Package 'AutoQuant'

February 28, 2023

Title AutoQuant

Version 1.0.0

Date 2022-12-1

Maintainer Adrian Antico <adrianantico@gmail.com>

Description

R package for the automation of machine learning, forecasting, feature engineering, model evaluation, and model interpretation. Built using data.table for all tabular data-related tasks.

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URL https://github.com/AdrianAntico/AutoQuant

BugReports https://github.com/AdrianAntico/AutoQuant/issues

Depends R (>= 3.5.0)

Imports bit64, data.table, doParallel, foreach, lubridate, timeDate

Suggests knitr, rmarkdown, gridExtra

VignetteBuilder knitr

Contact Adrian Antico

Encoding UTF-8

Language en-US

LazyData true

NeedsCompilation no

RoxygenNote 7.2.1

SystemRequirements Java (>= 7.0)

Author Adrian Antico [aut, cre]

ByteCompile TRUE

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`RemixAutoML-package` *Automated Machine Learning Remixed*

Description

Automated Machine Learning Remixed for real-world use-cases. The package utilizes data.table under the hood for all data wrangling like operations so it's super fast and memory efficient. All ML methods are available in R or Python. The forecasting functions are unique and state of the art. There are feature engineering functions in this package that you cannot find anywhere else.

Details

See the github README for details and examples www.github.com/AdrianAntico/RemixAutoML

Author(s)

Adrian Antico, adrianantico@gmail.com, Douglas Pestana

`AutoArfima` *AutoArfima*

Description

AutoArfima is a multi-armed bandit model testing framework for AR and SAR NNets. Randomized probability matching is the underlying bandit algorithm. Model evaluation is done by blending the training error and the validation error from testing the model on out of sample data. The bandit algorithm compares the performance of the current build against the previous builds which starts with the classic nnetar model from the forecast package. Depending on how many lags, seasonal lags, and fourier pairs you test the number of combinations of features to test begins to approach 10,000 different combinations of settings. The function tests out transformations, differencing, and variations of the lags, seasonal lags, and fourier pairs. The paramter space is broken up into various buckets that are increasing in sophistication. The bandit algorithm samples from those buckets

and based on many rounds of testing it determines which buckets to generate samples from more frequently based on the models performance coming from that bucket. All of the models have performance data collected on them and a final rebuild is initiated when a winner is found. The rebuild process begins by retraining the model with the settings that produced the best performance. If the model fails to build, for whatever reason, the next best buildable model is rebuilt.

Usage

```
AutoArfima(
  data,
  FilePath = NULL,
  TargetVariableName,
  DateColumnName,
  TimeAggLevel = "week",
  EvaluationMetric = "MAE",
  NumHoldOutPeriods = 5L,
  NumFCPeriods = 5L,
  MaxLags = 5L,
  MaxMovingAverages = 5L,
  TrainWeighting = 0.5,
  MaxConsecutiveFails = 12L,
  MaxNumberModels = 100L,
  MaxRunTimeMinutes = 10L,
  NumberCores = max(1L, min(4L, parallel::detectCores() - 2L))
)
```

Arguments

`data`	Source data.table
`FilePath`	NULL to return nothing. Provide a file path to save the model and xregs if available
`TargetVariableName`	Name of your time series target variable
`DateColumnName`	Name of your date column
`TimeAggLevel`	Choose from "year", "quarter", "month", "week", "day", "hour"
`EvaluationMetric`	Choose from MAE, MSE, and MAPE
`NumHoldOutPeriods`	Number of time periods to use in the out of sample testing
`NumFCPeriods`	Number of periods to forecast
`MaxLags`	A single value of the max number of lags to use in the internal auto.arima of tbats
`MaxMovingAverages`	A single value of the max number of moving averages to use in the internal auto.arima of arfima
`TrainWeighting`	Model ranking is based on a weighted average of training metrics and out of sample metrics. Supply the weight of the training metrics, such as 0.50 for 50 percent.
`MaxConsecutiveFails`	When a new best model is found MaxConsecutiveFails resets to zero. Indicated the number of model attemps without a new winner before terminating the procedure.

`MaxNumberModels`
: Indicate the maximum number of models to test.

`MaxRunTimeMinutes`
: Indicate the maximum number of minutes to wait for a result.

`NumberCores`
: Default max(1L, min(4L, parallel::detectCores()-2L))

Author(s)

Adrian Antico

See Also

Other Automated Time Series: `AutoBanditNNet()`, `AutoBanditSarima()`, `AutoETS()`, `AutoTBATS()`

Examples

```
## Not run:
# Create fake data
data <- AutoQuant::FakeDataGenerator(TimeSeries = TRUE, TimeSeriesTimeAgg = "days")

# Build model
Output <- AutoQuant::AutoArfima(
  data,
  FilePath = NULL,
  TargetVariableName = "Weekly_Sales",
  DateColumnName = "Date",
  TimeAggLevel = "weeks",
  EvaluationMetric = "MAE",
  NumHoldOutPeriods = 5L,
  NumFCPeriods = 5L,
  MaxLags = 5L,
  MaxMovingAverages = 5L,
  TrainWeighting = 0.50,
  MaxConsecutiveFails = 12L,
  MaxNumberModels = 100L,
  MaxRunTimeMinutes = 10L,
  NumberCores = max(1L, min(4L, parallel::detectCores()-2L)))

# Output
Output$ForecastPlot
Output$Forecast
Output$PerformanceGrid

## End(Not run)
```

`AutoBanditNNet` *AutoBanditNNet*

Description

AutoBanditNNet is a multi-armed bandit model testing framework for AR and SAR NNets. Randomized probability matching is the underlying bandit algorithm. Model evaluation is done by blending the training error and the validation error from testing the model on out of sample data. The bandit algorithm compares the performance of the current build against the previous builds

which starts with the classic nnetar model from the forecast package. Depending on how many lags, seasonal lags, and fourier pairs you test the number of combinations of features to test begins to approach 10,000 different combinations of settings. The function tests out transformations, differencing, and variations of the lags, seasonal lags, and fourier pairs. The paramter space is broken up into various buckets that are increasing in sophistication. The bandit algorithm samples from those buckets and based on many rounds of testing it determines which buckets to generate samples from more frequently based on the models performance coming from that bucket. All of the models have performance data collected on them and a final rebuild is initiated when a winner is found. The rebuild process begins by retraining the model with the settings that produced the best performance. If the model fails to build, for whatever reason, the next best buildable model is rebuilt.

Usage

```
AutoBanditNNet(
  data,
  FilePath = NULL,
  TargetVariableName,
  DateColumnName,
  TimeAggLevel = "week",
  EvaluationMetric = "MAE",
  NumHoldOutPeriods = 5L,
  NumFCPeriods = 5L,
  MaxLags = 5L,
  MaxSeasonalLags = 1L,
  MaxFourierPairs = 2L,
  TrainWeighting = 0.5,
  MaxConsecutiveFails = 12L,
  MaxNumberModels = 100L,
  MaxRunTimeMinutes = 10L,
  NumberCores = max(1L, min(4L, parallel::detectCores() - 2L)),
  Debug = FALSE
)
```

Arguments

`data`	Source data.table
`FilePath`	NULL to return nothing. Provide a file path to save the model and xregs if available
`TargetVariableName`	Name of your time series target variable
`DateColumnName`	Name of your date column
`TimeAggLevel`	Choose from "year", "quarter", "month", "week", "day", "hour"
`EvaluationMetric`	Choose from MAE, MSE, and MAPE
`NumHoldOutPeriods`	Number of time periods to use in the out of sample testing
`NumFCPeriods`	Number of periods to forecast
`MaxLags`	A single value of the max number of lags to test
`MaxSeasonalLags`	A single value of the max number of seasonal lags to test

MaxFourierPairs
: A single value of the max number of fourier pairs to test

TrainWeighting
: Model ranking is based on a weighted average of training metrics and out of sample metrics. Supply the weight of the training metrics, such as 0.50 for 50 percent.

MaxConsecutiveFails
: When a new best model is found MaxConsecutiveFails resets to zero. Indicated the number of model attemps without a new winner before terminating the procedure.

MaxNumberModels
: Indicate the maximum number of models to test.

MaxRunTimeMinutes
: Indicate the maximum number of minutes to wait for a result

NumberCores
: Default max(1L, min(4L, parallel::detectCores()-2L))

Debug
: Set to TRUE to print some steps

Author(s)

Adrian Antico

See Also

Other Automated Time Series: AutoArfima(), AutoBanditSarima(), AutoETS(), AutoTBATS()

Examples

```
## Not run:
# Create fake data
data <- AutoQuant::FakeDataGenerator(TimeSeries = TRUE, TimeSeriesTimeAgg = "days")

# Build models
Output <- AutoQuant::AutoBanditNNet(
  data = data,
  FilePath = NULL,
  TargetVariableName = "Weekly_Sales",
  DateColumnName = "Date",
  TimeAggLevel = "day",
  EvaluationMetric = "MAE",
  NumHoldOutPeriods = 5L,
  NumFCPeriods = 5L,
  MaxLags = 5L,
  MaxSeasonalLags = 1L,
  MaxFourierPairs = 2L,
  TrainWeighting = 0.50,
  MaxConsecutiveFails = 12L,
  MaxNumberModels = 100L,
  MaxRunTimeMinutes = 10L,
  NumberCores = max(1L, min(4L, parallel::detectCores()-2L)),
  Debug = FALSE)

# Output
Output$ForecastPlot
Output$Forecast
Output$PerformanceGrid
```

```
## End(Not run)
```

AutoBanditSarima *AutoBanditSarima*

Description

AutoBanditSarima is a multi-armed bandit model testing framework for SARIMA. Randomized probability matching is the underlying bandit algorithm. Model evaluation is done by blending the training error and the validation error from testing the model on out of sample data. The bandit algorithm compares the performance of the current build against the previous builds which starts with the classic auto.arima from the forecast package. Depending on how many lags, moving averages, seasonal lags and moving averages you test the number of combinations of features to test begins to approach 100,000 different combinations of settings. The function tests out transformations, differencing, and variations of the lags and moving averages. The paramter space is broken up into various buckets that are increasing in sophistication. The bandit algorithm samples from those buckets and based on many rounds of testing it determines which buckets to generate samples from more frequently based on the models performance coming from that bucket. All of the models have performance data collected on them and a final rebuild is initiated when a winner is found. The rebuild process begins by retraining the model with the settings that produced the best performance. If the model fails to build, for whatever reason, the next best buildable model is rebuilt.

Usage

```
AutoBanditSarima(
  data,
  FilePath = NULL,
  ByDataType = TRUE,
  TargetVariableName,
  DateColumnName,
  TimeAggLevel = "week",
  EvaluationMetric = "MAE",
  NumHoldOutPeriods = 5L,
  NumFCPeriods = 5L,
  MaxLags = 5L,
  MaxSeasonalLags = 0L,
  MaxMovingAverages = 5L,
  MaxSeasonalMovingAverages = 0L,
  MaxFourierPairs = 2L,
  TrainWeighting = 0.5,
  MaxConsecutiveFails = 25L,
  MaxNumberModels = 100L,
  MaxRunTimeMinutes = 10L,
  NumberCores = max(1L, min(4L, parallel::detectCores() - 2L)),
  DebugMode = FALSE
)
```

Arguments

data	Source data.table

`FilePath` NULL to return nothing. Provide a file path to save the model and xregs if available

`ByDataType` TRUE returns the best model from the four base sets of possible models. FALSE returns the best model.

`TargetVariableName`
Name of your time series target variable

`DateColumnName` Name of your date column

`TimeAggLevel` Choose from "year", "quarter", "month", "week", "day", "hour"

`EvaluationMetric`
Choose from MAE, MSE, and MAPE

`NumHoldOutPeriods`
Number of time periods to use in the out of sample testing

`NumFCPeriods` Number of periods to forecast

`MaxLags` A single value of the max number of lags to test

`MaxSeasonalLags`
A single value of the max number of seasonal lags to test

`MaxMovingAverages`
A single value of the max number of moving averages to test

`MaxSeasonalMovingAverages`
A single value of the max number of seasonal moving averages to test

`MaxFourierPairs`
A single value of the max number of fourier pairs to test

`TrainWeighting` Model ranking is based on a weighted average of training metrics and out of sample metrics. Supply the weight of the training metrics, such as 0.50 for 50 percent.

`MaxConsecutiveFails`
When a new best model is found MaxConsecutiveFails resets to zero. Indicated the number of model attemps without a new winner before terminating the procedure.

`MaxNumberModels`
Indicate the maximum number of models to test.

`MaxRunTimeMinutes`
Indicate the maximum number of minutes to wait for a result.

`NumberCores` Default max(1L, min(4L, parallel::detectCores()-2L))

`DebugMode` Set to TRUE to get print outs of particular steps helpful in tracing errors

Value

data.table containing historical values and the forecast values along with the grid tuning results in full detail, as a second data.table

Author(s)

Adrian Antico

See Also

Other Automated Time Series: `AutoArfima()`, `AutoBanditNNet()`, `AutoETS()`, `AutoTBATS()`

Examples

```
## Not run:
# Create fake data
data <- AutoQuant::FakeDataGenerator(TimeSeries = TRUE, TimeSeriesTimeAgg = "days")

# Build models
Output <- AutoQuant::AutoBanditSarima(
  data = data,
  FilePath = NULL,
  ByDataType = FALSE,
  TargetVariableName = "Weekly_Sales",
  DateColumnName = "Date",
  TimeAggLevel = "1min",
  EvaluationMetric = "MAE",
  NumHoldOutPeriods = 12L,
  NumFCPeriods = 16L,
  MaxLags = 10L,
  MaxSeasonalLags = 0L,
  MaxMovingAverages = 3L,
  MaxSeasonalMovingAverages = 0L,
  MaxFourierPairs = 2L,
  TrainWeighting = 0.50,
  MaxConsecutiveFails = 50L,
  MaxNumberModels = 100L,
  MaxRunTimeMinutes = 10L,
  NumberCores = max(1L, min(4L, parallel::detectCores()-2L)),
  DebugMode = FALSE)

# Output
Output$ForecastPlot
Output$Forecast
Output$PerformanceGrid
Output$ErrorLagMA2x2

## End(Not run)
```

`AutoCatBoostCARMA` *AutoCatBoostCARMA*

Description

AutoCatBoostCARMA Mutlivariate Forecasting with calendar variables, Holiday counts, holiday lags, holiday moving averages, differencing, transformations, interaction-based categorical encoding using target variable and features to generate various time-based aggregated lags, moving averages, moving standard deviations, moving skewness, moving kurtosis, moving quantiles, parallelized interaction-based fourier pairs by grouping variables, and Trend Variables.

