\(\)](#)
- [NoProbability\\$clone\(\)](#)

Method new(): The function defined during runtime the usage of five measures: 'Kappa', 'Accuracy', 'TCR_9', 'MCC' and 'PPV'.

Usage:

```
NoProbability$new()
```

Method execute(): The function computes the performance across resamples using the previously defined measures.

Usage:

```
NoProbability$execute(data, lev = NULL, model = NULL)
```

Arguments:

`data` A [data.frame](#) containing the data used to compute the performance.

`lev` An optional value used to define the levels of the target class.

`model` An optional value used to define the M.L. model used.

Returns: A vector of performance estimates.

Method `clone()`: The objects of this class are cloneable with this method.

Usage:

```
NoProbability$clone(deep = FALSE)
```

Arguments:

`deep` Whether to make a deep clone.

See Also

[SummaryFunction](#)

 NPV

Computes the Negative Predictive Value.

Description

Negative Predictive Values are the proportions of negative results in statistics and diagnostic tests that are true negative results.

Details

$$NPV = TN / (TN + FN)$$

Super class

[D2MCS::MeasureFunction](#) -> NPV

Methods**Public methods:**

- [NPV\\$new\(\)](#)
- [NPV\\$compute\(\)](#)
- [NPV\\$clone\(\)](#)

Method `new()`: Method for initializing the object arguments during runtime.

Usage:

```
NPV$new(performance.output = NULL)
```

Arguments:

performance.output An optional [ConfMatrix](#) parameter to define the type of object used as basis to compute the NPV measure.

Method compute(): The function computes the NPV achieved by the M.L. model.

Usage:

```
NPV$compute(performance.output = NULL)
```

Arguments:

performance.output An optional [ConfMatrix](#) parameter to define the type of object used as basis to compute the NPV measure.

Details: This function is automatically invoke by the [ClassificationOutput](#) object.

Returns: A [numeric](#) vector of size 1 or [NULL](#) if an error occurred.

Method clone(): The objects of this class are cloneable with this method.

Usage:

```
NPV$clone(deep = FALSE)
```

Arguments:

deep Whether to make a deep clone.

See Also

[MeasureFunction](#), [ClassificationOutput](#), [ConfMatrix](#)

OddsRatioHeuristic *Feature-clustering based on Odds Ratio measure.*

Description

Performs the feature-clustering using Odds Ratio methodology. Valid only for bi-class problems.

Super class

[D2MCS::GenericHeuristic](#) -> OddsRatioHeuristic

Methods**Public methods:**

- [OddsRatioHeuristic\\$new\(\)](#)
- [OddsRatioHeuristic\\$heuristic\(\)](#)
- [OddsRatioHeuristic\\$clone\(\)](#)

Method new(): Empty function used to initialize the object arguments in runtime.

Usage:

```
OddsRatioHeuristic$new()
```

Method heuristic(): Calculates the Odds Ratio method.

Usage:

```
OddsRatioHeuristic$heuristic(col1, col2, column.names = NULL)
```

Arguments:

col1 The object from whom odds ratio will be computed.

col2 A second [factor](#) or [numeric](#) object.

column.names An optional [character](#) vector with the names of both columns.

Returns: A [numeric](#) vector of length 1 or [NA](#) if an error occurs.

Method clone(): The objects of this class are cloneable with this method.

Usage:

```
OddsRatioHeuristic$clone(deep = FALSE)
```

Arguments:

deep Whether to make a deep clone.

See Also

[Dataset](#), [odds.ratio](#)

PearsonHeuristic

Feature-clustering based on Pearson Correlation Test.

Description

Performs the feature-clustering using Pearson correlation tests. Valid for both, bi-class and multi-class problems.

Details

The test statistic is based on Pearson's product moment correlation coefficient $\text{cor}(x, y)$ and follows a t distribution with $\text{length}(x)-2$ degrees of freedom if the samples follow independent normal distributions. If there are at least 4 complete pairs of observation, an asymptotic confidence interval is given based on Fisher's Z transform.

Super class

[D2MCS::GenericHeuristic](#) -> PearsonHeuristic

Methods

Public methods:

- [PearsonHeuristic\\$new\(\)](#)
- [PearsonHeuristic\\$heuristic\(\)](#)
- [PearsonHeuristic\\$clone\(\)](#)

Method `new()`: Creates a [PearsonHeuristic](#) object.

Usage:

```
PearsonHeuristic$new()
```

Method `heuristic()`: Test for association between paired samples using Pearson test.

Usage:

```
PearsonHeuristic$heuristic(col1, col2, column.names = NULL)
```

Arguments:

`col1` A [numeric](#) vector or matrix required to perform the clustering operation.

`col2` A [numeric](#) vector or matrix to perform the clustering operation.

`column.names` An optional [character](#) vector with the names of both columns.

Returns: A [numeric](#) vector of length 1 or [NA](#) if an error occurs.

Method `clone()`: The objects of this class are cloneable with this method.

Usage:

```
PearsonHeuristic$clone(deep = FALSE)
```

Arguments:

`deep` Whether to make a deep clone.

See Also

[Dataset](#), [cor](#)

PPV

Computes the Positive Predictive Value.

Description

Positive Predictive Values are the proportions of positive results in statistics and diagnostic tests that are true positive results.

Details

$$PPV = TP / (TP + FP)$$

Super class

[D2MCS::MeasureFunction](#) -> PPV

Methods

Public methods:

- [PPV\\$new\(\)](#)
- [PPV\\$compute\(\)](#)
- [PPV\\$clone\(\)](#)

Method `new()`: Method for initializing the object arguments during runtime.

Usage:

```
PPV$new(performance.output = NULL)
```

Arguments:

`performance.output` An optional [ConfMatrix](#) parameter to define the type of object used as basis to compute the **PPV** measure.

Method `compute()`: The function computes the **PPV** achieved by the M.L. model.

Usage:

```
PPV$compute(performance.output = NULL)
```

Arguments:

`performance.output` An optional [ConfMatrix](#) parameter to define the type of object used as basis to compute the **PPV** measure.

Details: This function is automatically invoke by the [ClassificationOutput](#) object.

Returns: A [numeric](#) vector of size 1 or [NULL](#) if an error occurred.

Method `clone()`: The objects of this class are cloneable with this method.

Usage:

```
PPV$clone(deep = FALSE)
```

Arguments:

`deep` Whether to make a deep clone.

See Also

[MeasureFunction](#), [ClassificationOutput](#), [ConfMatrix](#)

Precision

Computes the Precision Value.

Description

Precision is the fraction of relevant instances among the retrieved instances

Details

$$precision = TP / (TP + FP)$$

Super class

[D2MCS::MeasureFunction](#) -> Precision

Methods

Public methods:

- [Precision\\$new\(\)](#)
- [Precision\\$compute\(\)](#)
- [Precision\\$clone\(\)](#)

Method `new()`: Method for initializing the object arguments during runtime.

Usage:

```
Precision$new(performance.output = NULL)
```

Arguments:

`performance.output` An optional [ConfMatrix](#) parameter to define the type of object used as basis to compute the measure.

Method `compute()`: The function computes the **Precision** achieved by the M.L. model.

Usage:

```
Precision$compute(performance.output = NULL)
```

Arguments:

`performance.output` An optional [ConfMatrix](#) parameter to define the type of object used as basis to compute the **Precision** measure.

Details: This function is automatically invoke by the [ClassificationOutput](#) object.

Returns: A [numeric](#) vector of size 1 or [NULL](#) if an error occurred.

Method `clone()`: The objects of this class are cloneable with this method.

Usage:

```
Precision$clone(deep = FALSE)
```

Arguments:

`deep` Whether to make a deep clone.