Usage

```
AutoCatBoostCARMA(
  data,
  TimeWeights = NULL,
  NonNegativePred = FALSE,
```

```
  RoundPreds = FALSE,
  TrainOnFull = FALSE,
  TargetColumnName = NULL,
  DateColumnName = NULL,
  HierarchGroups = NULL,
  GroupVariables = NULL,
  FC_Periods = 1,
  TimeUnit = NULL,
  TimeGroups = NULL,
  SaveDataPath = NULL,
  NumOfParDepPlots = 10L,
  EncodingMethod = "target_encoding",
  TargetTransformation = FALSE,
  Methods = c("Asinh", "Log", "LogPlus1", "Sqrt"),
  AnomalyDetection = NULL,
  XREGS = NULL,
  Lags = NULL,
  MA_Periods = NULL,
  SD_Periods = NULL,
  Skew_Periods = NULL,
  Kurt_Periods = NULL,
  Quantile_Periods = NULL,
  Quantiles_Selected = c("q5", "q95"),
  Difference = FALSE,
  FourierTerms = 0L,
  CalendarVariables = NULL,
  HolidayVariable = NULL,
  HolidayLookback = NULL,
  HolidayLags = NULL,
  HolidayMovingAverages = NULL,
  TimeTrendVariable = FALSE,
  ZeroPadSeries = "maxmax",
  DataTruncate = FALSE,
  SplitRatios = c(0.85, 0.1, 0.05),
  PartitionType = "random",
  TaskType = "CPU",
  NumGPU = 1,
  DebugMode = FALSE,
  Timer = TRUE,
  EvalMetric = "RMSE",
  EvalMetricValue = 1.2,
  LossFunction = "RMSE",
  LossFunctionValue = 1.2,
  GridTune = FALSE,
  PassInGrid = NULL,
  ModelCount = 30,
  MaxRunsWithoutNewWinner = 20,
  MaxRunMinutes = 24L * 60L,
  Langevin = FALSE,
  DiffusionTemperature = 10000,
  NTrees = 500,
  L2_Leaf_Reg = 4,
```

```
  LearningRate = 0.5,
  RandomStrength = 1,
  BorderCount = 254,
  Depth = 6,
  RSM = 1,
  BootStrapType = "No",
  GrowPolicy = "SymmetricTree",
  ModelSizeReg = 1.2,
  FeatureBorderType = "GreedyLogSum",
  SamplingUnit = "Group",
  SubSample = 0.7,
  ScoreFunction = "Cosine",
  MinDataInLeaf = 1,
  ReturnShap = FALSE,
  SaveModel = FALSE,
  ArgsList = NULL,
  ModelID = "FC001",
  TVT = NULL
)
```

Arguments

data	Supply your full series data set here
TimeWeights	Supply a value that will be multiplied by he time trend value
NonNegativePred	TRUE or FALSE
RoundPreds	Rounding predictions to an integer value. TRUE or FALSE. Defaults to FALSE
TrainOnFull	Set to TRUE to train on full data
TargetColumnName	List the column name of your target variables column. E.g. 'Target'
DateColumnName	List the column name of your date column. E.g. 'DateTime'
HierarchGroups	Vector of hierachy categorical columns.
GroupVariables	Defaults to NULL. Use NULL when you have a single series. Add in GroupVariables when you have a series for every level of a group or multiple groups.
FC_Periods	Set the number of periods you want to have forecasts for. E.g. 52 for weekly data to forecast a year ahead
TimeUnit	List the time unit your data is aggregated by. E.g. '1min', '5min', '10min', '15min', '30min', 'hour', 'day', 'week', 'month', 'quarter', 'year'.
TimeGroups	Select time aggregations for adding various time aggregated GDL features.
SaveDataPath	NULL Or supply a path. Data saved will be called 'ModelID'_data.csv
NumOfParDepPlots	Supply a number for the number of partial dependence plots you want returned
EncodingMethod	'binary', 'credibility', 'woe', 'target_encoding', 'poly_encode', 'backward_difference', 'helmert'
TargetTransformation	TRUE or FALSE. If TRUE, select the methods in the Methods arg you want tested. The best one will be applied.
Methods	Choose from 'YeoJohnson', 'BoxCox', 'Asinh', 'Log', 'LogPlus1', 'Sqrt', 'Asin', or 'Logit'. If more than one is selected, the one with the best normalization pearson statistic will be used. Identity is automatically selected and compared.

`AnomalyDetection`
: NULL for not using the service. Other, provide a list, e.g. AnomalyDetection = list('tstat_high' = 4, 'tstat_low' = -4)

`XREGS`
: Additional data to use for model development and forecasting. Data needs to be a complete series which means both the historical and forward looking values over the specified forecast window needs to be supplied.

`Lags`
: Select the periods for all lag variables you want to create. E.g. c(1:5,52) or list('day' = c(1:10), 'weeks' = c(1:4))

`MA_Periods`
: Select the periods for all moving average variables you want to create. E.g. c(1:5,52) or list('day' = c(2:10), 'weeks' = c(2:4))

`SD_Periods`
: Select the periods for all moving standard deviation variables you want to create. E.g. c(1:5,52) or list('day' = c(2:10), 'weeks' = c(2:4))

`Skew_Periods`
: Select the periods for all moving skewness variables you want to create. E.g. c(1:5,52) or list('day' = c(2:10), 'weeks' = c(2:4))

`Kurt_Periods`
: Select the periods for all moving kurtosis variables you want to create. E.g. c(1:5,52) or list('day' = c(2:10), 'weeks' = c(2:4))

`Quantile_Periods`
: Select the periods for all moving quantiles variables you want to create. E.g. c(1:5,52) or list('day' = c(2:10), 'weeks' = c(2:4))

`Quantiles_Selected`
: Select from the following 'q5', 'q10', 'q15', 'q20', 'q25', 'q30', 'q35', 'q40', 'q45', 'q50', 'q55', 'q60', 'q65', 'q70', 'q75', 'q80', 'q85', 'q90', 'q95'

`Difference`
: Puts the I in ARIMA for single series and grouped series.

`FourierTerms`
: Set to the max number of pairs. E.g. 2 means to generate two pairs for by each group level and interations if hierarchy is enabled.

`CalendarVariables`
: NULL, or select from 'minute', 'hour', 'wday', 'mday', 'yday', 'week', 'isoweek', 'month', 'quarter', 'year'

`HolidayVariable`
: NULL, or select from 'USPublicHolidays', 'EasterGroup', 'ChristmasGroup', 'OtherEcclesticalFeasts'

`HolidayLookback`
: Number of days in range to compute number of holidays from a given date in the data. If NULL, the number of days are computed for you.

`HolidayLags`
: Number of lags to build off of the holiday count variable.

`HolidayMovingAverages`
: Number of moving averages to build off of the holiday count variable.

`TimeTrendVariable`
: Set to TRUE to have a time trend variable added to the model. Time trend is numeric variable indicating the numeric value of each record in the time series (by group). Time trend starts at 1 for the earliest point in time and increments by one for each success time point.

`ZeroPadSeries`
: NULL to do nothing. Otherwise, set to 'maxmax', 'minmax', 'maxmin', 'minmin'. See `TimeSeriesFill` for explanations of each type

`DataTruncate`
: Set to TRUE to remove records with missing values from the lags and moving average features created

`SplitRatios`
: E.g c(0.7,0.2,0.1) for train, validation, and test sets

`PartitionType` Select 'random' for random data partitioning 'timeseries' for partitioning by time frames

`TaskType` Default is 'GPU' but you can also set it to 'CPU'

`NumGPU` Defaults to 1. If CPU is set this argument will be ignored.

`DebugMode` Defaults to FALSE. Set to TRUE to get a print statement of each high level comment in function

`Timer` Set to FALSE to turn off the updating print statements for progress

`EvalMetric` Select from 'RMSE', 'MAE', 'MAPE', 'Poisson', 'Quantile', 'LogLinQuantile', 'Lq', 'NumErrors', 'SMAPE', 'R2', 'MSLE', 'MedianAbsoluteError'

`EvalMetricValue`
Used when EvalMetric accepts an argument. See `AutoCatBoostRegression`

`LossFunction` Used in model training for model fitting. Select from 'RMSE', 'MAE', 'Quantile', 'LogLinQuantile', 'MAPE', 'Poisson', 'PairLogitPairwise', 'Tweedie', 'QueryRMSE'

`LossFunctionValue`
Used when LossFunction accepts an argument. See `AutoCatBoostRegression`

`GridTune` Set to TRUE to run a grid tune

`PassInGrid` Defaults to NULL

`ModelCount` Set the number of models to try in the grid tune

`MaxRunsWithoutNewWinner`
Default is 50

`MaxRunMinutes` Default is 60*60

`Langevin` Enables the Stochastic Gradient Langevin Boosting mode. If TRUE and TaskType == 'GPU' then TaskType will be converted to 'CPU'

`DiffusionTemperature`
Default is 10000

`NTrees` Select the number of trees you want to have built to train the model

`L2_Leaf_Reg` l2 reg parameter

`LearningRate` Defaults to NULL. Catboost will dynamically define this if L2_Leaf_Reg is NULL and RMSE is chosen (otherwise catboost will default it to 0.03). Then you can pull it out of the model object and pass it back in should you wish.

`RandomStrength` Default is 1

`BorderCount` Default is 254

`Depth` Depth of catboost model

`RSM` CPU only. If TaskType is GPU then RSM will not be used

`BootStrapType` If NULL, then if TaskType is GPU then Bayesian will be used. If CPU then MVS will be used. If MVS is selected when TaskType is GPU, then BootStrapType will be switched to Bayesian

`GrowPolicy` Default is SymmetricTree. Others include Lossguide and Depthwise

`ModelSizeReg` Defaults to 0.5. Set to 0 to allow for bigger models. This is for models with high cardinality categorical features. Valuues greater than 0 will shrink the model and quality will decline but models won't be huge.

`FeatureBorderType`
Defaults to 'GreedyLogSum'. Other options include: Median, Uniform, UniformAndQuantiles, MaxLogSum, MinEntropy

SamplingUnit	Default is Group. Other option is Object. if GPU is selected, this will be turned off unless the loss_function is YetiRankPairWise
SubSample	Can use if BootStrapType is neither Bayesian nor No. Pass NULL to use Catboost default. Used for bagging.
ScoreFunction	Default is Cosine. CPU options are Cosine and L2. GPU options are Cosine, L2, NewtonL2, and NewtomCosine (not available for Lossguide)
MinDataInLeaf	Defaults to 1. Used if GrowPolicy is not SymmetricTree
SaveModel	Logical. If TRUE, output ArgsList will have a named element 'Model' with the CatBoost model object
ArgsList	ArgsList is for scoring. Must contain named element 'Model' with a catboost model object
ModelID	Something to name your model if you want it saved
TVT	Passthrough
ExpandEncoding	= FALSE

Value

See examples

Author(s)

Adrian Antico

See Also

Other Automated Panel Data Forecasting: AutoH2OCARMA(), AutoLightGBMCARMA(), AutoXGBoostCARMA()

Examples

```
## Not run:

# Set up your output file path for saving results as a .csv
Path <- 'C:/YourPathHere'

# Run on GPU or CPU (some options in the grid tuning force usage of CPU for some runs)
TaskType = 'GPU'

# Define number of CPU threads to allow data.table to utilize
data.table::setDTthreads(percent = max(1L, parallel::detectCores()-2L))

# Load data
data <- data.table::fread('https://www.dropbox.com/s/2str3ek4f4cheqi/walmart_train.csv?dl=1')
data <- Rappture::DM.pgQuery(Host = 'localhost', DataBase = 'AutoQuant', SELECT = NULL, FROM = 'WalmartFull', U

# Ensure series have no missing dates (also remove series with more than 25% missing values)
data <- AutoQuant::TimeSeriesFill(
  data,
  DateColumnName = 'Date',
  GroupVariables = c('Store','Dept'),
  TimeUnit = 'weeks',
  FillType = 'maxmax',
  MaxMissingPercent = 0.25,
  SimpleImpute = TRUE)
```

```
# Set negative numbers to 0
data <- data[, Weekly_Sales := data.table::fifelse(Weekly_Sales < 0, 0, Weekly_Sales)]

# Remove IsHoliday column
data[, IsHoliday := NULL]

# Create xregs (this is the include the categorical variables instead of utilizing only the interaction of them)
xregs <- data[, .SD, .SDcols = c('Date', 'Store', 'Dept')]

# Change data types
data[, ':=' (Store = as.character(Store), Dept = as.character(Dept))]
xregs[, ':=' (Store = as.character(Store), Dept = as.character(Dept))]

# Subset data so we have an out of time sample
data1 <- data.table::copy(data[, ID := 1L:.N, by = c('Store','Dept')][ID <= 125L][, ID := NULL])
data[, ID := NULL]

# Define values for SplitRatios and FCWindow Args
N1 <- data1[, .N, by = c('Store','Dept')][1L, N]
N2 <- xregs[, .N, by = c('Store','Dept')][1L, N]

# Setup Grid Tuning & Feature Tuning data.table using a cross join of vectors
Tuning <- data.table::CJ(
  TimeWeights = c('None',0.999),
  MaxTimeGroups = c('weeks','months'),
  TargetTransformation = c('TRUE','FALSE'),
  Difference = c('TRUE','FALSE'),
  HoldoutTrain = c(6,18),
  Langevin = c('TRUE','FALSE'),
  NTrees = c(2500,5000),
  Depth = c(6,9),
  RandomStrength = c(0.75,1),
  L2_Leaf_Reg = c(3.0,4.0),
  RSM = c(0.75,'NULL'),
  GrowPolicy = c('SymmetricTree','Lossguide','Depthwise'),
  BootStrapType = c('Bayesian','MVS','No'))

# Remove options that are not compatible with GPU (skip over this otherwise)
Tuning <- Tuning[Langevin == 'TRUE' | (Langevin == 'FALSE' & RSM == 'NULL' & BootStrapType %in% c('Bayesian','No

# Randomize order of Tuning data.table
Tuning <- Tuning[order(runif(.N))]

# Load grid results and remove rows that have already been tested
if(file.exists(file.path(Path, 'Walmart_CARMA_Metrics.csv'))) {
  Metrics <- data.table::fread(file.path(Path, 'Walmart_CARMA_Metrics.csv'))
  temp <- data.table::rbindlist(list(Metrics,Tuning), fill = TRUE)
  temp <- unique(temp, by = c(4:(ncol(temp)-1)))
  Tuning <- temp[is.na(RunTime)][, .SD, .SDcols = names(Tuning)]
  rm(Metrics,temp)
}

# Define the total number of runs
TotalRuns <- Tuning[,.N]

# Kick off feature + grid tuning
```

```
for(Run in seq_len(TotalRuns)) {

  # print run number
  for(zz in seq_len(100)) print(Run)

  # Use fresh data for each run
  xregs_new <- data.table::copy(xregs)
  data_new <- data.table::copy(data1)

  # Timer start
  StartTime <- Sys.time()

  # Run carma system
  CatBoostResults <- AutoQuant::AutoCatBoostCARMA(

    # data args
    data = data_new,
   TimeWeights = if(Tuning[Run, TimeWeights] == 'None') NULL else as.numeric(Tuning[Run, TimeWeights]),
    TargetColumnName = 'Weekly_Sales',
    DateColumnName = 'Date',
    HierarchGroups = NULL,
    GroupVariables = c('Store','Dept'),
    EncodingMethod = 'credibility',
    TimeUnit = 'weeks',
   TimeGroups = if(Tuning[Run, MaxTimeGroups] == 'weeks') 'weeks' else if(Tuning[Run, MaxTimeGroups] == 'months

    # Production args
    TrainOnFull = TRUE,
    SplitRatios = c(1 - Tuning[Run, HoldoutTrain] / N2, Tuning[Run, HoldoutTrain] / N2),
    PartitionType = 'random',
    FC_Periods = N2-N1,
    TaskType = TaskType,
    NumGPU = 1,
    Timer = TRUE,
    DebugMode = TRUE,

    # Target variable transformations
    TargetTransformation = as.logical(Tuning[Run, TargetTransformation]),
   Methods = c('YeoJohnson', 'BoxCox', 'Asinh', 'Log', 'LogPlus1', 'Sqrt', 'Asin', 'Logit'),
    Difference = as.logical(Tuning[Run, Difference]),
    NonNegativePred = TRUE,
    RoundPreds = FALSE,

    # Calendar-related features
    CalendarVariables = c('week','wom','month','quarter'),
    HolidayVariable = c('USPublicHolidays'),
    HolidayLookback = NULL,
    HolidayLags = c(1,2,3),
    HolidayMovingAverages = c(2,3),

    # Lags, moving averages, and other rolling stats
   Lags = if(Tuning[Run, MaxTimeGroups] == 'weeks') c(1,2,3,4,5,8,9,12,13,51,52,53) else if(Tuning[Run, MaxTim
   MA_Periods = if(Tuning[Run, MaxTimeGroups] == 'weeks') c(2,3,4,5,8,9,12,13,51,52,53) else if(Tuning[Run, Ma
    SD_Periods = NULL,
    Skew_Periods = NULL,
    Kurt_Periods = NULL,
    Quantile_Periods = NULL,
```

```
  Quantiles_Selected = NULL,

  # Bonus features
  AnomalyDetection = NULL,
  XREGS = xregs_new,
  FourierTerms = 0,
  TimeTrendVariable = TRUE,
  ZeroPadSeries = NULL,
  DataTruncate = FALSE,

  # ML grid tuning args
  GridTune = FALSE,
  PassInGrid = NULL,
  ModelCount = 5,
  MaxRunsWithoutNewWinner = 50,
  MaxRunMinutes = 60*60,

  # ML evaluation output
  SaveDataPath = NULL,
  NumOfParDepPlots = 0L,

  # ML loss functions
  EvalMetric = 'RMSE',
  EvalMetricValue = 1,
  LossFunction = 'RMSE',
  LossFunctionValue = 1,

  # ML tuning args
  NTrees = Tuning[Run, NTrees],
  Depth = Tuning[Run, Depth],
  L2_Leaf_Reg = Tuning[Run, L2_Leaf_Reg],
  LearningRate = 0.03,
  Langevin = as.logical(Tuning[Run, Langevin]),
  DiffusionTemperature = 10000,
  RandomStrength = Tuning[Run, RandomStrength],
  BorderCount = 254,
  RSM = if(Tuning[Run, RSM] == 'NULL') NULL else as.numeric(Tuning[Run, RSM]),
  GrowPolicy = Tuning[Run, GrowPolicy],
  BootStrapType = Tuning[Run, BootStrapType],
  ModelSizeReg = 0.5,
  FeatureBorderType = 'GreedyLogSum',
  SamplingUnit = 'Group',
  SubSample = NULL,
  ScoreFunction = 'Cosine',
  MinDataInLeaf = 1)

# Timer End
EndTime <- Sys.time()

# Prepare data for evaluation
Results <- CatBoostResults$Forecast
data.table::setnames(Results, 'Weekly_Sales', 'bla')
Results <- merge(Results, data, by = c('Store','Dept','Date'), all = FALSE)
Results <- Results[is.na(bla)][, bla := NULL]

# Create totals and subtotals
Results <- data.table::groupingsets(
```

```
    x = Results,
    j = list(Predictions = sum(Predictions), Weekly_Sales = sum(Weekly_Sales)),
    by = c('Date', 'Store', 'Dept'),
   sets = list(c('Date', 'Store', 'Dept'), c('Store', 'Dept'), 'Store', 'Dept', 'Date'))

 # Fill NAs with 'Total' for totals and subtotals
for(cols in c('Store','Dept')) Results[, eval(cols) := data.table::fifelse(is.na(get(cols)), 'Total', get(co

 # Add error measures
 Results[, Weekly_MAE := abs(Weekly_Sales - Predictions)]
 Results[, Weekly_MAPE := Weekly_MAE / Weekly_Sales]

 # Weekly results
 Weekly_MAPE <- Results[, list(Weekly_MAPE = mean(Weekly_MAPE)), by = list(Store,Dept)]

 # Monthly results
 temp <- data.table::copy(Results)
 temp <- temp[, Date := lubridate::floor_date(Date, unit = 'months')]
temp <- temp[, lapply(.SD, sum), by = c('Date','Store','Dept'), .SDcols = c('Predictions', 'Weekly_Sales')]
 temp[, Monthly_MAE := abs(Weekly_Sales - Predictions)]
 temp[, Monthly_MAPE := Monthly_MAE / Weekly_Sales]
 Monthly_MAPE <- temp[, list(Monthly_MAPE = mean(Monthly_MAPE)), by = list(Store,Dept)]

 # Collect metrics for Total (feel free to switch to something else or no filter at all)
 Metrics <- data.table::data.table(
   RunNumber = Run,
   Total_Weekly_MAPE = Weekly_MAPE[Store == 'Total' & Dept == 'Total', Weekly_MAPE],
   Total_Monthly_MAPE = Monthly_MAPE[Store == 'Total' & Dept == 'Total', Monthly_MAPE],
   Tuning[Run],
   RunTime = EndTime - StartTime)

 # Append to file (not overwrite)
data.table::fwrite(Metrics, file = file.path(Path, 'Walmart_CARMA_Metrics.csv'), append = TRUE)

 # Remove objects (clear space before new runs)
 rm(CatBoostResults, Results, temp, Weekly_MAE, Weekly_MAPE, Monthly_MAE, Monthly_MAPE)

 # Garbage collection because of GPU
 gc()
}

## End(Not run)
```

AutoCatBoostClassifier

AutoCatBoostClassifier

Description

AutoCatBoostClassifier is an automated modeling function that runs a variety of steps. First, a stratified sampling (by the target variable) is done to create train, validation, and test sets (if not supplied). Then, the function will run a random grid tune over N number of models and find which model is the best (a default model is always included in that set). Once the model is identified and built, several other outputs are generated: validation data with predictions (on test data), an

ROC plot, evaluation plot, evaluation metrics, variable importance, partial dependence calibration plots, partial dependence calibration box plots, and column names used in model fitting. You can download the catboost package using devtools, via: devtools::install_github('catboost/catboost', subdir = 'catboost/R-package')

Usage

```
AutoCatBoostClassifier(
 OutputSelection = c("Importances", "EvalPlots", "EvalMetrics", "Score_TrainData"),
  data = NULL,
  ValidationData = NULL,
  TestData = NULL,
  TargetColumnName = NULL,
  FeatureColNames = NULL,
  PrimaryDateColumn = NULL,
  WeightsColumnName = NULL,
  IDcols = NULL,
  EncodeMethod = "credibility",
  TrainOnFull = FALSE,
  task_type = "GPU",
  NumGPUs = 1,
  ReturnModelObjects = TRUE,
  SaveModelObjects = FALSE,
  SaveInfoToPDF = FALSE,
  ModelID = "FirstModel",
  model_path = NULL,
  metadata_path = NULL,
  EvalMetric = "MCC",
  LossFunction = "Logloss",
  grid_eval_metric = "MCC",
  ClassWeights = c(1, 1),
  CostMatrixWeights = c(0, 1, 1, 0),
  NumOfParDepPlots = 0L,
  PassInGrid = NULL,
  GridTune = FALSE,
  MaxModelsInGrid = 30L,
  MaxRunsWithoutNewWinner = 20L,
  MaxRunMinutes = 24L * 60L,
  BaselineComparison = "default",
  MetricPeriods = 10L,
  Trees = 50L,
  Depth = 6,
  LearningRate = NULL,
  L2_Leaf_Reg = 3,
  RandomStrength = 1,
  BorderCount = 128,
  RSM = NULL,
  BootStrapType = NULL,
  GrowPolicy = "SymmetricTree",
  langevin = FALSE,
  diffusion_temperature = 10000,
  model_size_reg = 0.5,
  feature_border_type = "GreedyLogSum",
```

```
  sampling_unit = "Object",
  subsample = NULL,
  score_function = "Cosine",
  min_data_in_leaf = 1,
  DebugMode = FALSE
)
```

Arguments

OutputSelection	You can select what type of output you want returned. Choose from c('Importances', 'EvalPlots', 'EvalMetrics', 'Score_TrainData')
data	This is your data set for training and testing your model
ValidationData	This is your holdout data set used in modeling either refine your hyperparameters. Catboost using both training and validation data in the training process so you should evaluate out of sample performance with this data set.
TestData	This is your holdout data set. Catboost using both training and validation data in the training process so you should evaluate out of sample performance with this data set.
TargetColumnName	Either supply the target column name OR the column number where the target is located, but not mixed types. Note that the target column needs to be a 0 | 1 numeric variable.
FeatureColNames	Either supply the feature column names OR the column number where the target is located, but not mixed types. Also, not zero-indexed.
PrimaryDateColumn	Supply a date or datetime column for catboost to utilize time as its basis for handling categorical features, instead of random shuffling
WeightsColumnName	Supply a column name for your weights column. Leave NULL otherwise
IDcols	A vector of column names or column numbers to keep in your data but not include in the modeling.
EncodeMethod	'credibility', 'binary', 'm_estimator', 'woe', 'target_encoding', 'poly_encode', 'backward_difference', 'helmert'
TrainOnFull	Set to TRUE to train on full data and skip over evaluation steps
task_type	Set to 'GPU' to utilize your GPU for training. Default is 'CPU'.
NumGPUs	Numeric. If you have 4 GPUs supply 4 as a value.
ReturnModelObjects	Set to TRUE to output all modeling objects. E.g. plots and evaluation metrics
SaveModelObjects	Set to TRUE to return all modeling objects to your environment
SaveInfoToPDF	Set to TRUE to save modeling information to PDF. If model_path or metadata_path aren't defined then output will be saved to the working directory
ModelID	A character string to name your model and output
model_path	A character string of your path file to where you want your output saved
metadata_path	A character string of your path file to where you want your model evaluation output saved. If left NULL, all output will be saved to model_path.

`EvalMetric` This is the metric used inside catboost to measure performance on validation data during a grid-tune. 'AUC' is the default. 'Logloss', 'CrossEntropy', 'Precision', 'Recall', 'F1', 'BalancedAccuracy', 'BalancedErrorRate', 'MCC', 'Accuracy', 'CtrFactor', 'AUC', 'BrierScore', 'HingeLoss', 'HammingLoss', 'ZeroOneLoss', 'Kappa', 'WKappa', 'LogLikelihoodOfPrediction', 'TotalF1', 'PairLogit', 'PairLogitPairwise', 'PairAccuracy', 'QueryCrossEntropy', 'QuerySoftMax', 'PFound', 'NDCG', 'AverageGain', 'PrecisionAt', 'RecallAt', 'MAP'

`LossFunction` Default is NULL. Select the loss function of choice. c('Logloss','CrossEntropy','Lq','PairLogit','Pair

`grid_eval_metric`
Case sensitive. I typically choose 'Utility' or 'MCC'. Choose from 'Utility', 'MCC', 'Acc', 'F1_Score', 'F2_Score', 'F0.5_Score', 'TPR', 'TNR', 'FNR', 'FPR', 'FDR', 'FOR', 'NPV', 'PPV', 'ThreatScore'

`ClassWeights` Supply a vector of weights for your target classes. E.g. c(0.25, 1) to weight your 0 class by 0.25 and your 1 class by 1.

`CostMatrixWeights`
A vector with 4 elements c(True Positive Cost, False Negative Cost, False Positive Cost, True Negative Cost). Default c(1,0,0,1)

`NumOfParDepPlots`
Tell the function the number of partial dependence calibration plots you want to create. Calibration boxplots will only be created for numerical features (not dummy variables)

`PassInGrid` Defaults to NULL. Pass in a single row of grid from a previous output as a data.table (they are collected as data.tables)

`GridTune` Set to TRUE to run a grid tuning procedure. Set a number in MaxModelsInGrid to tell the procedure how many models you want to test.

`MaxModelsInGrid`
Number of models to test from grid options.

`MaxRunsWithoutNewWinner`
A number

`MaxRunMinutes` In minutes

`BaselineComparison`
Set to either 'default' or 'best'. Default is to compare each successive model build to the baseline model using max trees (from function args). Best makes the comparison to the current best model.

`MetricPeriods` Number of trees to build before evaluating intermediate metrics. Default is 10L

`Trees` Bandit grid partitioned. Supply a single value for non-grid tuning cases. Otherwise, supply a vector for the trees numbers you want to test. For running grid tuning, a NULL value supplied will mean these values are tested seq(1000L, 10000L, 1000L)

`Depth` Bandit grid partitioned Number, or vector for depth to test. For running grid tuning, a NULL value supplied will mean these values are tested seq(4L, 16L, 2L)

`LearningRate` Bandit grid partitioned. Supply a single value for non-grid tuning cases. Otherwise, supply a vector for the LearningRate values to test. For running grid tuning, a NULL value supplied will mean these values are tested c(0.01,0.02,0.03,0.04)

`L2_Leaf_Reg` Random testing. Supply a single value for non-grid tuning cases. Otherwise, supply a vector for the L2_Leaf_Reg values to test. For running grid tuning, a NULL value supplied will mean these values are tested seq(1.0, 10.0, 1.0)

`RandomStrength` A multiplier of randomness added to split evaluations. Default value is 1 which adds no randomness.

`BorderCount` Number of splits for numerical features. Catboost defaults to 254 for CPU and 128 for GPU

`RSM` CPU only. Random testing. Supply a single value for non-grid tuning cases. Otherwise, supply a vector for the RSM values to test. For running grid tuning, a NULL value supplied will mean these values are tested c(0.80, 0.85, 0.90, 0.95, 1.0)

`BootStrapType` Random testing. Supply a single value for non-grid tuning cases. Otherwise, supply a vector for the BootStrapType values to test. For running grid tuning, a NULL value supplied will mean these values are tested c('Bayesian', 'Bernoulli', 'Poisson', 'MVS', 'No')

`GrowPolicy` Random testing. NULL, character, or vector for GrowPolicy to test. For grid tuning, supply a vector of values. For running grid tuning, a NULL value supplied will mean these values are tested c('SymmetricTree', 'Depthwise', 'Lossguide')

`langevin` TRUE or FALSE. TRUE enables

`diffusion_temperature` Default value is 10000

`model_size_reg` Defaults to 0.5. Set to 0 to allow for bigger models. This is for models with high cardinality categorical features. Valuues greater than 0 will shrink the model and quality will decline but models won't be huge.

`feature_border_type` Defaults to 'GreedyLogSum'. Other options include: Median, Uniform, UniformAndQuantiles, MaxLogSum, MinEntropy

`sampling_unit` Default is Group. Other option is Object. if GPU is selected, this will be turned off unless the LossFunction is YetiRankPairWise

`subsample` Default is NULL. Catboost will turn this into 0.66 for BootStrapTypes Poisson and Bernoulli. 0.80 for MVS. Doesn't apply to others.

`score_function` Default is Cosine. CPU options are Cosine and L2. GPU options are Cosine, L2, NewtonL2, and NewtomCosine (not available for Lossguide)

`min_data_in_leaf` Default is 1. Cannot be used with SymmetricTree is GrowPolicy

`DebugMode` Set to TRUE to get a printout of which step the function is on. FALSE, otherwise

Value

Saves to file and returned in list: VariableImportance.csv, Model (the model), ValidationData.csv, ROC_Plot.png, EvalutionPlot.png, EvaluationMetrics.csv, ParDepPlots.R a named list of features with partial dependence calibration plots, GridCollect, and GridList

Author(s)

Adrian Antico

See Also

Other Automated Supervised Learning - Binary Classification: `AutoH2oDRFClassifier()`, `AutoH2oGAMClassifier()`, `AutoH2oGBMClassifier()`, `AutoH2oGLMClassifier()`, `AutoH2oMLClassifier()`, `AutoLightGBMClassifier()`, `AutoXGBoostClassifier()`

Examples

```
## Not run:
# Create some dummy correlated data
data <- AutoQuant::FakeDataGenerator(
  Correlation = 0.85,
  N = 10000,
  ID = 2,
  ZIP = 0,
  AddDate = FALSE,
  Classification = TRUE,
  MultiClass = FALSE)

# Run function
TestModel <- AutoQuant::AutoCatBoostClassifier(

  # GPU or CPU and the number of available GPUs
  task_type = 'GPU',
  NumGPUs = 1,
  TrainOnFull = FALSE,
  DebugMode = FALSE,

  # Metadata args
  OutputSelection = c('Score_TrainData', 'Importances', 'EvalPlots', 'EvalMetrics'),
  ModelID = 'Test_Model_1',
  model_path = normalizePath('./'),
  metadata_path = normalizePath('./'),
  SaveModelObjects = FALSE,
  ReturnModelObjects = TRUE,
  SaveInfoToPDF = FALSE,

  # Data args
  data = data,
  ValidationData = NULL,
  TestData = NULL,
  TargetColumnName = 'Adrian',
  FeatureColNames = names(data)[!names(data) %in%
    c('IDcol_1','IDcol_2','Adrian')],
  PrimaryDateColumn = NULL,
  WeightsColumnName = NULL,
  IDcols = c('IDcol_1','IDcol_2'),
  EncodeMethod = 'credibility',

  # Evaluation args
  ClassWeights = c(1L,1L),
  CostMatrixWeights = c(0,1,1,0),
  EvalMetric = 'AUC',
  grid_eval_metric = 'MCC',
  LossFunction = 'Logloss',
  MetricPeriods = 10L,
  NumOfParDepPlots = ncol(data)-1L-2L,

  # Grid tuning args
  PassInGrid = NULL,
  GridTune = FALSE,
  MaxModelsInGrid = 30L,
  MaxRunsWithoutNewWinner = 20L,
```

```
  MaxRunMinutes = 24L*60L,
  BaselineComparison = 'default',

  # ML args
  Trees = 1000,
  Depth = 9,
  LearningRate = NULL,
  L2_Leaf_Reg = NULL,
  model_size_reg = 0.5,
  langevin = FALSE,
  diffusion_temperature = 10000,
  RandomStrength = 1,
  BorderCount = 128,
  RSM = 1,
  BootStrapType = 'Bayesian',
  GrowPolicy = 'SymmetricTree',
  feature_border_type = 'GreedyLogSum',
  sampling_unit = 'Object',
  subsample = NULL,
  score_function = 'Cosine',
  min_data_in_leaf = 1)

## End(Not run)
```

`AutoCatBoostMultiClass`

AutoCatBoostMultiClass

Description

AutoCatBoostMultiClass is an automated modeling function that runs a variety of steps. First, a stratified sampling (by the target variable) is done to create train and validation sets. Then, the function will run a random grid tune over N number of models and find which model is the best (a default model is always included in that set). Once the model is identified and built, several other outputs are generated: validation data with predictions, evaluation metrics, variable importance, and column names used in model fitting. You can download the catboost package using devtools, via: devtools::install_github('catboost/catboost', subdir = 'catboost/R-package').