See Also

[MeasureFunction](#), [ClassificationOutput](#), [ConfMatrix](#)

PredictionOutput *Encapsulates the achieved predictions.*

Description

The class used to encapsulates all the computed predictions to facilitate their access and maintenance.

Methods

Public methods:

- [PredictionOutput\\$new\(\)](#)
- [PredictionOutput\\$getPredictions\(\)](#)
- [PredictionOutput\\$getType\(\)](#)
- [PredictionOutput\\$getTarget\(\)](#)
- [PredictionOutput\\$clone\(\)](#)

Method `new()`: Method for initializing the object arguments during runtime.

Usage:

```
PredictionOutput$new(predictions, type, target)
```

Arguments:

`predictions` A list of [FinalPred](#) elements.

`type` A [character](#) to define which type of predictions should be returned. If not defined all type of probabilities will be returned. Conversely if "prob" or "raw" is defined then computed 'probabilistic' or 'class' values are returned.

`target` A [character](#) defining the value of the positive class.

Method `getPredictions()`: The function returns the final predictions.

Usage:

```
PredictionOutput$getPredictions()
```

Returns: A list containing the final predictions or [NULL](#) if classification stage was not successfully performed.

Method `getType()`: The function returns the type of prediction should be returned. If "prob" or "raw" is defined then computed 'probabilistic' or 'class' values are returned.

Usage:

```
PredictionOutput$getType()
```

Returns: A [character](#) value.

Method `getTarget()`: The function returns the value of the target class.

Usage:

```
PredictionOutput$getTarget()
```

Returns: A [character](#) value.

Method `clone()`: The objects of this class are cloneable with this method.

Usage:

```
PredictionOutput$clone(deep = FALSE)
```

Arguments:

`deep` Whether to make a deep clone.

See Also

[D2MCS](#)

ProbAverageVoting *Implementation of Probabilistic Average voting.*

Description

Computes the final prediction by performing the mean value of the probability achieved by each prediction.

Super class

[D2MCS::SimpleVoting](#) -> ProbAverageVoting

Methods

Public methods:

- [ProbAverageVoting\\$new\(\)](#)
- [ProbAverageVoting\\$getMajorityClass\(\)](#)
- [ProbAverageVoting\\$getClassTie\(\)](#)
- [ProbAverageVoting\\$execute\(\)](#)
- [ProbAverageVoting\\$clone\(\)](#)

Method `new()`: Method for initializing the object arguments during runtime.

Usage:

```
ProbAverageVoting$new(cutoff = 0.5, class.tie = NULL, majority.class = NULL)
```

Arguments:

`cutoff` A [character](#) vector defining the minimum probability used to perform a positive classification. If is not defined, 0.5 will be used as default value.

`class.tie` A [character](#) used to define the target class value used when a tie is found. If [NULL](#) positive class value will be assigned.

`majority.class` A [character](#) defining the value of the majority class. If [NULL](#) will be used same value as training stage.

Method `getMajorityClass()`: The function returns the value of the majority class.

Usage:

ProbAverageVoting\$getMajorityClass()

Returns: A [character](#) vector of length 1 with the name of the majority class.

Method getClassTie(): The function gets the class value assigned to solve ties.

Usage:

ProbAverageVoting\$getClassTie()

Returns: A [character](#) vector of length 1.

Method execute(): The function implements the majority voting procedure.

Usage:

ProbAverageVoting\$execute(predictions, verbose = FALSE)

Arguments:

predictions A [ClusterPredictions](#) object containing all the predictions achieved for each cluster.

verbose A [logical](#) value to specify if more verbosity is needed.

Method clone(): The objects of this class are cloneable with this method.

Usage:

ProbAverageVoting\$clone(deep = FALSE)

Arguments:

deep Whether to make a deep clone.

See Also

[D2MCS](#), [ClassMajorityVoting](#), [ClassWeightedVoting](#), [ProbAverageVoting](#), [ProbAverageWeightedVoting](#), [ProbBasedMethodology](#)

ProbAverageWeightedVoting

Implementation of Probabilistic Average Weighted voting.

Description

Computes the final prediction by performing the weighted mean of the probability achieved by each cluster prediction. By default, weight values are consistent with the performance value achieved by the best M.L. model on each cluster.

Super class

[D2MCS::SimpleVoting](#) -> ProbAverageWeightedVoting

Methods

Public methods:

- `ProbAverageWeightedVoting$new()`
- `ProbAverageWeightedVoting$getClassTie()`
- `ProbAverageWeightedVoting$getWeights()`
- `ProbAverageWeightedVoting$setWeights()`
- `ProbAverageWeightedVoting$execute()`
- `ProbAverageWeightedVoting$clone()`

Method `new()`: Method for initializing the object arguments during runtime.

Usage:

```
ProbAverageWeightedVoting$new(cutoff = 0.5, class.tie = NULL, weights = NULL)
```

Arguments:

`cutoff` A [character](#) vector defining the minimum probability used to perform a positive classification. If is not defined, 0.5 will be used as default value.

`class.tie` A [character](#) used to define the target class value used when a tie is found. If `NULL` positive class value will be assigned.

`weights` A [numeric](#) vector with the weights of each cluster. If `NULL` performance achieved during training will be used as default.

Method `getClassTie()`: The function gets the class value assigned to solve ties.

Usage:

```
ProbAverageWeightedVoting$getClassTie()
```

Returns: A [character](#) vector of length 1.

Method `getWeights()`: The function returns the value of the majority class.

Usage:

```
ProbAverageWeightedVoting$getWeights()
```

Returns: A [character](#) vector of length 1 with the name of the majority class.

Method `setWeights()`: The function allows changing the value of the weights.

Usage:

```
ProbAverageWeightedVoting$setWeights(weights)
```

Arguments:

`weights` A [numeric](#) vector containing the new weights.

Method `execute()`: The function implements the cluster-weighted probabilistic voting procedure.

Usage:

```
ProbAverageWeightedVoting$execute(predictions, verbose = FALSE)
```

Arguments:

`predictions` A [ClusterPredictions](#) object containing all the predictions achieved for each cluster.

verbose A [logical](#) value to specify if more verbosity is needed.

Method clone(): The objects of this class are cloneable with this method.

Usage:

```
ProbAverageWeightedVoting$clone(deep = FALSE)
```

Arguments:

deep Whether to make a deep clone.

See Also

[D2MCS](#), [ClassMajorityVoting](#), [ClassWeightedVoting](#), [ProbAverageVoting](#), [ProbAverageWeightedVoting](#), [ProbBasedMethodology](#)

ProbBasedMethodology *Methodology to obtain the combination of the probability of different metrics.*

Description

Calculates the mean of the probabilities of the different metrics.

Super class

[D2MCS::Methodology](#) -> ProbBasedMethodology

Methods

Public methods:

- [ProbBasedMethodology\\$new\(\)](#)
- [ProbBasedMethodology\\$compute\(\)](#)
- [ProbBasedMethodology\\$clone\(\)](#)

Method new(): Method for initializing the object arguments during runtime.

Usage:

```
ProbBasedMethodology$new(required.metrics = c("MCC", "PPV"))
```

Arguments:

required.metrics A [character](#) vector of length greater than 2 with the name of the required metrics.

Method compute(): Function to compute the probability of the final prediction based on different metrics.

Usage:

```

ProbBasedMethodology$compute(
  raw.pred,
  prob.pred,
  positive.class,
  negative.class
)

```

Arguments:

`raw.pred` A [character](#) list of length greater than 2 with the class value of the predictions made by the metrics.

`prob.pred` A [numeric](#) list of length greater than 2 with the probability of the predictions made by the metrics.

`positive.class` A [character](#) with the value of the positive class.

`negative.class` A [character](#) with the value of the negative class.

Returns: A [numeric](#) value indicating the probability of the instance is predicted as positive class.