Usage

```
AutoCatBoostMultiClass(
 OutputSelection = c("Importances", "EvalPlots", "EvalMetrics", "Score_TrainData"),
  data = NULL,
  ValidationData = NULL,
  TestData = NULL,
  TargetColumnName = NULL,
  FeatureColNames = NULL,
  PrimaryDateColumn = NULL,
  WeightsColumnName = NULL,
  IDcols = NULL,
  EncodeMethod = "credibility",
  TrainOnFull = FALSE,
  task_type = "GPU",
```

```
  NumGPUs = 1,
  DebugMode = FALSE,
  ReturnModelObjects = TRUE,
  SaveModelObjects = FALSE,
  ModelID = "FirstModel",
  model_path = NULL,
  metadata_path = NULL,
  ClassWeights = NULL,
  NumOfParDepPlots = 3,
  eval_metric = "MultiClassOneVsAll",
  loss_function = "MultiClassOneVsAll",
  grid_eval_metric = "Accuracy",
  BaselineComparison = "default",
  MetricPeriods = 10L,
  PassInGrid = NULL,
  GridTune = FALSE,
  MaxModelsInGrid = 30L,
  MaxRunsWithoutNewWinner = 20L,
  MaxRunMinutes = 24L * 60L,
  Trees = 50L,
  Depth = 6,
  LearningRate = NULL,
  L2_Leaf_Reg = NULL,
  RandomStrength = 1,
  BorderCount = 128,
  RSM = NULL,
  BootStrapType = NULL,
  GrowPolicy = NULL,
  langevin = FALSE,
  diffusion_temperature = 10000,
  model_size_reg = 0.5,
  feature_border_type = "GreedyLogSum",
  sampling_unit = "Object",
  subsample = NULL,
  score_function = "Cosine",
  min_data_in_leaf = 1
)
```

Arguments

`OutputSelection`	You can select what type of output you want returned. Choose from c('Importances', 'EvalPlots', 'EvalMetrics', 'Score_TrainData')
`data`	This is your data set for training and testing your model
`ValidationData`	This is your holdout data set used in modeling either refine your hyperparameters. Catboost using both training and validation data in the training process so you should evaluate out of sample performance with this data set.
`TestData`	This is your holdout data set. Catboost using both training and validation data in the training process so you should evaluate out of sample performance with this data set.
`TargetColumnName`	Either supply the target column name OR the column number where the target

is located, but not mixed types. Note that the target column needs to be a 0 | 1 numeric variable.

`FeatureColNames`
: Either supply the feature column names OR the column number where the target is located, but not mixed types. Also, not zero-indexed.

`PrimaryDateColumn`
: Supply a date or datetime column for catboost to utilize time as its basis for handling categorical features, instead of random shuffling

`WeightsColumnName`
: Supply a column name for your weights column. Leave NULL otherwise

`IDcols`
: A vector of column names or column numbers to keep in your data but not include in the modeling.

`EncodeMethod`
: 'binary', 'm_estimator', 'credibility', 'woe', 'target_encoding', 'poly_encode', 'backward_difference', 'helmert'

`TrainOnFull`
: Set to TRUE to train on full data and skip over evaluation steps

`task_type`
: Set to 'GPU' to utilize your GPU for training. Default is 'CPU'.

`NumGPUs`
: Set to 1, 2, 3, etc.

`DebugMode`
: TRUE to print out steps taken

`ReturnModelObjects`
: Set to TRUE to output all modeling objects. E.g. plots and evaluation metrics

`SaveModelObjects`
: Set to TRUE to return all modeling objects to your environment

`ModelID`
: A character string to name your model and output

`model_path`
: A character string of your path file to where you want your output saved

`metadata_path`
: A character string of your path file to where you want your model evaluation output saved. If left NULL, all output will be saved to model_path.

`ClassWeights`
: Supply a vector of weights for your target classes. E.g. c(0.25, 1) to weight your 0 class by 0.25 and your 1 class by 1.

`NumOfParDepPlots`
: Number of partial dependence plots to create for each target level

`eval_metric`
: Internal bandit metric. Select from 'MultiClass', 'MultiClassOneVsAll', 'AUC', 'TotalF1', 'MCC', 'Accuracy', 'HingeLoss', 'HammingLoss', 'ZeroOneLoss', 'Kappa', 'WKappa'

`loss_function`
: Select from 'MultiClass' or 'MultiClassOneVsAll'

`grid_eval_metric`
: For evaluating models within grid tuning. Choices include, 'accuracy', 'microauc', 'logloss'

`BaselineComparison`
: Set to either 'default' or 'best'. Default is to compare each successive model build to the baseline model using max trees (from function args). Best makes the comparison to the current best model.

`MetricPeriods`
: Number of trees to build before evaluating intermediate metrics. Default is 10L

`PassInGrid`
: Defaults to NULL. Pass in a single row of grid from a previous output as a data.table (they are collected as data.tables)

`GridTune`
: Set to TRUE to run a grid tuning procedure. Set a number in MaxModelsInGrid to tell the procedure how many models you want to test.

`MaxModelsInGrid`
: Number of models to test from grid options.

`MaxRunsWithoutNewWinner`
: A number

`MaxRunMinutes`
: In minutes

`Trees`
: Bandit grid partitioned. Supply a single value for non-grid tuning cases. Otherwise, supply a vector for the trees numbers you want to test. For running grid tuning, a NULL value supplied will mean these values are tested seq(1000L, 10000L, 1000L)

`Depth`
: Bandit grid partitioned. Number, or vector for depth to test. For running grid tuning, a NULL value supplied will mean these values are tested seq(4L, 16L, 2L)

`LearningRate`
: Bandit grid partitioned. Supply a single value for non-grid tuning cases. Otherwise, supply a vector for the LearningRate values to test. For running grid tuning, a NULL value supplied will mean these values are tested c(0.01,0.02,0.03,0.04)

`L2_Leaf_Reg`
: Random testing. Supply a single value for non-grid tuning cases. Otherwise, supply a vector for the L2_Leaf_Reg values to test. For running grid tuning, a NULL value supplied will mean these values are tested seq(1.0, 10.0, 1.0)

`RandomStrength`
: A multiplier of randomness added to split evaluations. Default value is 1 which adds no randomness.

`BorderCount`
: Number of splits for numerical features. Catboost defaults to 254 for CPU and 128 for GPU

`RSM`
: CPU only. Random testing. Supply a single value for non-grid tuning cases. Otherwise, supply a vector for the RSM values to test. For running grid tuning, a NULL value supplied will mean these values are tested c(0.80, 0.85, 0.90, 0.95, 1.0)

`BootStrapType`
: Random testing. Supply a single value for non-grid tuning cases. Otherwise, supply a vector for the BootStrapType values to test. For running grid tuning, a NULL value supplied will mean these values are tested c('Bayesian', 'Bernoulli', 'Poisson', 'MVS', 'No')

`GrowPolicy`
: Random testing. NULL, character, or vector for GrowPolicy to test. For grid tuning, supply a vector of values. For running grid tuning, a NULL value supplied will mean these values are tested c('SymmetricTree', 'Depthwise', 'Lossguide')

`langevin`
: TRUE or FALSE. Enable stochastic gradient langevin boosting

`diffusion_temperature`
: Default is 10000 and is only used when langevin is set to TRUE

`model_size_reg`
: Defaults to 0.5. Set to 0 to allow for bigger models. This is for models with high cardinality categorical features. Valuues greater than 0 will shrink the model and quality will decline but models won't be huge.

`feature_border_type`
: Defaults to 'GreedyLogSum'. Other options include: Median, Uniform, UniformAndQuantiles, MaxLogSum, MinEntropy

`sampling_unit`
: Default is Group. Other option is Object. if GPU is selected, this will be turned off unless the loss_function is YetiRankPairWise

`subsample`
: Default is NULL. Catboost will turn this into 0.66 for BootStrapTypes Poisson and Bernoulli. 0.80 for MVS. Doesn't apply to others.

score_function Default is Cosine. CPU options are Cosine and L2. GPU options are Cosine, L2, NewtonL2, and NewtomCosine (not available for Lossguide)

min_data_in_leaf
Default is 1. Cannot be used with SymmetricTree is GrowPolicy

Value

Saves to file and returned in list: VariableImportance.csv, Model (the model), ValidationData.csv, EvaluationMetrics.csv, GridCollect, and GridList

Author(s)

Adrian Antico

See Also

Other Automated Supervised Learning - Multiclass Classification: AutoH2oDRFMultiClass(), AutoH2oGAMMultiClass(), AutoH2oGBMMultiClass(), AutoH2oGLMMultiClass(), AutoH2oMLMultiClass(), AutoXGBoostMultiClass()

Examples

```
## Not run:
# Create some dummy correlated data
data <- AutoQuant::FakeDataGenerator(
  Correlation = 0.85,
  N = 10000L,
  ID = 2L,
  ZIP = 0L,
  AddDate = FALSE,
  Classification = FALSE,
  MultiClass = TRUE)

# Run function
TestModel <- AutoQuant::AutoCatBoostMultiClass(

 # GPU or CPU and the number of available GPUs
 task_type = 'GPU',
 NumGPUs = 1,
 TrainOnFull = FALSE,
 DebugMode = FALSE,

 # Metadata args
 OutputSelection = c('Importances', 'EvalPlots', 'EvalMetrics', 'Score_TrainData'),
 ModelID = 'Test_Model_1',
 model_path = normalizePath('./'),
 metadata_path = normalizePath('./'),
 SaveModelObjects = FALSE,
 ReturnModelObjects = TRUE,

 # Data args
 data = data,
 ValidationData = NULL,
 TestData = NULL,
 TargetColumnName = 'Adrian',
 FeatureColNames = names(data)[!names(data) %in%
```

```
  c('IDcol_1', 'IDcol_2','Adrian')],
PrimaryDateColumn = NULL,
WeightsColumnName = NULL,
ClassWeights = c(1L,1L,1L,1L,1L),
IDcols = c('IDcol_1','IDcol_2'),
EncodeMethod = 'credibility',

# Model evaluation
eval_metric = 'MCC',
loss_function = 'MultiClassOneVsAll',
grid_eval_metric = 'Accuracy',
MetricPeriods = 10L,
NumOfParDepPlots = 3,

# Grid tuning args
PassInGrid = NULL,
GridTune = FALSE,
MaxModelsInGrid = 30L,
MaxRunsWithoutNewWinner = 20L,
MaxRunMinutes = 24L*60L,
BaselineComparison = 'default',

# ML args
langevin = FALSE,
diffusion_temperature = 10000,
Trees = 100L,
Depth = 4L,
LearningRate = NULL,
L2_Leaf_Reg = NULL,
RandomStrength = 1,
BorderCount = 254,
RSM = NULL,
BootStrapType = 'Bayesian',
GrowPolicy = 'SymmetricTree',
model_size_reg = 0.5,
feature_border_type = 'GreedyLogSum',
sampling_unit = 'Object',
subsample = NULL,
score_function = 'Cosine',
min_data_in_leaf = 1)

## End(Not run)
```

`AutoCatBoostRegression` *AutoCatBoostRegression*

Description

AutoCatBoostRegression is an automated modeling function that runs a variety of steps. First, the function will run a random grid tune over N number of models and find which model is the best (a default model is always included in that set). Once the model is identified and built, several other

outputs are generated: validation data with predictions, evaluation plot, evaluation boxplot, evaluation metrics, variable importance, partial dependence calibration plots, partial dependence calibration box plots, and column names used in model fitting. You can download the catboost package using devtools, via: devtools::install_github('catboost/catboost', subdir = 'catboost/R-package')

Usage

```
AutoCatBoostRegression(
 OutputSelection = c("Importances", "EvalPlots", "EvalMetrics", "Score_TrainData"),
  ReturnShap = TRUE,
  data = NULL,
  ValidationData = NULL,
  TestData = NULL,
  TargetColumnName = NULL,
  FeatureColNames = NULL,
  PrimaryDateColumn = NULL,
  WeightsColumnName = NULL,
  IDcols = NULL,
  EncodeMethod = "credibility",
  TransformNumericColumns = NULL,
  Methods = c("BoxCox", "Asinh", "Log", "LogPlus1", "Sqrt", "Asin", "Logit"),
  TrainOnFull = FALSE,
  task_type = "GPU",
  NumGPUs = 1,
  DebugMode = FALSE,
  ReturnModelObjects = TRUE,
  SaveModelObjects = FALSE,
  ModelID = "FirstModel",
  model_path = NULL,
  metadata_path = NULL,
  SaveInfoToPDF = FALSE,
  eval_metric = "RMSE",
  eval_metric_value = 1.5,
  loss_function = "RMSE",
  loss_function_value = 1.5,
  grid_eval_metric = "r2",
  NumOfParDepPlots = 0L,
  PassInGrid = NULL,
  GridTune = FALSE,
  MaxModelsInGrid = 30L,
  MaxRunsWithoutNewWinner = 20L,
  MaxRunMinutes = 24L * 60L,
  BaselineComparison = "default",
  MetricPeriods = 10L,
  Trees = 500L,
  Depth = 9,
  L2_Leaf_Reg = 3,
  RandomStrength = 1,
  BorderCount = 254,
  LearningRate = NULL,
  RSM = 1,
  BootStrapType = NULL,
  GrowPolicy = "SymmetricTree",
```

```
  langevin = FALSE,
  diffusion_temperature = 10000,
  model_size_reg = 0.5,
  feature_border_type = "GreedyLogSum",
  sampling_unit = "Object",
  subsample = NULL,
  score_function = "Cosine",
  min_data_in_leaf = 1
)
```

Arguments

OutputSelection	You can select what type of output you want returned. Choose from c('Importances', 'EvalPlots', 'EvalMetrics', 'Score_TrainData')
ReturnShap	TRUE. Set to FALSE to not generate shap values.
data	This is your data set for training and testing your model
ValidationData	This is your holdout data set used in modeling either refine your hyperparameters. Catboost using both training and validation data in the training process so you should evaluate out of sample performance with this data set.
TestData	This is your holdout data set. Catboost using both training and validation data in the training process so you should evaluate out of sample performance with this data set.
TargetColumnName	Either supply the target column name OR the column number where the target is located (but not mixed types).
FeatureColNames	Either supply the feature column names OR the column number where the target is located (but not mixed types)
PrimaryDateColumn	Supply a date or datetime column for catboost to utilize time as its basis for handling categorical features, instead of random shuffling
WeightsColumnName	Supply a column name for your weights column. Leave NULL otherwise
IDcols	A vector of column names or column numbers to keep in your data but not include in the modeling.
EncodeMethod	'binary', 'm_estimator', 'credibility', 'woe', 'target_encoding', 'poly_encode', 'backward_difference', 'helmert'
TransformNumericColumns	Set to NULL to do nothing; otherwise supply the column names of numeric variables you want transformed
Methods	Choose from 'YeoJohnson', 'BoxCox', 'Asinh', 'Log', 'LogPlus1', 'Sqrt', 'Asin', or 'Logit'. If more than one is selected, the one with the best normalization pearson statistic will be used. Identity is automatically selected and compared.
TrainOnFull	Set to TRUE to train on full data and skip over evaluation steps
task_type	Set to 'GPU' to utilize your GPU for training. Default is 'CPU'.
NumGPUs	Set to 1, 2, 3, etc.
DebugMode	Set to TRUE to get a printout of which step the function is on. FALSE, otherwise

`ReturnModelObjects`
: Set to TRUE to output all modeling objects (E.g. plots and evaluation metrics)

`SaveModelObjects`
: Set to TRUE to return all modeling objects to your environment

`ModelID`
: A character string to name your model and output

`model_path`
: A character string of your path file to where you want your output saved

`metadata_path`
: A character string of your path file to where you want your model evaluation output saved. If left NULL, all output will be saved to model_path.

`SaveInfoToPDF`
: Set to TRUE to save modeling information to PDF. If model_path or metadata_path aren't defined then output will be saved to the working directory

`eval_metric`
: Select from 'RMSE', 'MAE', 'MAPE', 'R2', 'Poisson', 'MedianAbsoluteError', 'SMAPE', 'MSLE', 'NumErrors', 'FairLoss', 'Tweedie', 'Huber', 'LogLinQuantile', 'Quantile', 'Lq', 'Expectile', 'MultiRMSE'

`eval_metric_value`
: Used with the specified eval_metric. See https://catboost.ai/docs/concepts/loss-functions-regression.html

`loss_function`
: Used in model training for model fitting. 'MAPE', 'MAE', 'RMSE', 'Poisson', 'Tweedie', 'Huber', 'LogLinQuantile', 'Quantile', 'Lq', 'Expectile', 'MultiRMSE'

`loss_function_value`
: Used with the specified loss function if an associated value is required. 'Tweedie', 'Huber', 'LogLinQuantile', 'Quantile' 'Lq', 'Expectile'. See https://catboost.ai/docs/concepts/loss-functions-regression.html

`grid_eval_metric`
: Choose from 'mae', 'mape', 'rmse', 'r2'. Case sensitive

`NumOfParDepPlots`
: Tell the function the number of partial dependence calibration plots you want to create. Calibration boxplots will only be created for numerical features (not dummy variables)

`PassInGrid`
: Defaults to NULL. Pass in a single row of grid from a previous output as a data.table (they are collected as data.tables)

`GridTune`
: Set to TRUE to run a grid tuning procedure. Set a number in MaxModelsInGrid to tell the procedure how many models you want to test.