Method `clone()`: The objects of this class are cloneable with this method.

Usage:

```
ProbBasedMethodology$clone(deep = FALSE)
```

Arguments:

`deep` Whether to make a deep clone.

See Also

[Methodology](#)

Recall

Computes the Recall Value.

Description

Recall (also known as sensitivity) is the fraction of the total amount of relevant instances that were actually retrieved.

Details

$$recall = TP / (TP + FN)$$

Super class

[D2MCS::MeasureFunction](#) -> Recall

Methods

Public methods:

- [Recall\\$new\(\)](#)
- [Recall\\$compute\(\)](#)
- [Recall\\$clone\(\)](#)

Method `new()`: Method for initializing the object arguments during runtime.

Usage:

```
Recall$new(performance.output = NULL)
```

Arguments:

`performance.output` An optional [ConfMatrix](#) parameter to define the type of object used as basis to compute the measure.

Method `compute()`: The function computes the **Recall** achieved by the M.L. model.

Usage:

```
Recall$compute(performance.output = NULL)
```

Arguments:

`performance.output` An optional [ConfMatrix](#) parameter to define the type of object used as basis to compute the **Recall** measure.

Details: This function is automatically invoke by the [ClassificationOutput](#) object.

Returns: A [numeric](#) vector of size 1 or [NULL](#) if an error occurred.

Method `clone()`: The objects of this class are cloneable with this method.

Usage:

```
Recall$clone(deep = FALSE)
```

Arguments:

`deep` Whether to make a deep clone.

See Also

[MeasureFunction](#), [ClassificationOutput](#), [ConfMatrix](#)

Sensitivity

Computes the Sensitivity Value.

Description

Sensitivity is a measure of the proportion of actual positive cases that got predicted as positive (or true positive).

Details

$$\text{Sensitivity} = TP / (TP + FN)$$

Super class

[D2MCS::MeasureFunction](#) -> Sensitivity

Methods**Public methods:**

- [Sensitivity\\$new\(\)](#)
- [Sensitivity\\$compute\(\)](#)
- [Sensitivity\\$clone\(\)](#)

Method `new()`: Method for initializing the object arguments during runtime.

Usage:

```
Sensitivity$new(performance.output = NULL)
```

Arguments:

`performance.output` An optional [ConfMatrix](#) parameter to define the type of object used as basis to compute the Sensitivity measure.

Method `compute()`: The function computes the **Sensitivity** achieved by the M.L. model.

Usage:

```
Sensitivity$compute(performance.output = NULL)
```

Arguments:

`performance.output` An optional [ConfMatrix](#) parameter to define the type of object used as basis to compute the **Sensitivity** measure.

Details: This function is automatically invoke by the [ClassificationOutput](#) object.

Returns: A [numeric](#) vector of size 1 or [NULL](#) if an error occurred.

Method `clone()`: The objects of this class are cloneable with this method.

Usage:

```
Sensitivity$clone(deep = FALSE)
```

Arguments:

`deep` Whether to make a deep clone.

See Also

[MeasureFunction](#), [ClassificationOutput](#), [ConfMatrix](#)

SimpleStrategy	<i>Simple feature clustering strategy.</i>
----------------	--

Description

Features are sorted by descendant according to the relevance value obtained after applying an specific heuristic. Next, features are distributed into N clusters following a card-dealing methodology. Finally best distribution is assigned to the distribution having highest homogeneity.

Details

The strategy is suitable for all features that are valid for the indicated heuristics. Invalid features are automatically grouped into a specific cluster named as 'unclustered'.

Super class

`D2MCS::GenericClusteringStrategy` -> SimpleStrategy

Methods

Public methods:

- `SimpleStrategy$new()`
- `SimpleStrategy$execute()`
- `SimpleStrategy$getBestClusterDistribution()`
- `SimpleStrategy$getUnclustered()`
- `SimpleStrategy$getDistribution()`
- `SimpleStrategy$createTrain()`
- `SimpleStrategy$plot()`
- `SimpleStrategy$saveCSV()`
- `SimpleStrategy$clone()`

Method `new()`: Method for initializing the object arguments during runtime.

Usage:

```
SimpleStrategy$new(  
  subset,  
  heuristic,  
  configuration = StrategyConfiguration$new()  
)
```

Arguments:

`subset` The `Subset` used to apply the feature-clustering strategy.

`heuristic` The heuristic used to compute the relevance of each feature. Must inherit from `GenericHeuristic` abstract class.

`configuration` Optional parameter to customize configuration parameters for the strategy. Must inherited from `StrategyConfiguration` abstract class.

Method `execute()`: Function responsible of performing the clustering strategy over the defined `Subset`.

Usage:

```
SimpleStrategy$execute(verbose = FALSE)
```

Arguments:

`verbose` A logical value to specify if more verbosity is needed.

Method `getBestClusterDistribution()`: The function obtains the best clustering distribution.

Usage:

```
SimpleStrategy$getBestClusterDistribution()
```

Returns: A [list](#) of clusters. Each list element represents a feature group.

Method `getUnclustered()`: The function is used to return the features that cannot be clustered due to incompatibilities with the used heuristic.

Usage:

```
SimpleStrategy$getUnclustered()
```

Returns: A [character](#) vector containing the unclassified features.

Method `getDistribution()`: Function used to obtain a specific cluster distribution.

Usage:

```
SimpleStrategy$getDistribution(
  num.clusters = NULL,
  num.groups = NULL,
  include.unclustered = FALSE
)
```

Arguments:

`num.clusters` A [numeric](#) value to select the number of clusters (define the distribution).

`num.groups` A single or [numeric](#) vector value to identify a specific group that forms the clustering distribution.

`include.unclustered` A [logical](#) value to determine if unclustered features should be included.

Returns: A [list](#) with the features comprising an specific clustering distribution.

Method `createTrain()`: The function is used to create a [Trainset](#) object from a specific clustering distribution.

Usage:

```
SimpleStrategy$createTrain(
  subset,
  num.clusters = NULL,
  num.groups = NULL,
  include.unclustered = FALSE
)
```

Arguments:

`subset` The [Subset](#) object used as a basis to create the train set (see [Trainset](#) class).

`num.clusters` A [numeric](#) value to select the number of clusters (define the distribution).

`num.groups` A single or [numeric](#) vector value to identify a specific group that forms the clustering distribution.

`include.unclustered` A [logical](#) value to determine if unclustered features should be included.

Details: If `num.clusters` and `num.groups` are not defined, best clustering distribution is used to create the train set.

Returns: A [Trainset](#) object.

Method `plot()`: The function is responsible for creating a plot to visualize the clustering distribution.

Usage:

```
SimpleStrategy$plot(dir.path = NULL, file.name = NULL)
```

Arguments:

`dir.path` An optional argument to define the name of the directory where the exported plot will be saved. If not defined, the file path will be automatically assigned to the current working directory, `'getwd()'`.

`file.name` A character to define the name of the PDF file where the plot is exported.

Method `saveCSV()`: The function is used to save the clustering distribution to a CSV file.

Usage:

```
SimpleStrategy$saveCSV(dir.path, name = NULL, num.clusters = NULL)
```

Arguments:

`dir.path` The name of the directory to save the CSV file.

`name` Defines the name of the CSV file.

`num.clusters` An optional parameter to select the number of clusters to be saved. If not defined, all cluster distributions will be saved.

Method `clone()`: The objects of this class are cloneable with this method.

Usage:

```
SimpleStrategy$clone(deep = FALSE)
```

Arguments:

`deep` Whether to make a deep clone.

See Also

[GenericClusteringStrategy](#), [StrategyConfiguration](#)

SimpleVoting

Abstract class to define simple voting schemes.