`MaxModelsInGrid`
: Number of models to test from grid options

`MaxRunsWithoutNewWinner`
: Number of models built before calling it quits

`MaxRunMinutes`
: Maximum number of minutes to let this run

`BaselineComparison`
: Set to either 'default' or 'best'. Default is to compare each successive model build to the baseline model using max trees (from function args). Best makes the comparison to the current best model.

`MetricPeriods`
: Number of periods to use between Catboost evaluations

`Trees`
: Standard + Grid Tuning. Bandit grid partitioned. The maximum number of trees you want in your models

`Depth`
: Standard + Grid Tuning. Bandit grid partitioned. Number, or vector for depth to test. For running grid tuning, a NULL value supplied will mean these values are tested seq(4L, 16L, 2L)

`L2_Leaf_Reg` Standard + Grid Tuning. Random testing. Supply a single value for non-grid tuning cases. Otherwise, supply a vector for the L2_Leaf_Reg values to test. For running grid tuning, a NULL value supplied will mean these values are tested seq(1.0, 10.0, 1.0)

`RandomStrength` Standard + Grid Tuning. A multiplier of randomness added to split evaluations. Default value is 1 which adds no randomness.

`BorderCount` Standard + Grid Tuning. Number of splits for numerical features. Catboost defaults to 254 for CPU and 128 for GPU

`LearningRate` Standard + Grid Tuning. Default varies if RMSE, MultiClass, or Logloss is utilized. Otherwise default is 0.03. Bandit grid partitioned. Supply a single value for non-grid tuning cases. Otherwise, supply a vector for the LearningRate values to test. For running grid tuning, a NULL value supplied will mean these values are tested c(0.01,0.02,0.03,0.04)

`RSM` CPU only. Standard + Grid Tuning. If GPU is set, this is turned off. Random testing. Supply a single value for non-grid tuning cases. Otherwise, supply a vector for the RSM values to test. For running grid tuning, a NULL value supplied will mean these values are tested c(0.80, 0.85, 0.90, 0.95, 1.0)

`BootStrapType` Standard + Grid Tuning. NULL value to default to catboost default (Bayesian for GPU and MVS for CPU). Random testing. Supply a single value for non-grid tuning cases. Otherwise, supply a vector for the BootStrapType values to test. For running grid tuning, a NULL value supplied will mean these values are tested c('Bayesian', 'Bernoulli', 'Poisson', 'MVS', 'No')

`GrowPolicy` Standard + Grid Tuning. Catboost default of SymmetricTree. Random testing. Default 'SymmetricTree', character, or vector for GrowPolicy to test. For grid tuning, supply a vector of values. For running grid tuning, a NULL value supplied will mean these values are tested c('SymmetricTree', 'Depthwise', 'Lossguide')

`langevin` Set to TRUE to enable

`diffusion_temperature`
Defaults to 10000

`model_size_reg` Defaults to 0.5. Set to 0 to allow for bigger models. This is for models with high cardinality categorical features. Valuues greater than 0 will shrink the model and quality will decline but models won't be huge.

`feature_border_type`
Defaults to 'GreedyLogSum'. Other options include: Median, Uniform, UniformAndQuantiles, MaxLogSum, MinEntropy

`sampling_unit` Default is Group. Other option is Object. if GPU is selected, this will be turned off unless the loss_function is YetiRankPairWise

`subsample` Default is NULL. Catboost will turn this into 0.66 for BootStrapTypes Poisson and Bernoulli. 0.80 for MVS. Doesn't apply to others.

`score_function` Default is Cosine. CPU options are Cosine and L2. GPU options are Cosine, L2, NewtonL2, and NewtomCosine (not available for Lossguide)

`min_data_in_leaf`
Default is 1. Cannot be used with SymmetricTree is GrowPolicy

Value

Saves to file and returned in list: VariableImportance.csv, Model, ValidationData.csv, EvalutionPlot.png, EvalutionBoxPlot.png, EvaluationMetrics.csv, ParDepPlots.R a named list of features with partial dependence calibration plots, ParDepBoxPlots.R, GridCollect, catboostgrid, and a transformation details file.

Author(s)

Adrian Antico

See Also

Other Automated Supervised Learning - Regression: AutoH2oDRFRegression(), AutoH2oGAMRegression(), AutoH2oGBMRegression(), AutoH2oGLMRegression(), AutoH2oMLRegression(), AutoLightGBMRegression(), AutoXGBoostRegression()

Examples

```
## Not run:
# Create some dummy correlated data
data <- AutoQuant::FakeDataGenerator(
  Correlation = 0.85,
  N = 10000,
  ID = 2,
  ZIP = 0,
  AddDate = FALSE,
  Classification = FALSE,
  MultiClass = FALSE)

# Run function
TestModel <- AutoQuant::AutoCatBoostRegression(

  # GPU or CPU and the number of available GPUs
  TrainOnFull = FALSE,
  task_type = 'GPU',
  NumGPUs = 1,
  DebugMode = FALSE,

  # Metadata args
  OutputSelection = c('Importances', 'EvalPlots', 'EvalMetrics', 'Score_TrainData'),
  ModelID = 'Test_Model_1',
  model_path = normalizePath('./'),
  metadata_path = normalizePath('./'),
  SaveModelObjects = FALSE,
  SaveInfoToPDF = FALSE,
  ReturnModelObjects = TRUE,

  # Data args
  data = data,
  ValidationData = NULL,
  TestData = NULL,
  TargetColumnName = 'Adrian',
  FeatureColNames = names(data)[!names(data) %in%
    c('IDcol_1', 'IDcol_2','Adrian')],
  PrimaryDateColumn = NULL,
  WeightsColumnName = NULL,
  IDcols = c('IDcol_1','IDcol_2'),
  EncodeMethod = 'credibility',
  TransformNumericColumns = 'Adrian',
  Methods = c('BoxCox', 'Asinh', 'Asin', 'Log',
    'LogPlus1', 'Sqrt', 'Logit'),

  # Model evaluation
```

```
  eval_metric = 'RMSE',
  eval_metric_value = 1.5,
  loss_function = 'RMSE',
  loss_function_value = 1.5,
  MetricPeriods = 10L,
  NumOfParDepPlots = ncol(data)-1L-2L,

  # Grid tuning args
  PassInGrid = NULL,
  GridTune = FALSE,
  MaxModelsInGrid = 30L,
  MaxRunsWithoutNewWinner = 20L,
  MaxRunMinutes = 60*60,
  BaselineComparison = 'default',

  # ML args
  langevin = FALSE,
  diffusion_temperature = 10000,
  Trees = 1000,
  Depth = 9,
  L2_Leaf_Reg = NULL,
  RandomStrength = 1,
  BorderCount = 128,
  LearningRate = NULL,
  RSM = 1,
  BootStrapType = NULL,
  GrowPolicy = 'SymmetricTree',
  model_size_reg = 0.5,
  feature_border_type = 'GreedyLogSum',
  sampling_unit = 'Object',
  subsample = NULL,
  score_function = 'Cosine',
  min_data_in_leaf = 1)

## End(Not run)
```

AutoCatBoostScoring *AutoCatBoostScoring*

Description

AutoCatBoostScoring is an automated scoring function that compliments the AutoCatBoost model training functions. This function requires you to supply features for scoring. It will run ModelDataPrep() to prepare your features for catboost data conversion and scoring.

Usage

```
AutoCatBoostScoring(
  TargetType = NULL,
  ScoringData = NULL,
  FeatureColumnNames = NULL,
  FactorLevelsList = NULL,
  IDcols = NULL,
  OneHot = FALSE,
```

```
  ReturnShapValues = FALSE,
  ModelObject = NULL,
  ModelPath = NULL,
  ModelID = NULL,
  ReturnFeatures = TRUE,
  MultiClassTargetLevels = NULL,
  TransformNumeric = FALSE,
  BackTransNumeric = FALSE,
  TargetColumnName = NULL,
  TransformationObject = NULL,
  TransID = NULL,
  TransPath = NULL,
  MDP_Impute = FALSE,
  MDP_CharToFactor = FALSE,
  MDP_RemoveDates = FALSE,
  MDP_MissFactor = "0",
  MDP_MissNum = -1,
  RemoveModel = FALSE,
  Debug = FALSE
)
```

Arguments

TargetType	Set this value to 'regression', 'classification', 'multiclass', or 'multiregression' to score models built using AutoCatBoostRegression(), AutoCatBoostClassifier() or AutoCatBoostMultiClass().
ScoringData	This is your data.table of features for scoring. Can be a single row or batch.
FeatureColumnNames	Supply either column names or column numbers used in the AutoCatBoostRegression() function
FactorLevelsList	List of factors levels to CharacterEncode()
IDcols	Supply ID column numbers for any metadata you want returned with your predicted values
OneHot	Passsed to DummifyD
ReturnShapValues	Set to TRUE to return a data.table of feature contributions to all predicted values generated
ModelObject	Supply the model object directly for scoring instead of loading it from file. If you supply this, ModelID and ModelPath will be ignored.
ModelPath	Supply your path file used in the AutoCatBoost__() function
ModelID	Supply the model ID used in the AutoCatBoost__() function
ReturnFeatures	Set to TRUE to return your features with the predicted values.
MultiClassTargetLevels	For use with AutoCatBoostMultiClass(). If you saved model objects then this scoring function will locate the target levels file. If you did not save model objects, you can supply the target levels returned from AutoCatBoostMultiClass().
TransformNumeric	Set to TRUE if you have features that were transformed automatically from an Auto__Regression() model AND you haven't already transformed them.

`BackTransNumeric`
: Set to TRUE to generate back-transformed predicted values. Also, if you return features, those will also be back-transformed.

`TargetColumnName`
: Input your target column name used in training if you are utilizing the transformation service

`TransformationObject`
: Set to NULL if you didn't use transformations or if you want the function to pull from the file output from the Auto__Regression() function. You can also supply the transformation data.table object with the transformation details versus having it pulled from file.

`TransID`
: Set to the ID used for saving the transformation data.table object or set it to the ModelID if you are pulling from file from a build with Auto__Regression().

`TransPath`
: Set the path file to the folder where your transformation data.table detail object is stored. If you used the Auto__Regression() to build, set it to the same path as ModelPath.

`MDP_Impute`
: Set to TRUE if you did so for modeling and didn't do so before supplying ScoringData in this function

`MDP_CharToFactor`
: Set to TRUE to turn your character columns to factors if you didn't do so to your ScoringData that you are supplying to this function

`MDP_RemoveDates`
: Set to TRUE if you have date of timestamp columns in your ScoringData

`MDP_MissFactor`
: If you set MDP_Impute to TRUE, supply the character values to replace missing values with

`MDP_MissNum`
: If you set MDP_Impute to TRUE, supply a numeric value to replace missing values with

`RemoveModel`
: Set to TRUE if you want the model removed immediately after scoring

`Debug`
: = FALSE

Value

A data.table of predicted values with the option to return model features as well.

Author(s)

Adrian Antico

See Also

Other Automated Model Scoring: `AutoH2OMLScoring()`, `AutoLightGBMScoring()`, `AutoXGBoostScoring()`

Examples

```
## Not run:

# CatBoost Regression Example

# Create some dummy correlated data
data <- AutoQuant::FakeDataGenerator(
  Correlation = 0.85,
```

```
  N = 10000,
  ID = 2,
  ZIP = 0,
  AddDate = FALSE,
  Classification = FALSE,
  MultiClass = FALSE)

# Copy data
data1 <- data.table::copy(data)

# Run function
TestModel <- AutoQuant::AutoCatBoostRegression(

  # GPU or CPU and the number of available GPUs
  TrainOnFull = FALSE,
  task_type = 'CPU',
  NumGPUs = 1,
  DebugMode = FALSE,

  # Metadata args
  OutputSelection = c('Importances','EvalPlots','EvalMetrics','Score_TrainData'),
  ModelID = 'Test_Model_1',
  model_path = getwd(),
  metadata_path = getwd(),
  SaveModelObjects = FALSE,
  SaveInfoToPDF = FALSE,
  ReturnModelObjects = TRUE,

  # Data args
  data = data1,
  ValidationData = NULL,
  TestData = NULL,
  TargetColumnName = 'Adrian',
  FeatureColNames = names(data1)[!names(data1) %in% c('IDcol_1', 'IDcol_2','Adrian')],
  PrimaryDateColumn = NULL,
  WeightsColumnName = NULL,
  IDcols = c('IDcol_1','IDcol_2'),
  TransformNumericColumns = 'Adrian',
  Methods = c('Asinh','Asin','Log','LogPlus1','Sqrt','Logit'),

  # Model evaluation
  eval_metric = 'RMSE',
  eval_metric_value = 1.5,
  loss_function = 'RMSE',
  loss_function_value = 1.5,
  MetricPeriods = 10L,
  NumOfParDepPlots = ncol(data1)-1L-2L,

  # Grid tuning args
  PassInGrid = NULL,
  GridTune = FALSE,
  MaxModelsInGrid = 30L,
  MaxRunsWithoutNewWinner = 20L,
  MaxRunMinutes = 60*60,
  BaselineComparison = 'default',

  # ML args
```

```
  langevin = FALSE,
  diffusion_temperature = 10000,
  Trees = 1000,
  Depth = 9,
  L2_Leaf_Reg = NULL,
  RandomStrength = 1,
  BorderCount = 128,
  LearningRate = NULL,
  RSM = 1,
  BootStrapType = NULL,
  GrowPolicy = 'SymmetricTree',
  model_size_reg = 0.5,
  feature_border_type = 'GreedyLogSum',
  sampling_unit = 'Object',
  subsample = NULL,
  score_function = 'Cosine',
  min_data_in_leaf = 1)

# Trained Model Object
TestModel$Model

# Train Data (includes validation data) and Test Data with predictions and shap values
TestModel$TrainData
TestModel$TestData

# Calibration Plots
TestModel$PlotList$Train_EvaluationPlot
TestModel$PlotList$Test_EvaluationPlot

# Calibration Box Plots
TestModel$PlotList$Train_EvaluationBoxPlot
TestModel$PlotList$Test_EvaluationBoxPlot

# Residual Analysis Plots
TestModel$PlotList$Train_ResidualsHistogram
TestModel$PlotList$Test_ResidualsHistogram

# Preds vs Actuals Scatterplots
TestModel$PlotList$Train_ScatterPlot
TestModel$PlotList$Test_ScatterPlot

# Preds vs Actuals Copula Plot
TestModel$PlotList$Train_CopulaPlot
TestModel$PlotList$Test_CopulaPlot

# Variable Importance Plots
TestModel$PlotList$Train_VariableImportance
TestModel$PlotList$Validation_VariableImportance
TestModel$PlotList$Test_VariableImportance

# Evaluation Metrics
TestModel$EvaluationMetrics$TrainData
TestModel$EvaluationMetrics$TestData

# Variable Importance Tables
TestModel$VariableImportance$Train_Importance
TestModel$VariableImportance$Validation_Importance
```

```
TestModel$VariableImportance$Test_Importance

# Interaction Importance
TestModel$InteractionImportance$Train_Interaction
TestModel$InteractionImportance$Validation_Interaction
TestModel$InteractionImportance$Test_Interaction

# Meta Data
TestModel$ColNames
TestModel$TransformationResults
TestModel$GridList

# Score data
Preds <- AutoQuant::AutoCatBoostScoring(
  TargetType = 'regression',
  ScoringData = data,
  FeatureColumnNames = names(data)[!names(data) %in% c('IDcol_1', 'IDcol_2','Adrian')],
  FactorLevelsList = TestModel$FactorLevelsList,
  IDcols = c('IDcol_1','IDcol_2'),
  OneHot = FALSE,
  ReturnShapValues = TRUE,
  ModelObject = TestModel$Model,
  ModelPath = NULL,
  ModelID = 'Test_Model_1',
  ReturnFeatures = TRUE,
  MultiClassTargetLevels = NULL,
  TransformNumeric = FALSE,
  BackTransNumeric = FALSE,
  TargetColumnName = NULL,
  TransformationObject = NULL,
  TransID = NULL,
  TransPath = NULL,
  MDP_Impute = TRUE,
  MDP_CharToFactor = TRUE,
  MDP_RemoveDates = TRUE,
  MDP_MissFactor = '0',
  MDP_MissNum = -1,
  RemoveModel = FALSE)

  # Step through scoring function
  library(AutoQuant)
  library(data.table)
  TargetType = 'regression'
  ScoringData = data
  FeatureColumnNames = names(data)[!names(data) %in% c('IDcol_1', 'IDcol_2','Adrian')]
  FactorLevelsList = TestModel$FactorLevelsList
  IDcols = c('IDcol_1','IDcol_2')
  OneHot = FALSE
  ReturnShapValues = TRUE
  ModelObject = TestModel$Model
  ModelPath = NULL
  ModelID = 'Test_Model_1'
  ReturnFeatures = TRUE
  MultiClassTargetLevels = NULL
  TransformNumeric = FALSE
  BackTransNumeric = FALSE
  TargetColumnName = NULL
```

```
  TransformationObject = NULL
  TransID = NULL
  TransPath = NULL
  MDP_Impute = TRUE
  MDP_CharToFactor = TRUE
  MDP_RemoveDates = TRUE
  MDP_MissFactor = '0'
  MDP_MissNum = -1
  RemoveModel = FALSE
  Debug = TRUE

## End(Not run)
```

`AutoClustering` *AutoClustering*

Description

AutoClustering adds a column to your original data with a cluster number identifier. You can run request an autoencoder to be built to reduce the dimensionality of your data before running the clusering algo.