Description

Abstract class used as a template to define new customized simple voting schemes.

Methods

Public methods:

- `SimpleVoting$new()`
- `SimpleVoting$getCutoff()`
- `SimpleVoting$getFinalPred()`
- `SimpleVoting$execute()`
- `SimpleVoting$clone()`

Method `new()`: Method for initializing the object arguments during runtime.

Usage:

```
SimpleVoting$new(cutoff = NULL)
```

Arguments:

`cutoff` A [character](#) vector defining the minimum probability used to perform a positive classification. If is not defined, 0.5 will be used as default value.

Method `getCutoff()`: The function obtains the minimum probabilistic value used to perform a positive classification.

Usage:

```
SimpleVoting$getCutoff()
```

Returns: A [numeric](#) value.

Method `getFinalPred()`: The function is used to return the prediction values computed by a voting strategy.

Usage:

```
SimpleVoting$getFinalPred(type = NULL, target = NULL, filter = NULL)
```

Arguments:

`type` A [character](#) to define which type of predictions should be returned. If not defined all type of probabilities will be returned. Conversely if 'prob' or 'raw' is defined then computed 'probabilistic' or 'class' values are returned.

`target` A [character](#) defining the value of the positive class.

`filter` A [logical](#) value used to specify if only predictions matching the target value should be returned or not. If [TRUE](#) the function returns only the predictions matching the target value. Conversely if [FALSE](#) (by default) the function returns all the predictions.

Returns: A [FinalPred](#) object.

Method `execute()`: Abstract function used to implement the operation of the voting scheme.

Usage:

```
SimpleVoting$execute(predictions, verbose = FALSE)
```

Arguments:

`predictions` A [ClusterPredictions](#) object containing all the predictions achieved for each cluster.

`verbose` A [logical](#) value to specify if more verbosity is needed.

Method `clone()`: The objects of this class are cloneable with this method.

Usage:

```
SimpleVoting$clone(deep = FALSE)
```

Arguments:

`deep` Whether to make a deep clone.

See Also

[D2MCS](#), [ClassMajorityVoting](#), [ClassWeightedVoting](#), [ProbAverageVoting](#), [ProbAverageWeightedVoting](#), [ProbBasedMethodology](#), [CombinedVoting](#)

SingleVoting

Manages the execution of Simple Votings.

Description

The class is responsible of initializing and executing voting schemes. Additionally, to ensure a proper operation, the class automatically checks the compatibility of defined voting schemes.

Super class

[D2MCS::VotingStrategy](#) -> [SingleVoting](#)

Methods

Public methods:

- [SingleVoting\\$new\(\)](#)
- [SingleVoting\\$execute\(\)](#)
- [SingleVoting\\$clone\(\)](#)

Method `new()`: The function initializes the object arguments during runtime.

Usage:

```
SimpleVoting$new(voting.schemes, metrics)
```

Arguments:

`voting.schemes` A [vector](#) of voting schemes inheriting from [SimpleVoting](#) class.

`metrics` A [list](#) containing the metrics used as basis to perform the voting strategy.

Method `execute()`: The function is used to execute all the previously defined (and compatible) voting schemes.

Usage:

`SingleVoting$execute(predictions, verbose = FALSE)`

Arguments:

`predictions` A [ClusterPredictions](#) object containing all the predictions computed in the classification stage.

`verbose` A [logical](#) value to specify if more verbosity is needed.

Method `clone()`: The objects of this class are cloneable with this method.

Usage:

`SingleVoting$clone(deep = FALSE)`

Arguments:

`deep` Whether to make a deep clone.

See Also

[D2MCS](#), [SimpleVoting](#), [CombinedVoting](#)

SpearmanHeuristic

Feature-clustering based on Spearman Correlation Test.

Description

Performs the feature-clustering using Spearman's rho statistic.

Details

Spearman's rho statistic is to estimate a rank-based measure of association. These tests may be used if the data do not necessarily come from a bivariate normal distribution.

Super class

[D2MCS::GenericHeuristic](#) -> SpearmanHeuristic

Methods

Public methods:

- [SpearmanHeuristic\\$new\(\)](#)
- [SpearmanHeuristic\\$heuristic\(\)](#)
- [SpearmanHeuristic\\$clone\(\)](#)

Method `new()`: Creates a [SpearmanHeuristic](#) object.

Usage:

`SpearmanHeuristic$new()`

Method `heuristic()`: Test for correlation between paired samples using Spearman rho statistic.

Usage:

```
SpearmanHeuristic$heuristic(col1, col2, column.names = NULL)
```

Arguments:

`col1` A **numeric** vector or matrix required to perform the clustering operation.

`col2` A **numeric** vector or matrix to perform the clustering operation.

`column.names` An optional **character** vector with the names of both columns.

Returns: A **numeric** vector of length 1 or **NA** if an error occurs.

Method `clone()`: The objects of this class are cloneable with this method.

Usage:

```
SpearmanHeuristic$clone(deep = FALSE)
```

Arguments:

`deep` Whether to make a deep clone.

See Also

[Dataset](#), [cor.test](#)

Specificity

Computes the Specificity Value.

Description

Specificity is defined as the proportion of actual negatives, which got predicted as the negative (or true negative). This implies that there will be another proportion of actual negative, which got predicted as positive and could be termed as false positives.

Details

$$\text{Specificity} = \text{TrueNegative} / (\text{TrueNegative} + \text{FalsePositive})$$

Super class

[D2MCS::MeasureFunction](#) -> Specificity

Methods

Public methods:

- [Specificity\\$new\(\)](#)
- [Specificity\\$compute\(\)](#)
- [Specificity\\$clone\(\)](#)

Method `new()`: Method for initializing the object arguments during runtime.

Usage:

```
Specificity$new(performance.output = NULL)
```

Arguments:

`performance.output` An optional [ConfMatrix](#) parameter to define the type of object used as basis to compute the measure.

Method `compute()`: The function computes the **Specificity** achieved by the M.L. model.

Usage:

```
Specificity$compute(performance.output = NULL)
```

Arguments:

`performance.output` An optional [ConfMatrix](#) parameter to define the type of object used as basis to compute the **Specificity** measure.

Details: This function is automatically invoke by the [ClassificationOutput](#) object.

Returns: A [numeric](#) vector of size 1 or [NULL](#) if an error occurred.

Method `clone()`: The objects of this class are cloneable with this method.

Usage:

```
Specificity$clone(deep = FALSE)
```

Arguments:

`deep` Whether to make a deep clone.

See Also

[MeasureFunction](#), [ClassificationOutput](#), [ConfMatrix](#)

StrategyConfiguration *Default Strategy Configuration handler.*

Description

Define default configuration parameters for the clustering strategies.

Details

The [StrategyConfiguration](#) can be used to define the default configuration parameters for a feature clustering strategy or as an archetype to define new customized parameters.

Methods

Public methods:

- [StrategyConfiguration\\$new\(\)](#)
- [StrategyConfiguration\\$minNumClusters\(\)](#)
- [StrategyConfiguration\\$maxNumClusters\(\)](#)
- [StrategyConfiguration\\$clone\(\)](#)

Method `new()`: Empty function used to initialize the object arguments in runtime.

Usage:

```
StrategyConfiguration$new()
```

Method `minNumClusters()`: Function used to return the minimum number of clusters distributions used. By default the minimum is set in 2.

Usage:

```
StrategyConfiguration$minNumClusters(...)
```

Arguments:

... Further arguments passed down to `minNumClusters` function.

Returns: A [numeric](#) vector of length 1.

Method `maxNumClusters()`: The function is responsible of returning the maximum number of cluster distributions used. By default the maximum number is set in 50.

Usage:

```
StrategyConfiguration$maxNumClusters(...)
```

Arguments:

... Further arguments passed down to `maxNumClusters` function.