Usage

```
AutoClustering(
  data,
  FeatureColumns = NULL,
  ModelID = "TestModel",
  SavePath = NULL,
  NThreads = 8,
  MaxMemory = "28G",
  MaxClusters = 50,
  ClusterMetric = "totss",
  RunDimReduction = TRUE,
  ShrinkRate = (sqrt(5) - 1)/2,
  Epochs = 5L,
  L2_Reg = 0.1,
  ElasticAveraging = TRUE,
  ElasticAveragingMovingRate = 0.9,
  ElasticAveragingRegularization = 0.001
)
```

Arguments

`data`	is the source time series data.table
`FeatureColumns`	Independent variables
`ModelID`	For naming the files to save
`SavePath`	Directory path for saving models
`NThreads`	set based on number of threads your machine has available
`MaxMemory`	set based on the amount of memory your machine has available

MaxClusters	number of factors to test out in k-means to find the optimal number
ClusterMetric	pick the metric to identify top model in grid tune c('totss','betweenss','withinss')
RunDimReduction	If TRUE, an autoencoder will be built to reduce the feature space. Otherwise, all features in FeatureColumns will be used for clustering
ShrinkRate	Node shrink rate for H2OAutoencoder. See that function for details.
Epochs	For the autoencoder
L2_Reg	For the autoencoder
ElasticAveraging	For the autoencoder
ElasticAveragingMovingRate	For the autoencoder
ElasticAveragingRegularization	For the autoencoder

Value

Original data.table with added column with cluster number identifier

Author(s)

Adrian Antico

See Also

Other Unsupervised Learning: AutoClusteringScoring(), GenTSAnomVars(), H2OIsolationForestScoring(), H2OIsolationForest(), ResidualOutliers()

Examples

```
## Not run:
#########################
# Training Setup
#########################

# Create fake data
data <- AutoQuant::FakeDataGenerator(
  Correlation = 0.85,
  N = 1000,
  ID = 2,
  ZIP = 0,
  AddDate = TRUE,
  Classification = FALSE,
  MultiClass = FALSE)

# Run function
data <- AutoQuant::AutoClustering(
  data,
  FeatureColumns = names(data)[2:(ncol(data)-1)],
  ModelID = 'TestModel',
  SavePath = getwd(),
  NThreads = 8,
  MaxMemory = '28G',
  MaxClusters = 50,
```

```
  ClusterMetric = 'totss',
  RunDimReduction = TRUE,
  ShrinkRate = (sqrt(5) - 1) / 2,
  Epochs = 5L,
  L2_Reg = 0.10,
  ElasticAveraging = TRUE,
  ElasticAveragingMovingRate = 0.90,
  ElasticAveragingRegularization = 0.001)

#########################
# Scoring Setup
#########################

Sys.sleep(10)

# Create fake data
data <- AutoQuant::FakeDataGenerator(
  Correlation = 0.85,
  N = 1000,
  ID = 2,
  ZIP = 0,
  AddDate = TRUE,
  Classification = FALSE,
  MultiClass = FALSE)

# Run function
data <- AutoQuant::AutoClusteringScoring(
  data,
  FeatureColumns = names(data)[2:(ncol(data)-1)],
  ModelID = 'TestModel',
  SavePath = getwd(),
  NThreads = 8,
  MaxMemory = '28G',
  DimReduction = TRUE)

## End(Not run)
```

`AutoClusteringScoring` *AutoClusteringScoring*

Description

AutoClusteringScoring adds a column to your original data with a cluster number identifier. You can run request an autoencoder to be built to reduce the dimensionality of your data before running the clusering algo.

Usage

```
AutoClusteringScoring(
  data,
  FeatureColumns = NULL,
  ModelID = "TestModel",
  SavePath = NULL,
```

```
  NThreads = 8,
  MaxMemory = "28G",
  DimReduction = TRUE
)
```

Arguments

data	is the source time series data.table
FeatureColumns	Independent variables
ModelID	This is returned from the training run in the output list with element named 'model_name'. It's not identical to the ModelID used in training due to the grid tuning.
SavePath	Directory path for saving models
NThreads	set based on number of threads your machine has available
MaxMemory	set based on the amount of memory your machine has available
DimReduction	Set to TRUE if you set RunDimReduction in the training version of this function

Value

Original data.table with added column with cluster number identifier

Author(s)

Adrian Antico

See Also

Other Unsupervised Learning: AutoClustering(), GenTSAnomVars(), H2OIsolationForestScoring(), H2OIsolationForest(), ResidualOutliers()

Examples

```
## Not run:
#########################
# Training Setup
#########################

# Create fake data
data <- AutoQuant::FakeDataGenerator(
  Correlation = 0.85,
  N = 1000,
  ID = 2,
  ZIP = 0,
  AddDate = TRUE,
  Classification = FALSE,
  MultiClass = FALSE)

# Run function
data <- AutoQuant::AutoClustering(
  data,
  FeatureColumns = names(data)[2:(ncol(data)-1)],
  ModelID = 'TestModel',
  SavePath = getwd(),
  NThreads = 8,
```

```
  MaxMemory = '28G',
  MaxClusters = 50,
  ClusterMetric = 'totss',
  RunDimReduction = TRUE,
  ShrinkRate = (sqrt(5) - 1) / 2,
  Epochs = 5L,
  L2_Reg = 0.10,
  ElasticAveraging = TRUE,
  ElasticAveragingMovingRate = 0.90,
  ElasticAveragingRegularization = 0.001)

##########################
# Scoring Setup
##########################

Sys.sleep(10)

# Create fake data
data <- AutoQuant::FakeDataGenerator(
  Correlation = 0.85,
  N = 1000,
  ID = 2,
  ZIP = 0,
  AddDate = TRUE,
  Classification = FALSE,
  MultiClass = FALSE)

# Run function
data <- AutoQuant::AutoClusteringScoring(
  data,
  FeatureColumns = names(data)[2:(ncol(data)-1)],
  ModelID = 'TestModel',
  SavePath = getwd(),
  NThreads = 8,
  MaxMemory = '28G',
  DimReduction = TRUE)

## End(Not run)
```

AutoDataDictionaries *AutoDataDictionaries*

Description

AutoDataDictionaries is a function to return data dictionary data in table form

Usage

```
AutoDataDictionaries(
  Type = "sqlserver",
  DBConnection,
  DDType = 1L,
  Query = NULL,
```

```
  ASIS = FALSE,
  CloseChannel = TRUE
)
```

Arguments

Type	= "sqlserver" is currently the only system supported
DBConnection	This is a RODBC connection object for sql server
DDType	Select from 1 - 6 based on this article
Query	Supply a query
ASIS	Set to TRUE to pull in values without coercing types
CloseChannel	Set to TRUE to disconnect

Author(s)

Adrian Antico

See Also

Other Database: PostGRE_AppendData(), PostGRE_CreateTable(), PostGRE_GetTableNames(), PostGRE_ListTables(), PostGRE_Query(), PostGRE_RemoveCreateAppend(), PostGRE_RemoveTable(), PosteGRE_CreateDatabase(), PosteGRE_DropDB(), PosteGRE_ListDatabases(), SQL_ClearTable(), SQL_DropTable(), SQL_Query_Push(), SQL_Query(), SQL_SaveTable(), SQL_Server_DBConnection()

AutoDataPartition *AutoDataPartition*

Description

This function will take your ratings matrix and model and score your data in parallel.

Usage

```
AutoDataPartition(
  data,
  NumDataSets = 3L,
  Ratios = c(0.7, 0.2, 0.1),
  PartitionType = "random",
  StratifyColumnNames = NULL,
  TimeColumnName = NULL
)
```

Arguments

data	Source data to do your partitioning on
NumDataSets	The number of total data sets you want built
Ratios	A vector of values for how much data each data set should get in each split. E.g. c(0.70, 0.20, 0.10)

`PartitionType` Set to either "random", "timeseries", or "time". With "random", your data will be paritioned randomly (with stratified sampling if column names are supplied). With "timeseries", you can partition by time with a stratify option (so long as you have an equal number of records for each strata). With "time" you will have data sets generated so that the training data contains the earliest records in time, validation data the second earliest, test data the third earliest, etc.

`StratifyColumnNames`
Supply column names of categorical features to use in a stratified sampling procedure for partitioning the data. Partition type must be "random" to use this option

`TimeColumnName` Supply a date column name or a name of a column with an ID for sorting by time such that the smallest number is the earliest in time.

Value

Returns a list of data.tables

Author(s)

Adrian Antico

See Also

Other Feature Engineering: `AutoDiffLagN()`, `AutoHierarchicalFourier()`, `AutoInteraction()`, `AutoLagRollMode()`, `AutoLagRollStatsScoring()`, `AutoLagRollStats()`, `AutoTransformationCreate()`, `AutoTransformationScore()`, `AutoWord2VecModeler()`, `AutoWord2VecScoring()`, `CategoricalEncoding()`, `CreateCalendarVariables()`, `CreateHolidayVariables()`, `DummifyDT()`, `H2OAutoencoderScoring()`, `H2OAutoencoder()`, `ModelDataPrep()`, `PercRankScoring()`, `PercRank()`, `StandardizeScoring()`, `Standardize()`, `TimeSeriesFillRoll()`, `TimeSeriesFill()`

Examples

```
# Create fake data
data <- AutoQuant::FakeDataGenerator(
  Correlation = 0.85,
  N = 1000,
  ID = 2,
  ZIP = 0,
  AddDate = FALSE,
  Classification = FALSE,
  MultiClass = FALSE)

# Run data partitioning function
dataSets <- AutoQuant::AutoDataPartition(
  data,
  NumDataSets = 3L,
  Ratios = c(0.70,0.20,0.10),
  PartitionType = "random",
  StratifyColumnNames = NULL,
  TimeColumnName = NULL)

# Collect data
TrainData <- dataSets$TrainData
ValidationData <- dataSets$ValidationData
TestData <- dataSets$TestData
```

AutoDiffLagN *AutoDiffLagN*

Description

AutoDiffLagN create differences for selected numerical columns

Usage

```
AutoDiffLagN(
  data,
  DateVariable = NULL,
  GroupVariables = NULL,
  DiffVariables = NULL,
  DiffDateVariables = NULL,
  DiffGroupVariables = NULL,
  NLag1 = 0L,
  NLag2 = 1L,
  Type = "lag",
  Sort = FALSE,
  RemoveNA = TRUE
)
```

Arguments

data	Source data
DateVariable	Date column used for sorting
GroupVariables	Difference data by group
DiffVariables	Column names of numeric columns to difference
DiffDateVariables	Columns names for date variables to difference. Output is a numeric value representing the difference in days.
DiffGroupVariables	Column names for categorical variables to difference. If no change then the output is 'No_Change' else 'New=NEWVAL Old=OLDVAL' where NEWVAL and OLDVAL are placeholders for the actual values
NLag1	If the diff calc, we have column 1 - column 2. NLag1 is in reference to column 1. If you want to take the current value minus the previous weeks value, supply a zero. If you want to create a lag2 - lag4 NLag1 gets a 2.
NLag2	If the diff calc, we have column 1 - column 2. NLag2 is in reference to column 2. If you want to take the current value minus the previous weeks value, supply a 1. If you want to create a lag2 - lag4 NLag1 gets a 4.
Type	'lag' or 'lead'
Sort	TRUE to sort your data inside the function
RemoveNA	Set to TRUE to remove rows with NA generated by the lag operation

Author(s)

Adrian Antico

See Also

Other Feature Engineering: AutoDataPartition(), AutoHierarchicalFourier(), AutoInteraction(), AutoLagRollMode(), AutoLagRollStatsScoring(), AutoLagRollStats(), AutoTransformationCreate(), AutoTransformationScore(), AutoWord2VecModeler(), AutoWord2VecScoring(), CategoricalEncoding(), CreateCalendarVariables(), CreateHolidayVariables(), DummifyDT(), H2OAutoencoderScoring(), H2OAutoencoder(), ModelDataPrep(), PercRankScoring(), PercRank(), StandardizeScoring(), Standardize(), TimeSeriesFillRoll(), TimeSeriesFill()

Examples

```
## Not run:

# Create fake data
data <- AutoQuant::FakeDataGenerator(
  Correlation = 0.70,
  N = 50000,
  ID = 2L,
  FactorCount = 3L,
  AddDate = TRUE,
  ZIP = 0L,
  TimeSeries = FALSE,
  ChainLadderData = FALSE,
  Classification = FALSE,
  MultiClass = FALSE)

# Store Cols to diff
Cols <- names(data)[which(unlist(data[, lapply(.SD, is.numeric)]))]

# Clean data before running AutoDiffLagN
data <- AutoQuant::ModelDataPrep(data = data, Impute = FALSE, CharToFactor = FALSE, FactorToChar = TRUE)

# Run function
data <- AutoQuant::AutoDiffLagN(
  data,
  DateVariable = "DateTime",
  GroupVariables = c("Factor_1", "Factor_2"),
  DiffVariables = Cols,
  DiffDateVariables = NULL,
  DiffGroupVariables = NULL,
  NLag1 = 0L,
  NLag2 = 1L,
  Sort = TRUE,
  RemoveNA = TRUE)

## End(Not run)
```

AutoETS *AutoETS*

Description

AutoETS is a multi-armed bandit model testing framework for AR and SAR NNets. Randomized probability matching is the underlying bandit algorithm. Model evaluation is done by blending the training error and the validation error from testing the model on out of sample data. The bandit algorithm compares the performance of the current build against the previous builds which starts with the classic nnetar model from the forecast package. Depending on how many lags, seasonal lags, and fourier pairs you test the number of combinations of features to test begins to approach 10,000 different combinations of settings. The function tests out transformations, differencing, and variations of the lags, seasonal lags, and fourier pairs. The paramter space is broken up into various buckets that are increasing in sophistication. The bandit algorithm samples from those buckets and based on many rounds of testing it determines which buckets to generate samples from more frequently based on the models performance coming from that bucket. All of the models have performance data collected on them and a final rebuild is initiated when a winner is found. The rebuild process begins by retraining the model with the settings that produced the best performance. If the model fails to build, for whatever reason, the next best buildable model is rebuilt.

Usage

```
AutoETS(
  data,
  FilePath = NULL,
  TargetVariableName,
  DateColumnName,
  TimeAggLevel = "week",
  EvaluationMetric = "MAE",
  NumHoldOutPeriods = 5L,
  NumFCPeriods = 5L,
  TrainWeighting = 0.5,
  MaxConsecutiveFails = 12L,
  MaxNumberModels = 100L,
  MaxRunTimeMinutes = 10L,
  NumberCores = max(1L, min(4L, parallel::detectCores() - 2L))
)
```

Arguments

`data`	Source data.table
`FilePath`	NULL to return nothing. Provide a file path to save the model and xregs if available
`TargetVariableName`	Name of your time series target variable
`DateColumnName`	Name of your date column
`TimeAggLevel`	Choose from "year", "quarter", "month", "week", "day", "hour"
`EvaluationMetric`	Choose from MAE, MSE, and MAPE

`NumHoldOutPeriods`
: Number of time periods to use in the out of sample testing

`NumFCPeriods`
: Number of periods to forecast

`TrainWeighting`
: Model ranking is based on a weighted average of training metrics and out of sample metrics. Supply the weight of the training metrics, such as 0.50 for 50 percent.

`MaxConsecutiveFails`
: When a new best model is found MaxConsecutiveFails resets to zero. Indicated the number of model attemps without a new winner before terminating the procedure.

`MaxNumberModels`
: Indicate the maximum number of models to test.

`MaxRunTimeMinutes`
: Indicate the maximum number of minutes to wait for a result.

`NumberCores`
: Default max(1L, min(4L, parallel::detectCores()-2L))

Author(s)

Adrian Antico

See Also

Other Automated Time Series: `AutoArfima()`, `AutoBanditNNet()`, `AutoBanditSarima()`, `AutoTBATS()`

Examples

```
## Not run:
# Create fake data
data <- AutoQuant::FakeDataGenerator(TimeSeries = TRUE, TimeSeriesTimeAgg = "days")

# Build model
Output <- AutoQuant::AutoETS(
  data,
  FilePath = NULL,
  TargetVariableName = "Weekly_Sales",
  DateColumnName = "Date",
  TimeAggLevel = "weeks",
  EvaluationMetric = "MAE",
  NumHoldOutPeriods = 5L,
  NumFCPeriods = 5L,
  TrainWeighting = 0.50,
  MaxConsecutiveFails = 12L,
  MaxNumberModels = 100L,
  MaxRunTimeMinutes = 10L,
  NumberCores = max(1L, min(4L, parallel::detectCores()-2L)))

# Output
Output$ForecastPlot
Output$Forecast
Output$PerformanceGrid

## End(Not run)
```

AutoH2OCARMA *AutoH2OCARMA*

Description

AutoH2OCARMA Mutlivariate Forecasting with calendar variables, Holiday counts, holiday lags, holiday moving averages, differencing, transformations, interaction-based categorical encoding using target variable and features to generate various time-based aggregated lags, moving averages, moving standard deviations, moving skewness, moving kurtosis, moving quantiles, parallelized interaction-based fourier pairs by grouping variables, and Trend Variables.

Usage

```
AutoH2OCARMA(
  AlgoType = "drf",
  ExcludeAlgos = "XGBoost",
  data,
  TrainOnFull = FALSE,
  TargetColumnName = "Target",
  PDFOutputPath = NULL,
  SaveDataPath = NULL,
  TimeWeights = NULL,
  NonNegativePred = FALSE,
  RoundPreds = FALSE,
  DateColumnName = "DateTime",
  GroupVariables = NULL,
  HierarchGroups = NULL,
  TimeUnit = "week",
  TimeGroups = c("weeks", "months"),
  FC_Periods = 30,
  PartitionType = "timeseries",
  MaxMem = {
     gc()

   paste0(as.character(floor(as.numeric(system("awk '/MemFree/ {print $2}' /proc/meminfo",
     intern = TRUE))/1e+06)), "G")
 },
  NThreads = max(1, parallel::detectCores() - 2),
  Timer = TRUE,
  DebugMode = FALSE,
  TargetTransformation = FALSE,
 Methods = c("YeoJohnson", "BoxCox", "Asinh", "Log", "LogPlus1", "Sqrt", "Asin",
    "Logit"),
  XREGS = NULL,
  Lags = c(1:5),
  MA_Periods = c(1:5),
  SD_Periods = NULL,
  Skew_Periods = NULL,
  Kurt_Periods = NULL,
  Quantile_Periods = NULL,
  Quantiles_Selected = NULL,
```

```
  AnomalyDetection = NULL,
  Difference = TRUE,
  FourierTerms = 6,
  CalendarVariables = c("second", "minute", "hour", "wday", "mday", "yday", "week",
    "wom", "isoweek", "month", "quarter", "year"),
  HolidayVariable = c("USPublicHolidays", "EasterGroup", "ChristmasGroup",
    "OtherEcclesticalFeasts"),
  HolidayLookback = NULL,
  HolidayLags = 1,
  HolidayMovingAverages = 1:2,
  TimeTrendVariable = FALSE,
  DataTruncate = FALSE,
  ZeroPadSeries = NULL,
  SplitRatios = c(0.7, 0.2, 0.1),
  EvalMetric = "rmse",
  NumOfParDepPlots = 0L,
  GridTune = FALSE,
  ModelCount = 1,
  NTrees = 1000,
  LearnRate = 0.1,
  LearnRateAnnealing = 1,
  GridStrategy = "Cartesian",
  MaxRunTimeSecs = 60 * 60 * 24,
  StoppingRounds = 10,
  MaxDepth = 20,
  SampleRate = 0.632,
  MTries = -1,
  ColSampleRate = 1,
  ColSampleRatePerTree = 1,
  ColSampleRatePerTreeLevel = 1,
  MinRows = 1,
  NBins = 20,
  NBinsCats = 1024,
  NBinsTopLevel = 1024,
  CategoricalEncoding = "AUTO",
  HistogramType = "AUTO",
  Distribution = "gaussian",
  Link = "identity",
  RandomDistribution = NULL,
  RandomLink = NULL,
  Solver = "AUTO",
  Alpha = NULL,
  Lambda = NULL,
  LambdaSearch = FALSE,
  NLambdas = -1,
  Standardize = TRUE,
  RemoveCollinearColumns = FALSE,
  InterceptInclude = TRUE,
  NonNegativeCoefficients = FALSE,
  RandomColNumbers = NULL,
  InteractionColNumbers = NULL
)
```

Arguments

AlgoType	Select from "dfr" for RandomForecast, "gbm" for gradient boosting, "glm" for generalized linear model, "automl" for H2O's AutoML algo, and "gam" for H2O's Generalized Additive Model.
ExcludeAlgos	For use when AlgoType = "AutoML". Selections include "DRF","GLM","XGBoost","GBM","DeepL and "Stacke-dEnsemble"
data	Supply your full series data set here
TrainOnFull	Set to TRUE to train on full data
TargetColumnName	List the column name of your target variables column. E.g. "Target"
PDFOutputPath	NULL or a path file to output PDFs to a specified folder
SaveDataPath	NULL Or supply a path. Data saved will be called 'ModelID'_data.csv
TimeWeights	1 or a value between zero and 1. Data will be weighted less and less the more historic it gets, by group
NonNegativePred	TRUE or FALSE
RoundPreds	Rounding predictions to an integer value. TRUE or FALSE. Defaults to FALSE
DateColumnName	List the column name of your date column. E.g. "DateTime"
GroupVariables	Defaults to NULL. Use NULL when you have a single series. Add in GroupVariables when you have a series for every level of a group or multiple groups.
HierarchGroups	Vector of hierachy categorical columns.
TimeUnit	List the time unit your data is aggregated by. E.g. "1min", "5min", "10min", "15min", "30min", "hour", "day", "week", "month", "quarter", "year".
TimeGroups	Select time aggregations for adding various time aggregated GDL features.
FC_Periods	Set the number of periods you want to have forecasts for. E.g. 52 for weekly data to forecast a year ahead
PartitionType	Select "random" for random data partitioning "time" for partitioning by time frames
MaxMem	Set to the maximum amount of memory you want to allow for running this function. Default is "32G".
NThreads	Set to the number of threads you want to dedicate to this function.
Timer	Set to FALSE to turn off the updating print statements for progress
DebugMode	Defaults to FALSE. Set to TRUE to get a print statement of each high level comment in function
TargetTransformation	Run AutoTransformationCreate() to find best transformation for the target variable. Tests YeoJohnson, BoxCox, and Asigh (also Asin and Logit for proportion target variables).
Methods	Choose from "YeoJohnson", "BoxCox", "Asinh", "Log", "LogPlus1", "Sqrt", "Asin", or "Logit". If more than one is selected, the one with the best normalization pearson statistic will be used. Identity is automatically selected and compared.
XREGS	Additional data to use for model development and forecasting. Data needs to be a complete series which means both the historical and forward looking values over the specified forecast window needs to be supplied.

`Lags` Select the periods for all lag variables you want to create. E.g. c(1:5,52) or list("day" = c(1:10), "weeks" = c(1:4))

`MA_Periods` Select the periods for all moving average variables you want to create. E.g. c(1:5,52) or list("day" = c(2:10), "weeks" = c(2:4))

`SD_Periods` Select the periods for all moving standard deviation variables you want to create. E.g. c(1:5,52) or list("day" = c(2:10), "weeks" = c(2:4))

`Skew_Periods` Select the periods for all moving skewness variables you want to create. E.g. c(1:5,52) or list("day" = c(2:10), "weeks" = c(2:4))

`Kurt_Periods` Select the periods for all moving kurtosis variables you want to create. E.g. c(1:5,52) or list("day" = c(2:10), "weeks" = c(2:4))

`Quantile_Periods`
Select the periods for all moving quantiles variables you want to create. E.g. c(1:5,52) or list("day" = c(2:10), "weeks" = c(2:4))

`Quantiles_Selected`
Select from the following c("q5","q10","q15","q20","q25","q30","q35","q40","q45","q50","q55","q6

`AnomalyDetection`
NULL for not using the service. Other, provide a list, e.g. AnomalyDetection = list("tstat_high" = 4, tstat_low = -4)

`Difference` Puts the I in ARIMA for single series and grouped series.

`FourierTerms` Set to the max number of pairs. E.g. 2 means to generate two pairs for by each group level and interations if hierarchy is enabled.

`CalendarVariables`
NULL, or select from "second", "minute", "hour", "wday", "mday", "yday", "week", "isoweek", "month", "quarter", "year"

`HolidayVariable`
NULL, or select from "USPublicHolidays", "EasterGroup", "ChristmasGroup", "OtherEcclesticalFeasts"

`HolidayLookback`
Number of days in range to compute number of holidays from a given date in the data. If NULL, the number of days are computed for you.

`HolidayLags` Number of lags to build off of the holiday count variable.

`HolidayMovingAverages`
Number of moving averages to build off of the holiday count variable.

`TimeTrendVariable`
Set to TRUE to have a time trend variable added to the model. Time trend is numeric variable indicating the numeric value of each record in the time series (by group). Time trend starts at 1 for the earliest point in time and increments by one for each success time point.

`DataTruncate` Set to TRUE to remove records with missing values from the lags and moving average features created

`ZeroPadSeries` NULL to do nothing. Otherwise, set to "maxmax", "minmax", "maxmin", "minmin". See `TimeSeriesFill` for explanations of each type

`SplitRatios` E.g c(0.7,0.2,0.1) for train, validation, and test sets

`EvalMetric` Select from "RMSE", "MAE", "MAPE", "Poisson", "Quantile", "LogLinQuantile", "Lq", "SMAPE", "R2", "MSLE", "MedianAbsoluteError"

`NumOfParDepPlots`
Set to zeros if you do not want any returned. Can set to a very large value and it will adjust to the max number of features if it's too high

GridTune Set to TRUE to run a grid tune

ModelCount Set the number of models to try in the grid tune

NTrees Select the number of trees you want to have built to train the model

LearnRate Default 0.10, models available include gbm

LearnRateAnnealing
Default 1, models available include gbm

GridStrategy Default "Cartesian", models available include

MaxRunTimeSecs Default 60*60*24, models available include

StoppingRounds Default 10, models available include

MaxDepth Default 20, models available include drf, gbm

SampleRate Default 0.632, models available include drf, gbm

MTries Default 1, models available include drf

ColSampleRate Default 1, model available include gbm

ColSampleRatePerTree
Default 1, models available include drf, gbm

ColSampleRatePerTreeLevel
Default 1, models available include drf, gbm

MinRows Default 1, models available include drf, gbm

NBins Default 20, models available include drf, gbm

NBinsCats Default 1024, models available include drf, gbm

NBinsTopLevel Default 1024, models available include drf, gbm

CategoricalEncoding
Default "AUTO". Choices include : "AUTO", "Enum", "OneHotInternal", "OneHotExplicit", "Binary", "Eigen", "LabelEncoder", "Sort-ByResponse", "EnumLimited"

HistogramType Default "AUTO". Select from "AUTO", "UniformAdaptive", "Random", "QuantilesGlobal", "RoundRobin"

Distribution Model family

Link Link for model family

RandomDistribution
Default NULL

RandomLink Default NULL

Solver Model optimizer

Alpha Default NULL

Lambda Default NULL

LambdaSearch Default FALSE,

NLambdas Default -1

Standardize Default TRUE

RemoveCollinearColumns
Default FALSE

InterceptInclude
Default TRUE

NonNegativeCoefficients
Default FALSE

RandomColNumbers
NULL

InteractionColNumbers
NULL

Value

See examples

Author(s)

Adrian Antico

See Also

Other Automated Panel Data Forecasting: AutoCatBoostCARMA(), AutoLightGBMCARMA(), AutoXGBoostCARMA()

Examples

```
## Not run:

# Load data
data <- data.table::fread("https://www.dropbox.com/s/2str3ek4f4cheqi/walmart_train.csv?dl=1")

# Ensure series have no missing dates (also remove series with more than 25% missing values)
data <- AutoQuant::TimeSeriesFill(
  data,
  DateColumnName = "Date",
  GroupVariables = c("Store","Dept"),
  TimeUnit = "weeks",
  FillType = "maxmax",
  MaxMissingPercent = 0.25,
  SimpleImpute = TRUE)

# Set negative numbers to 0
data <- data[, Weekly_Sales := data.table::fifelse(Weekly_Sales < 0, 0, Weekly_Sales)]

# Remove IsHoliday column
data[, IsHoliday := NULL]

# Create xregs (this is the include the categorical variables instead of utilizing only the interaction of them)
xregs <- data[, .SD, .SDcols = c("Date", "Store", "Dept")]

# Change data types
data[, ":=" (Store = as.character(Store), Dept = as.character(Dept))]
xregs[, ":=" (Store = as.character(Store), Dept = as.character(Dept))]

# Build forecast
Results <- AutoQuant::AutoH2OCARMA(

  # Data Artifacts
  AlgoType = "drf",
  ExcludeAlgos = NULL,
  data = data,
  TargetColumnName = "Weekly_Sales",
  DateColumnName = "Date",
  HierarchGroups = NULL,
  GroupVariables = c("Dept"),
  TimeUnit = "week",
  TimeGroups = c("weeks","months"),

  # Data Wrangling Features
```

```
  SplitRatios = c(1 - 10 / 138, 10 / 138),
  PartitionType = "random",

  # Production args
  FC_Periods = 4L,
  TrainOnFull = FALSE,
 MaxMem = {gc();paste0(as.character(floor(max(32, as.numeric(system("awk '/MemFree/ {print $2}' /proc/meminfo
  NThreads = parallel::detectCores(),
  PDFOutputPath = NULL,
  SaveDataPath = NULL,
  Timer = TRUE,
  DebugMode = TRUE,

  # Target Transformations
  TargetTransformation = FALSE,
  Methods = c("BoxCox", "Asinh", "Asin", "Log",
    "LogPlus1", "Sqrt", "Logit", "YeoJohnson"),
  Difference = FALSE,
  NonNegativePred = FALSE,
  RoundPreds = FALSE,

  # Calendar features
  CalendarVariables = c("week", "wom", "month", "quarter", "year"),
  HolidayVariable = c("USPublicHolidays","EasterGroup",
    "ChristmasGroup","OtherEcclesticalFeasts"),
  HolidayLookback = NULL,
  HolidayLags = 1:7,
  HolidayMovingAverages = 2:7,
  TimeTrendVariable = TRUE,

  # Time series features
  Lags = list("weeks" = c(1:4), "months" = c(1:3)),
  MA_Periods = list("weeks" = c(2:8), "months" = c(6:12)),
  SD_Periods = NULL,
  Skew_Periods = NULL,
  Kurt_Periods = NULL,
  Quantile_Periods = NULL,
  Quantiles_Selected = NULL,

  # Bonus Features
  XREGS = NULL,
  FourierTerms = 2L,
  AnomalyDetection = NULL,
  ZeroPadSeries = NULL,
  DataTruncate = FALSE,

  # ML evaluation args
  EvalMetric = "RMSE",
  NumOfParDepPlots = 0L,

  # ML grid tuning args
  GridTune = FALSE,
  GridStrategy = "Cartesian",
  ModelCount = 5,
  MaxRunTimeSecs = 60*60*24,
  StoppingRounds = 10,
```

```
  # ML Args
  NTrees = 1000L,
  MaxDepth = 20,
  SampleRate = 0.632,
  MTries = -1,
  ColSampleRatePerTree = 1,
  ColSampleRatePerTreeLevel  = 1,
  MinRows = 1,
  NBins = 20,
  NBinsCats = 1024,
  NBinsTopLevel = 1024,
  HistogramType = "AUTO",
  CategoricalEncoding = "AUTO",
  RandomColNumbers = NULL,
  InteractionColNumbers = NULL,
  WeightsColumn = NULL,

  # ML args
  Distribution = "gaussian",
  Link = "identity",
  RandomDistribution = NULL,
  RandomLink = NULL,
  Solver = "AUTO",
  Alpha = NULL,
  Lambda = NULL,
  LambdaSearch = FALSE,
  NLambdas = -1,
  Standardize = TRUE,
  RemoveCollinearColumns = FALSE,
  InterceptInclude = TRUE,
  NonNegativeCoefficients = FALSE)

UpdateMetrics <-
  Results$ModelInformation$EvaluationMetrics[
    Metric == "MSE", MetricValue := sqrt(MetricValue)]
print(UpdateMetrics)

# Get final number of trees actually used
Results$Model@model$model_summary$number_of_internal_trees

# Inspect performance
Results$ModelInformation$EvaluationMetricsByGroup[order(-R2_Metric)]
Results$ModelInformation$EvaluationMetricsByGroup[order(MAE_Metric)]
Results$ModelInformation$EvaluationMetricsByGroup[order(MSE_Metric)]
Results$ModelInformation$EvaluationMetricsByGroup[order(MAPE_Metric)]

## End(Not run)
```

`AutoH2oDRFClassifier` *AutoH2oDRFClassifier*

Description

AutoH2oDRFClassifier is an automated H2O modeling framework with grid-tuning and model evaluation that runs a variety of steps. First, a stratified sampling (by the target variable) is done to

create train and validation sets. Then, the function will run a random grid tune over N number of models and find which model is the best (a default model is always included in that set). Once the model is identified and built, several other outputs are generated: validation data with predictions, evaluation plot, evaluation metrics, variable importance, partial dependence calibration plots, and column names used in model fitting.