Returns: A [numeric](#) vector of length 1.

Method `clone()`: The objects of this class are cloneable with this method.

Usage:

```
StrategyConfiguration$clone(deep = FALSE)
```

Arguments:

`deep` Whether to make a deep clone.

See Also

[DependencyBasedStrategyConfiguration](#)

Subset	<i>Classification set.</i>
--------	----------------------------

Description

The [Subset](#) is used for testing or classification purposes. If a target class is defined the [Subset](#) can be used as test and classification, otherwise the [Subset](#) only classification is compatible.

Details

Use [Dataset](#) to ensure the creation of a valid [Subset](#) object.

Methods

Public methods:

- [Subset\\$new\(\)](#)
- [Subset\\$getColumnNames\(\)](#)
- [Subset\\$getFeatures\(\)](#)
- [Subset\\$getID\(\)](#)
- [Subset\\$getIterator\(\)](#)
- [Subset\\$getClassValues\(\)](#)
- [Subset\\$getClassBalance\(\)](#)
- [Subset\\$getClassIndex\(\)](#)
- [Subset\\$getClassName\(\)](#)
- [Subset\\$getNcol\(\)](#)
- [Subset\\$getNrow\(\)](#)
- [Subset\\$getPositiveClass\(\)](#)
- [Subset\\$isBlinded\(\)](#)

Method `new()`: Method for initializing the object arguments during runtime.

Usage:

```
Subset$new(  
  dataset,  
  class.index = NULL,  
  class.values = NULL,  
  positive.class = NULL,  
  feature.id = NULL  
)
```

Arguments:

`dataset` A fully filled [data.frame](#).

`class.index` A [numeric](#) value identifying the column representing the target class

`class.values` A [character](#) vector containing all the values of the target class.

`positive.class` A [character](#) value representing the positive class value.

feature.id A [numeric](#) value specifying the column number used as identifier.

Method getColumnNames(): Get the name of the columns comprising the subset.

Usage:

```
Subset$getColumnNames()
```

Returns: A [character](#) vector containing the name of each column.

Method getFeatures(): Gets the values of all features or those indicated by arguments.

Usage:

```
Subset$getFeatures(feature.names = NULL)
```

Arguments:

feature.names A [character](#) vector comprising the name of the features to be obtained.

Returns: A [character](#) vector or NULL if subset is empty.

Method getID(): Gets the column name used as identifier.

Usage:

```
Subset$getID()
```

Returns: A [character](#) vector of size 1 or NULL if column id is not defined.

Method getIterator(): Creates the [DIterator](#) object.

Usage:

```
Subset$getIterator(chunk.size = private$chunk.size, verbose = FALSE)
```

Arguments:

chunk.size An [integer](#) value indicating the size of chunks taken over each iteration. By default chunk.size is defined as 10000.

verbose A [logical](#) value to specify if more verbosity is needed.

Returns: A [DIterator](#) object to transverse through [Subset](#) instances.

Method getClassValues(): Gets all the values of the target class.

Usage:

```
Subset$getClassValues()
```

Returns: A [factor](#) vector with all the values of the target class.

Method getClassBalance(): The function is used to compute the ratio of each class value in the [Subset](#).

Usage:

```
Subset$getClassBalance(target.value = NULL)
```

Arguments:

target.value The class value used as reference to perform the comparison.

Returns: A [numeric](#) value.

Method getClassIndex(): The function is used to obtain the index of the column containing the target class.

Usage:

```
Subset$classIndex()
```

Returns: A [numeric](#) value.

Method `getClassName()`: The function is used to specify the name of the column containing the target class.

Usage:

```
Subset$className()
```

Returns: A [character](#) value.

Method `getNcol()`: The function is in charge of obtaining the number of columns comprising the [Subset](#). See [ncol](#) for more information.

Usage:

```
Subset$ncol()
```

Returns: An [integer](#) of length 1 or [NULL](#).

Method `getNrow()`: The function is used to determine the number of rows present in the [Subset](#). See [nrow](#) for more information.

Usage:

```
Subset$nrow()
```

Returns: An [integer](#) of length 1 or [NULL](#).

Method `getPositiveClass()`: The function returns the value of the positive class.

Usage:

```
Subset$positiveClass()
```

Returns: A [character](#) vector of size 1 or [NULL](#) if not defined.

Method `isBlinded()`: The function is used to check if the [Subset](#) contains a target class.

Usage:

```
Subset$isBlinded()
```

Returns: A [logical](#) value where [TRUE](#) represents the absence of target class and [FALSE](#) its presence.

See Also

[Dataset](#), [DatasetLoader](#), [Trainset](#)

SummaryFunction	<i>Abstract class to computing performance across resamples.</i>
-----------------	--

Description

Abstract used as template to define customized metrics to compute model performance during train.

Details

This class is an archetype, so it cannot be instantiated.

Methods

Public methods:

- [SummaryFunction\\$new\(\)](#)
- [SummaryFunction\\$execute\(\)](#)
- [SummaryFunction\\$getMeasures\(\)](#)
- [SummaryFunction\\$clone\(\)](#)

Method `new()`: The function carries out the initialization of parameters during runtime.

Usage:

```
SummaryFunction$new(measures)
```

Arguments:

measures A [character](#) vector with the measures used.

Method `execute()`: Abstract function used to implement the performance calculator method. To guarantee a proper operation, this method is automatically invoked by [D2MCS](#) framework.

Usage:

```
SummaryFunction$execute()
```

Method `getMeasures()`: The function obtains the measures used to compute the performance across resamples.

Usage:

```
SummaryFunction$getMeasures()
```

Returns: A [character](#) vector of `NULL` if measures are not defined.

Method `clone()`: The objects of this class are cloneable with this method.

Usage:

```
SummaryFunction$clone(deep = FALSE)
```

Arguments:

deep Whether to make a deep clone.

See Also

[NoProbability](#), [UseProbability](#)

TN

Computes the True Negative value.

Description

This is the number of individuals with a negative condition for which the test result is negative. The value entered here must be non-negative.

Super class

[D2MCS::MeasureFunction](#) -> TN

Methods

Public methods:

- [TN\\$new\(\)](#)
- [TN\\$compute\(\)](#)
- [TN\\$clone\(\)](#)

Method `new()`: Method for initializing the object arguments during runtime.

Usage:

```
TN$new(performance.output = NULL)
```

Arguments:

`performance.output` An optional [ConfMatrix](#) parameter to define the type of object used to compute the **TN** measure.

Method `compute()`: The function computes the **TN** achieved by the M.L. model.

Usage:

```
TN$compute(performance.output = NULL)
```

Arguments:

`performance.output` An optional [ConfMatrix](#) parameter to define the type of object used as basis to compute the **TN** measure.

Details: This function is automatically invoke by the [ClassificationOutput](#) object.

Returns: A [numeric](#) vector of size 1 or **NULL** if an error occurred.

Method `clone()`: The objects of this class are cloneable with this method.

Usage:

```
TN$clone(deep = FALSE)
```

Arguments:

`deep` Whether to make a deep clone.

See Also

[MeasureFunction](#), [ClassificationOutput](#), [ConfMatrix](#)

TP	<i>Computes the True Positive Value.</i>
----	--

Description

TP is the number of individuals with a positive condition for which the test result is positive. The value entered here must be non-negative.

Super class

[D2MCS::MeasureFunction](#) -> TP

Methods

Public methods:

- [TP\\$new\(\)](#)
- [TP\\$compute\(\)](#)
- [TP\\$clone\(\)](#)

Method [new\(\)](#): Method for initializing the object arguments during runtime.

Usage:

```
TP$new(performance.output = NULL)
```

Arguments:

`performance.output` An optional [ConfMatrix](#) parameter to define the type of object used to compute the measure.

Method [compute\(\)](#): The function computes the **TP** achieved by the M.L. model.

Usage:

```
TP$compute(performance.output = NULL)
```

Arguments:

`performance.output` An optional [ConfMatrix](#) parameter to define the type of object used as basis to compute the **TP** measure.

Details: This function is automatically invoke by the [ClassificationOutput](#) object.

Returns: A [numeric](#) vector of size 1 or [NULL](#) if an error occurred.

Method [clone\(\)](#): The objects of this class are cloneable with this method.

Usage:

```
TP$clone(deep = FALSE)
```

Arguments:

`deep` Whether to make a deep clone.

See Also

[MeasureFunction](#), [ClassificationOutput](#), [ConfMatrix](#)

TrainFunction	<i>Control parameters for train stage.</i>
---------------	--

Description

Abstract class used as template to define customized functions to control the computational nuances of train function.

Methods

Public methods:

- [TrainFunction\\$new\(\)](#)
- [TrainFunction\\$create\(\)](#)
- [TrainFunction\\$getResamplingMethod\(\)](#)
- [TrainFunction\\$getNumberFolds\(\)](#)
- [TrainFunction\\$getSavePredictions\(\)](#)
- [TrainFunction\\$getClassProbs\(\)](#)
- [TrainFunction\\$getAllowParallel\(\)](#)
- [TrainFunction\\$getVerboseIter\(\)](#)
- [TrainFunction\\$getTrFunction\(\)](#)
- [TrainFunction\\$getMeasures\(\)](#)
- [TrainFunction\\$getType\(\)](#)
- [TrainFunction\\$getSeed\(\)](#)
- [TrainFunction\\$setSummaryFunction\(\)](#)
- [TrainFunction\\$setClassProbs\(\)](#)
- [TrainFunction\\$clone\(\)](#)

Method `new()`: Function used to initialize the object parameters during execution time.

Usage:

```
TrainFunction$new(
  method,
  number,
  savePredictions,
  classProbs,
  allowParallel,
  verboseIter,
  seed
)
```

Arguments:

`method` The resampling method: "boot", "boot632", "optimism_boot", "boot_all", "cv", "repeatedcv", "LOOCV", "LGOCV" (for repeated training/test splits), "none" (only fits one model to the entire training set), "oob" (only for random forest, bagged trees, bagged earth, bagged flexible discriminant analysis, or conditional tree forest models), timeslice, "adaptive_cv", "adaptive_boot" or "adaptive_LGOCV"

number Either the number of folds or number of resampling iterations

savePredictions An indicator of how much of the hold-out predictions for each resample should be saved. Values can be either "all", "final", or "none". A logical value can also be used that convert to "all" (for true) or "none" (for false). "final" saves the predictions for the optimal tuning parameters.

classProbs A [logical](#) value. Should class probabilities be computed for classification models (along with predicted values) in each resample?

allowParallel A [logical](#) value. If a parallel backend is loaded and available, should the function use it?

verboseIter A [logical](#) for printing a training log.

seed An optional [integer](#) that will be used to set the seed during model training stage.

Method create(): Creates a [trainControl](#) requires for the training stage.

Usage:

```
TrainFunction$create(summaryFunction, search.method = "grid", class.probs)
```

Arguments:

summaryFunction An object inherited from [SummaryFunction](#) class.

search.method Either "grid" or "random", describing how the tuning parameter grid is determined.

class.probs A [logical](#) indicating if class probabilities should be computed for classification models (along with predicted values) in each resample.

Method getResamplingMethod(): Returns the resampling method used during training staged.

Usage:

```
TrainFunction$getResamplingMethod()
```

Returns: A [character](#) vector or length 1 or [NULL](#) if not defined.

Method getNumberFolds(): Returns the number or folds or number of iterations used during training.

Usage:

```
TrainFunction$getNumberFolds()
```

Returns: An [integer](#) vector or length 1 or [NULL](#) if not defined.

Method getSavePredictions(): Indicates if the predictions for each resample should be saved.

Usage:

```
TrainFunction$getSavePredictions()
```

Returns: A [logical](#) value or [NULL](#) if not defined.

Method getClassProbs(): Indicates if class probabilities should be computed for classification models in each resample.

Usage:

```
TrainFunction$getClassProbs()
```

Returns: A [logical](#) value.

Method `getAllowParallel()`: Determines if model training is performed in parallel.

Usage:

```
TrainFunction$getAllowParallel()
```

Returns: A **logical** value. **TRUE** indicates parallelization is enabled and **FALSE** otherwise.

Method `getVerboseIter()`: Determines if training log should be printed.

Usage:

```
TrainFunction$getVerboseIter()
```

Returns: A **logical** value. **TRUE** indicates training log is enabled and **FALSE** otherwise.

Method `getTrFunction()`: Function used to return the `trainControl` object.

Usage:

```
TrainFunction$getTrFunction()
```

Returns: A `trainControl` object.

Method `getMeasures()`: Returns the measures used to optimize model hyperparameters.

Usage:

```
TrainFunction$getMeasures()
```

Returns: A **character** vector.

Method `getType()`: Obtains the type of classification problem ("Bi-class" or "Multi-class").

Usage:

```
TrainFunction$getType()
```

Returns: A **character** vector with length 1. Either "Bi-class" or "Multi-class".

Method `getSeed()`: Indicates seed used during model training stage.

Usage:

```
TrainFunction$getSeed()
```

Returns: An **integer** value or **NULL** if not defined.

Method `setSummaryFunction()`: Function used to change the `SummaryFunction` used in the training stage.

Usage:

```
TrainFunction$setSummaryFunction(summaryFunction)
```

Arguments:

`summaryFunction` An object inherited from `SummaryFunction` class.

Method `setClassProbs()`: The function allows changing the class computation capabilities.

Usage:

```
TrainFunction$setClassProbs(class.probs)
```

Arguments:

`class.probs` A **logical** indicating if class probabilities should be computed for classification models (along with predicted values) in each resample

Method clone(): The objects of this class are cloneable with this method.

Usage:

```
TrainFunction$clone(deep = FALSE)
```

Arguments:

deep Whether to make a deep clone.

See Also

[TwoClass](#)

TrainOutput	<i>Stores the results achieved during training.</i>
-------------	---

Description

This class manages the results achieved during training stage (such as optimized hyperparameters, model information, utilized metrics).

Methods

Public methods:

- [TrainOutput\\$new\(\)](#)
- [TrainOutput\\$getModels\(\)](#)
- [TrainOutput\\$getPerformance\(\)](#)
- [TrainOutput\\$savePerformance\(\)](#)
- [TrainOutput\\$plot\(\)](#)
- [TrainOutput\\$getMetrics\(\)](#)
- [TrainOutput\\$classValues\(\)](#)
- [TrainOutput\\$getPositiveClass\(\)](#)
- [TrainOutput\\$getSize\(\)](#)
- [TrainOutput\\$clone\(\)](#)

Method new(): Function used to initialize the object arguments during runtime.

Usage:

```
TrainOutput$new(models, class.values, positive.class)
```

Arguments:

models A [list](#) containing the best M.L. model for each cluster.

class.values A [character](#) vector containing the values of the target class.

positive.class A [character](#) with the value of the positive class.

Method getModels(): The function is used to obtain the best M.L. model of each cluster.

Usage:

```
TrainOutput$getModels(metric)
```

Arguments:

metric A **character** vector which specifies the metric(s) used for configuring M.L. hyperparameters.

Returns: A **list** is returned of class train.

Method `getPerformance()`: The function returns the performance value of M.L. models during training stage.

Usage:

```
TrainOutput$getPerformance(metrics = NULL)
```

Arguments:

metrics A **character** vector which specifies the metric(s) used to train the M.L. models.

Returns: A **character** vector containing the metrics used for configuring M.L. hyperparameters.

Method `savePerformance()`: The function is used to save into CSV file the performance achieved by the M.L. models during training stage.

Usage:

```
TrainOutput$savePerformance(dir.path, metrics = NULL)
```

Arguments:

dir.path The location to store the into a CSV file the performance of the trained M.L.

metrics An optional parameter specifying the metric(s) used to train the M.L. models. If not defined, all the metrics used in train stage will be saved.

Method `plot()`: The function is responsible for creating a plot to visualize the performance achieved by the best M.L. model on each cluster.

Usage:

```
TrainOutput$plot(dir.path, metrics = NULL)
```

Arguments:

dir.path The location to store the exported plot will be saved.

metrics An optional parameter specifying the metric(s) used to train the M.L. models. If not defined, all the metrics used in train stage will be plotted.

Method `getMetrics()`: The function returns all metrics used for configuring M.L. hyperparameters during train stage.

Usage:

```
TrainOutput$getMetrics()
```

Returns: A **character** value.

Method `getClassValues()`: The function is used to get the values of the target class.

Usage:

```
TrainOutput$getClassValues()
```

Returns: A **character** containing the values of the target class.

Method `getPositiveClass()`: The function returns the value of the positive class.

Usage:

```
TrainOutput$getPositiveClass()
```

Returns: A [character](#) vector of size 1.

Method `getSize()`: The function is used to get the number of the trained M.L. models. Each cluster contains the best M.L. model.

Usage:

```
TrainOutput$getSize()
```

Returns: A [numeric](#) value or [NULL](#) training was not successfully performed.

Method `clone()`: The objects of this class are cloneable with this method.

Usage:

```
TrainOutput$clone(deep = FALSE)
```

Arguments:

`deep` Whether to make a deep clone.

See Also

[D2MCS](#)

Trainset

Training set.

Description

The [Trainset](#) is used to perform training operations over M.L. models. A target class should be defined to guarantee a full compatibility with supervised models.

Details

Use [Dataset](#) object to ensure the creation of a valid [Trainset](#) object.

Methods

Public methods:

- [Trainset\\$new\(\)](#)
- [Trainset\\$getPositiveClass\(\)](#)
- [Trainset\\$getClassNames\(\)](#)
- [Trainset\\$getClassValues\(\)](#)
- [Trainset\\$getColumnNames\(\)](#)
- [Trainset\\$getFeatureValues\(\)](#)
- [Trainset\\$getInstances\(\)](#)
- [Trainset\\$getNumClusters\(\)](#)

Method `new()`: Method for initializing the object arguments during runtime.

Usage:

```
Trainset$new(cluster.dist, class.name, class.values, positive.class)
```

Arguments:

`cluster.dist` The type of cluster distribution used as basis to build the `Trainset`. See [GenericClusteringStrategy](#) for more information.

`class.name` Used to specify the name of the column containing the target class.

`class.values` Specifies all the possible values of the target class.

`positive.class` A [character](#) with the value of the positive class.

Method `getPositiveClass()`: The function is used to obtain the value of the positive class.

Usage:

```
Trainset$getPositiveClass()
```

Returns: A [numeric](#) value with the positive class value.

Method `getClassName()`: The function is used to return the name of the target class.

Usage:

```
Trainset$getClassName()
```

Returns: A [character](#) vector with length 1.

Method `getClassValues()`: The function is used to compute all the possible target class values.

Usage:

```
Trainset$getClassValues()
```

Returns: A [factor](#) value.

Method `getColumnNames()`: The function returns the name of the columns comprising an specific cluster distribution.

Usage:

```
Trainset$getColumnNames(num.cluster)
```

Arguments:

`num.cluster` A [numeric](#) value used to specify the cluster number of the cluster distribution used when creating the `Trainset`.

Returns: A [character](#) vector with all column names.

Method `getFeatureValues()`: The function returns the values of the columns comprising an specific cluster distribution. Target class is omitted.

Usage:

```
Trainset$getFeatureValues(num.cluster)
```

Arguments:

`num.cluster` A [numeric](#) value used to specify the cluster number of the cluster distribution used when creating the `Trainset`.

Returns: A [data.frame](#) with the values of the features comprising the selected cluster distribution.

Method `getInstances()`: The function returns the values of the columns comprising an specific cluster distribution. Target class is included as the last column.

Usage:

```
Trainset$getInstances(num.cluster)
```

Arguments:

`num.cluster` A [numeric](#) value used to specify the cluster number of the cluster distribution used when creating the [Trainset](#).

Returns: A [data.frame](#) with the values of the features comprising the selected cluster distribution.

Method `getNumClusters()`: The function obtains the number of groups (clusters) that forms the cluster distribution.

Usage:

```
Trainset$getNumClusters()
```

Returns: A [numeric](#) vector of size 1.

See Also

[Dataset](#), [DatasetLoader](#), [Subset](#), [GenericClusteringStrategy](#)

TwoClass

Control parameters for train stage (Bi-class problem).

Description

Implementation to control the computational nuances of train function for bi-class problems.

Super class

[D2MCS::TrainFunction](#) -> TwoClass

Methods

Public methods:

- [TwoClass\\$new\(\)](#)
- [TwoClass\\$create\(\)](#)
- [TwoClass\\$getTrFunction\(\)](#)
- [TwoClass\\$setClassProbs\(\)](#)
- [TwoClass\\$getMeasures\(\)](#)
- [TwoClass\\$getType\(\)](#)
- [TwoClass\\$setSummaryFunction\(\)](#)
- [TwoClass\\$clone\(\)](#)

Method `new()`:

Usage:

```
TwoClass$new(
  method,
  number,
  savePredictions,
  classProbs,
  allowParallel,
  verboseIter,
  seed = NULL
)
```

Arguments:

method The resampling method: "boot", "boot632", "optimism_boot", "boot_all", "cv", "repeatedcv", "LOOCV", "LGOCV" (for repeated training/test splits), "none" (only fits one model to the entire training set), "oob" (only for random forest, bagged trees, bagged earth, bagged flexible discriminant analysis, or conditional tree forest models), timeslice, "adaptive_cv", "adaptive_boot" or "adaptive_LGOCV"

number Either the number of folds or number of resampling iterations

savePredictions An indicator of how much of the hold-out predictions for each resample should be saved. Values can be either "all", "final", or "none". A logical value can also be used that convert to "all" (for true) or "none" (for false). "final" saves the predictions for the optimal tuning parameters.

classProbs A [logical](#) value. Should class probabilities be computed for classification models (along with predicted values) in each resample?

allowParallel A [logical](#) value. If a parallel backend is loaded and available, should the function use it?

verboseIter A [logical](#) for printing a training log.

seed An optional [integer](#) that will be used to set the seed during model training stage.

Method `create()`: Creates a [trainControl](#) requires for the training stage.

Usage:

```
TwoClass$create(summaryFunction, search.method = "grid", class.probs = NULL)
```

Arguments:

summaryFunction An object inherited from [SummaryFunction](#) class.

search.method Either "grid" or "random", describing how the tuning parameter grid is determined.

class.probs A [logical](#) indicating if class probabilities should be computed for classification models (along with predicted values) in each resample

Method `getTrFunction()`: Function used to return the [trainControl](#) object.

Usage:

```
TwoClass$getTrFunction()
```

Returns: A [trainControl](#) object.

Method `setClassProbs()`: The function allows changing the class computation capabilities.

Usage:

```
TwoClass$setClassProbs(class.probs)
```

Arguments:

`class.probs` A [logical](#) value. [TRUE](#) implies classification probabilities should be computed for classification models and [FALSE](#) otherwise.

Method `getMeasures()`: Returns the measures used to optimize model hyperparameters.

Usage:

```
TwoClass$getMeasures()
```

Returns: A [character](#) vector.

Method `getType()`: Obtains the type of classification problem ("Bi-class" or "Multi-class").

Usage:

```
TwoClass$getType()
```

Returns: A [character](#) vector with "Bi-class" value.

Method `setSummaryFunction()`: Function used to change the [SummaryFunction](#) used in the training stage.

Usage:

```
TwoClass$setSummaryFunction(summaryFunction)
```

Arguments:

`summaryFunction` An object inherited from [SummaryFunction](#) class.

Method `clone()`: The objects of this class are cloneable with this method.

Usage:

```
TwoClass$clone(deep = FALSE)
```

Arguments:

`deep` Whether to make a deep clone.

See Also

[TrainFunction](#)

TypeBasedStrategy *Feature clustering strategy.*

Description

Features are sorted by descendant according to the relevance value obtained after applying an specific heuristic. Next, features are distributed into N clusters following a card-dealing methodology. Finally best distribution is assigned to the distribution having highest homogeneity.

Details

The strategy is suitable only for binary and real features. Other features are automatically grouped into a specific cluster named as 'unclustered'.

Super class

`D2MCS::GenericClusteringStrategy` -> `TypeBasedStrategy`

Methods**Public methods:**

- `TypeBasedStrategy$new()`
- `TypeBasedStrategy$execute()`
- `TypeBasedStrategy$getDistribution()`
- `TypeBasedStrategy$createTrain()`
- `TypeBasedStrategy$plot()`
- `TypeBasedStrategy$saveCSV()`
- `TypeBasedStrategy$clone()`

Method `new()`: Method for initializing the object arguments during runtime.

Usage:

```
TypeBasedStrategy$new(
  subset,
  heuristic,
  configuration = StrategyConfiguration$new()
)
```

Arguments:

`subset` The [Subset](#) used to apply the feature-clustering strategy.

`heuristic` The heuristic used to compute the relevance of each feature. Must inherit from [GenericHeuristic](#) abstract class.

`configuration` Optional parameter to customize configuration parameters for the strategy. Must inherited from [StrategyConfiguration](#) abstract class.

Method `execute()`: Function responsible of performing the clustering strategy over the defined [Subset](#).

Usage:

```
TypeBasedStrategy$execute(verbose = FALSE)
```

Arguments:

`verbose` A [logical](#) value to specify if more verbosity is needed.

Method `getDistribution()`: Function used to obtain a specific cluster distribution.

Usage:

```
TypeBasedStrategy$getDistribution(
  num.clusters = NULL,
  num.groups = NULL,
  include.unclustered = FALSE
)
```

Arguments:

`num.clusters` A [numeric](#) value to select the number of clusters (define the distribution).

`num.groups` A single or **numeric** vector value to identify a specific group that forms the clustering distribution.

`include.unclustered` A **logical** value to determine if unclustered features should be included.

Returns: A **list** with the features comprising an specific clustering distribution.

Method `createTrain()`: The function is used to create a **Trainset** object from a specific clustering distribution.

Usage:

```
TypeBasedStrategy$createTrain(  
  subset,  
  num.clusters = NULL,  
  num.groups = NULL,  
  include.unclustered = FALSE  
)
```

Arguments:

`subset` The **Subset** object used as a basis to create the train set (see **Trainset** class).

`num.clusters` A **numeric** value to select the number of clusters (define the distribution).

`num.groups` A single or **numeric** vector value to identify a specific group that forms the clustering distribution.

`include.unclustered` A **logical** value to determine if unclustered features should be included.

Details: If `num.clusters` and `num.groups` are not defined, best clustering distribution is used to create the train set.

Returns: A **Trainset** object.

Method `plot()`: The function is responsible for creating a plot to visualize the clustering distribution.

Usage:

```
TypeBasedStrategy$plot(dir.path = NULL, file.name = NULL)
```

Arguments:

`dir.path` An optional **character** argument to define the name of the directory where the exported plot will be saved. If not defined, the file path will be automatically assigned to the current working directory, `'getwd()'`.

`file.name` A **character** to define the name of the PDF file where the plot is exported.

Method `saveCSV()`: The function is used to save the clustering distribution to a CSV file.

Usage:

```
TypeBasedStrategy$saveCSV(dir.path = NULL, name = NULL, num.clusters = NULL)
```

Arguments:

`dir.path` The name of the directory to save the CSV file.

`name` Defines the name of the CSV file.

`num.clusters` An optional parameter to select the number of clusters to be saved. If not defined, all cluster distributions will be saved.

Method `clone()`: The objects of this class are cloneable with this method.

Usage:

```
TypeBasedStrategy$clone(deep = FALSE)
```

Arguments:

deep Whether to make a deep clone.

See Also

[GenericClusteringStrategy](#), [StrategyConfiguration](#)

UseProbability

Compute performance across resamples.

Description

Computes the performance across resamples when class probabilities can be computed.

Super class

[D2MCS::SummaryFunction](#) -> UseProbability

Methods**Public methods:**

- [UseProbability\\$new\(\)](#)
- [UseProbability\\$execute\(\)](#)
- [UseProbability\\$clone\(\)](#)

Method new(): The function defined during runtime the usage of seven measures: 'ROC', 'Sens', 'Kappa', 'Accuracy', 'TCR_9', 'MCC' and 'PPV'.

Usage:

```
UseProbability$new()
```

Method execute(): The function computes the performance across resamples using the previously defined measures.

Usage:

```
UseProbability$execute(data, lev = NULL, model = NULL)
```

Arguments:

data A [data.frame](#) containing the data used to compute the performance.

lev An optional value used to define the levels of the target class.

model An optional value used to define the M.L. model used.

Returns: A vector of performance estimates.

Method clone(): The objects of this class are cloneable with this method.

Usage:

```
UseProbability$clone(deep = FALSE)
```

Arguments:

deep Whether to make a deep clone.

See Also[SummaryFunction](#)

`VotingStrategy`*Voting Strategy template.*

Description

Abstract class used to define new [SingleVoting](#) and [CombinedVoting](#) schemes.

Methods**Public methods:**

- [VotingStrategy\\$new\(\)](#)
- [VotingStrategy\\$getVotingSchemes\(\)](#)
- [VotingStrategy\\$getMetrics\(\)](#)
- [VotingStrategy\\$execute\(\)](#)
- [VotingStrategy\\$getName\(\)](#)
- [VotingStrategy\\$clone\(\)](#)

Method `new()`: Abstract method used to initialize the object arguments during runtime.

Usage:

```
VotingStrategy$new()
```

Method `getVotingSchemes()`: The function returns the voting schemes that will participate in the voting strategy.

Usage:

```
VotingStrategy$getVotingSchemes()
```

Returns: A vector of object inheriting from [VotingStrategy](#) class.

Method `getMetrics()`: The function is used to get the metric that will be used during the voting strategy.

Usage:

```
VotingStrategy$getMetrics()
```

Returns: A [character](#) vector.

Method `execute()`: Abstract function used to implement the operation of the voting schemes.

Usage:

```
VotingStrategy$execute(predictions, ...)
```

Arguments:

`predictions` A [ClusterPredictions](#) object containing the prediction achieved for each cluster.

`...` Further arguments passed down to execute function.

Method `getName()`: The function returns the name of the voting scheme.

Usage:

```
VotingStrategy$getName()
```

Returns: A [character](#) vector of size 1.

Method `clone()`: The objects of this class are cloneable with this method.

Usage:

```
VotingStrategy$clone(deep = FALSE)
```

Arguments:

`deep` Whether to make a deep clone.

See Also

[D2MCS](#), [SingleVoting](#), [CombinedVoting](#)

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