Usage

```
AutoH2oDRFClassifier(
  OutputSelection = c("EvalMetrics", "Score_TrainData"),
  data = NULL,
  TrainOnFull = FALSE,
  ValidationData = NULL,
  TestData = NULL,
  TargetColumnName = NULL,
  FeatureColNames = NULL,
  WeightsColumn = NULL,
  MaxMem = {
     gc()

   paste0(as.character(floor(as.numeric(system("awk '/MemFree/ {print $2}' /proc/meminfo",
     intern = TRUE))/1e+06)), "G")
 },
  NThreads = max(1L, parallel::detectCores() - 2L),
  model_path = NULL,
  metadata_path = NULL,
  ModelID = "FirstModel",
  NumOfParDepPlots = 3L,
  ReturnModelObjects = TRUE,
  SaveModelObjects = FALSE,
  SaveInfoToPDF = FALSE,
  IfSaveModel = "mojo",
  H2OShutdown = FALSE,
  H2OStartUp = TRUE,
  GridTune = FALSE,
  GridStrategy = "RandomDiscrete",
  MaxRunTimeSecs = 60 * 60 * 24,
  StoppingRounds = 10,
  MaxModelsInGrid = 2,
  DebugMode = FALSE,
  eval_metric = "auc",
  CostMatrixWeights = c(1, 0, 0, 1),
  Trees = 50L,
  MaxDepth = 20L,
  SampleRate = 0.632,
  MTries = -1,
  ColSampleRatePerTree = 1,
  ColSampleRatePerTreeLevel = 1,
  MinRows = 1,
  NBins = 20,
  NBinsCats = 1024,
  NBinsTopLevel = 1024,
  HistogramType = "AUTO",
```

```
  CategoricalEncoding = "AUTO"
)
```

Arguments

OutputSelection	You can select what type of output you want returned. Choose from "EvalMetrics", "Score_TrainData", "h2o.explain"
data	This is your data set for training and testing your model
TrainOnFull	Set to TRUE to train on full data
ValidationData	This is your holdout data set used in modeling either refine your hyperparameters.
TestData	This is your holdout data set. Catboost using both training and validation data in the training process so you should evaluate out of sample performance with this data set.
TargetColumnName	Either supply the target column name OR the column number where the target is located (but not mixed types). Note that the target column needs to be a 0 | 1 numeric variable.
FeatureColNames	Either supply the feature column names OR the column number where the target is located (but not mixed types)
WeightsColumn	Column name of a weights column
MaxMem	Set the maximum amount of memory you'd like to dedicate to the model run. E.g. "32G"
NThreads	Set the number of threads you want to dedicate to the model building
model_path	A character string of your path file to where you want your output saved
metadata_path	A character string of your path file to where you want your model evaluation output saved. If left NULL, all output will be saved to model_path.
ModelID	A character string to name your model and output
NumOfParDepPlots	Tell the function the number of partial dependence calibration plots you want to create.
ReturnModelObjects	Set to TRUE to output all modeling objects (E.g. plots and evaluation metrics)
SaveModelObjects	Set to TRUE to return all modeling objects to your environment
SaveInfoToPDF	Set to TRUE to save modeling information to PDF. If model_path or metadata_path aren't defined then output will be saved to the working directory
IfSaveModel	Set to "mojo" to save a mojo file, otherwise "standard" to save a regular H2O model object
H2OShutdown	Set to TRUE to shutdown H2O after running the function
H2OStartUp	Defaults to TRUE which means H2O will be started inside the function
GridTune	Set to TRUE to run a grid tuning procedure. Set a number in MaxModelsInGrid to tell the procedure how many models you want to test.
GridStrategy	Default "Cartesian"
MaxRunTimeSecs	Default 86400

`StoppingRounds` Default 10

`MaxModelsInGrid`
Number of models to test from grid options (1080 total possible options)

`DebugMode` Set to TRUE to get a printout of each step taken internally

`eval_metric` This is the metric used to identify best grid tuned model. Choose from "AUC" or "logloss"

`CostMatrixWeights`
A vector with 4 elements c(True Positive Cost, False Negative Cost, False Positive Cost, True Negative Cost). Default c(1,0,0,1),

`Trees` The maximum number of trees you want in your models

`MaxDepth` Default 20

`SampleRate` Default 0.632

`MTries` Default -1 means it will default to number of features divided by 3

`ColSampleRatePerTree`
Default 1

`ColSampleRatePerTreeLevel`
Default 1

`MinRows` Default 1

`NBinsCats` Default 1024

`NBinsTopLevel` Default 1024

`HistogramType` Default "AUTO"

`CategoricalEncoding`
Default "AUTO"

Value

Saves to file and returned in list: VariableImportance.csv, Model, ValidationData.csv, EvalutionPlot.png, EvaluationMetrics.csv, ParDepPlots.R a named list of features with partial dependence calibration plots, GridCollect, and GridList

Author(s)

Adrian Antico

See Also

Other Automated Supervised Learning - Binary Classification: `AutoCatBoostClassifier()`, `AutoH2oGAMClassifier()`, `AutoH2oGBMClassifier()`, `AutoH2oGLMClassifier()`, `AutoH2oMLClassifier()`, `AutoLightGBMClassifier()`, `AutoXGBoostClassifier()`

Examples

```
## Not run:
# Create some dummy correlated data
data <- AutoQuant::FakeDataGenerator(
  Correlation = 0.85,
  N = 1000L,
  ID = 2L,
  ZIP = 0L,
  AddDate = FALSE,
```

```
  Classification = TRUE,
  MultiClass = FALSE)

TestModel <- AutoQuant::AutoH2oDRFClassifier(

  # Compute management args
 MaxMem = {gc();paste0(as.character(floor(as.numeric(system("awk '/MemFree/ {print $2}' /proc/meminfo", inter
  NThreads = max(1L, parallel::detectCores() - 2L),
  IfSaveModel = "mojo",
  H2OShutdown = FALSE,
  H2OStartUp = TRUE,

  # Model evaluation args
  eval_metric = "auc",
  NumOfParDepPlots = 3L,
  CostMatrixWeights = c(1,0,0,1),

  # Metadata args
  OutputSelection = c("EvalMetrics","Score_TrainData"),
  model_path = normalizePath("./"),
  metadata_path = NULL,
  ModelID = "FirstModel",
  ReturnModelObjects = TRUE,
  SaveModelObjects = FALSE,
  SaveInfoToPDF = FALSE,
  DebugMode = FALSE,

  # Data args
  data,
  TrainOnFull = FALSE,
  ValidationData = NULL,
  TestData = NULL,
  TargetColumnName = "Adrian",
  FeatureColNames = names(data)[!names(data) %in% c("IDcol_1", "IDcol_2", "Adrian")],
  WeightsColumn = NULL,

  # Grid Tuning Args
  GridStrategy = "RandomDiscrete",
  GridTune = FALSE,
  MaxModelsInGrid = 10,
  MaxRunTimeSecs = 60*60*24,
  StoppingRounds = 10,

  # Model args
  Trees = 50L,
  MaxDepth = 20,
  SampleRate = 0.632,
  MTries = -1,
  ColSampleRatePerTree = 1,
  ColSampleRatePerTreeLevel = 1,
  MinRows = 1,
  NBins = 20,
  NBinsCats = 1024,
  NBinsTopLevel = 1024,
  HistogramType = "AUTO",
  CategoricalEncoding = "AUTO")
```

```
## End(Not run)
```

AutoH2oDRFHurdleModel *AutoH2oDRFHurdleModel*

Description

AutoH2oDRFHurdleModel for hurdle modeling

Usage

```
AutoH2oDRFHurdleModel(
  data,
  TrainOnFull = FALSE,
  ValidationData = NULL,
  TestData = NULL,
  Buckets = 0L,
  TargetColumnName = NULL,
  FeatureColNames = NULL,
  TransformNumericColumns = NULL,
  SplitRatios = c(0.7, 0.2, 0.1),
  ModelID = "ModelTest",
  Paths = NULL,
  MetaDataPaths = NULL,
  SaveModelObjects = TRUE,
  IfSaveModel = "mojo",
  MaxMem = {
     gc()

   paste0(as.character(floor(as.numeric(system("awk '/MemFree/ {print $2}' /proc/meminfo",
     intern = TRUE))/1e+06)), "G")
 },
  NThreads = max(1L, parallel::detectCores() - 2L),
  Trees = 1000L,
  GridTune = TRUE,
  MaxModelsInGrid = 1L,
  NumOfParDepPlots = 10L,
  PassInGrid = NULL
)
```

Arguments

data	Source training data. Do not include a column that has the class labels for the buckets as they are created internally.
TrainOnFull	Set to TRUE to train on full data
ValidationData	Source validation data. Do not include a column that has the class labels for the buckets as they are created internally.
TestData	Souce test data. Do not include a column that has the class labels for the buckets as they are created internally.

`Buckets` A numeric vector of the buckets used for subsetting the data. NOTE: the final Bucket value will first create a subset of data that is less than the value and a second one thereafter for data greater than the bucket value.

`TargetColumnName`
Supply the column name or number for the target variable

`FeatureColNames`
Supply the column names or number of the features (not included the PrimaryDateColumn)

`TransformNumericColumns`
Transform numeric column inside the AutoCatBoostRegression() function

`SplitRatios` Supply vector of partition ratios. For example, c(0.70,0.20,0,10).

`ModelID` Define a character name for your models

`Paths` The path to your folder where you want your model information saved

`MetaDataPaths` A character string of your path file to where you want your model evaluation output saved. If left NULL, all output will be saved to Paths.

`SaveModelObjects`
Set to TRUE to save the model objects to file in the folders listed in Paths

`IfSaveModel` Save as "mojo" or "standard"

`MaxMem` Set the maximum memory your system can provide

`NThreads` Set the number of threads you want to dedicate to the model building

`Trees` Default 1000

`GridTune` Set to TRUE if you want to grid tune the models

`MaxModelsInGrid`
Set to a numeric value for the number of models to try in grid tune

`NumOfParDepPlots`
Set to pull back N number of partial dependence calibration plots.

`PassInGrid` Pass in a grid for changing up the parameter settings for catboost

Value

Returns AutoXGBoostRegression() model objects: VariableImportance.csv, Model, ValidationData.csv, EvalutionPlot.png, EvalutionBoxPlot.png, EvaluationMetrics.csv, ParDepPlots.R a named list of features with partial dependence calibration plots, ParDepBoxPlots.R, GridCollect, and the grid used

Author(s)

Adrian Antico

See Also

Other Supervised Learning - Hurdle Modeling: `AutoH2oGBMHurdleModel()`

Examples

```
## Not run:
Output <- AutoH2oDRFHurdleModel(
  data,
  TrainOnFull = FALSE,
```

```
  ValidationData = NULL,
  TestData = NULL,
  Buckets = 1L,
  TargetColumnName = "Target_Variable",
  FeatureColNames = 4:ncol(data),
  TransformNumericColumns = NULL,
  SplitRatios = c(0.7, 0.2, 0.1),
  NThreads = max(1L, parallel::detectCores()-2L),
  ModelID = "ModelID",
  Paths = NULL,
  MetaDataPaths = NULL,
  SaveModelObjects = TRUE,
  IfSaveModel = "mojo",
 MaxMem = {gc();paste0(as.character(floor(as.numeric(system("awk '/MemFree/ {print $2}' /proc/meminfo", inter
  NThreads = max(1L, parallel::detectCores()-2L),
  Trees = 1000L,
  GridTune = FALSE,
  MaxModelsInGrid = 1L,
  NumOfParDepPlots = 10L,
  PassInGrid = NULL)

## End(Not run)
```

AutoH2oDRFMultiClass *AutoH2oDRFMultiClass*

Description

AutoH2oDRFMultiClass is an automated H2O modeling framework with grid-tuning and model evaluation that runs a variety of steps. First, a stratified sampling (by the target variable) is done to create train and validation sets. Then, the function will run a random grid tune over N number of models and find which model is the best (a default model is always included in that set). Once the model is identified and built, several other outputs are generated: validation data with predictions, evaluation metrics, confusion matrix, and variable importance.

Usage

```
AutoH2oDRFMultiClass(
  OutputSelection = c("EvalMetrics", "Score_TrainData"),
  data = NULL,
  TrainOnFull = FALSE,
  ValidationData = NULL,
  TestData = NULL,
  TargetColumnName = NULL,
  FeatureColNames = NULL,
  WeightsColumn = NULL,
  ReturnModelObjects = TRUE,
  SaveModelObjects = FALSE,
  IfSaveModel = "mojo",
  MaxMem = {
     gc()

   paste0(as.character(floor(as.numeric(system("awk '/MemFree/ {print $2}' /proc/meminfo",
```

```
    intern = TRUE))/1e+06)), "G")
 },
  NThreads = max(1, parallel::detectCores() - 2),
  model_path = NULL,
  metadata_path = NULL,
  ModelID = "FirstModel",
  H2OShutdown = FALSE,
  H2OStartUp = TRUE,
  DebugMode = FALSE,
  eval_metric = "logloss",
  GridTune = FALSE,
  GridStrategy = "RandomDiscrete",
  MaxRunTimeSecs = 60 * 60 * 24,
  StoppingRounds = 10,
  MaxModelsInGrid = 2,
  Trees = 50,
  MaxDepth = 20L,
  SampleRate = 0.632,
  MTries = -1,
  ColSampleRatePerTree = 1,
  ColSampleRatePerTreeLevel = 1,
  MinRows = 1,
  NBins = 20,
  NBinsCats = 1024,
  NBinsTopLevel = 1024,
  HistogramType = "AUTO",
  CategoricalEncoding = "AUTO"
)
```

Arguments

`OutputSelection`	You can select what type of output you want returned. Choose from "EvalMetrics", "Score_TrainData", "h2o.explain"
`data`	This is your data set for training and testing your model
`TrainOnFull`	Set to TRUE to train on full data
`ValidationData`	This is your holdout data set used in modeling either refine your hyperparameters.
`TestData`	This is your holdout data set. Catboost using both training and validation data in the training process so you should evaluate out of sample performance with this data set.
`TargetColumnName`	Either supply the target column name OR the column number where the target is located (but not mixed types).
`FeatureColNames`	Either supply the feature column names OR the column number where the target is located (but not mixed types)
`WeightsColumn`	Column name of a weights column
`ReturnModelObjects`	Set to TRUE to output all modeling objects (E.g. plots and evaluation metrics)

SaveModelObjects
: Set to TRUE to return all modeling objects to your environment

IfSaveModel
: Set to "mojo" to save a mojo file, otherwise "standard" to save a regular H2O model object

MaxMem
: Set the maximum amount of memory you'd like to dedicate to the model run. E.g. "32G"

NThreads
: Set the number of threads you want to dedicate to the model building

model_path
: A character string of your path file to where you want your output saved

metadata_path
: A character string of your path file to where you want your model evaluation output saved. If left NULL, all output will be saved to model_path.

ModelID
: A character string to name your model and output

H2OShutdown
: Set to TRUE to have H2O shutdown after running this function

H2OStartUp
: Defaults to TRUE which means H2O will be started inside the function

DebugMode
: Set to TRUE to print steps to screen

eval_metric
: This is the metric used to identify best grid tuned model. Choose from "logloss", "r2", "RMSE", "MSE"

GridTune
: Set to TRUE to run a grid tuning procedure. Set a number in MaxModelsInGrid to tell the procedure how many models you want to test.

GridStrategy
: Default "Cartesian"

MaxRunTimeSecs
: Default 86400

StoppingRounds
: Default 10

MaxModelsInGrid
: Number of models to test from grid options (1080 total possible options)

Trees
: The maximum number of trees you want in your models

MaxDepth
: Default 20

SampleRate
: Default 0.632

MTries
: Default -1 means it will default to number of features divided by 3

ColSampleRatePerTree
: Default 1

ColSampleRatePerTreeLevel
: Default 1

MinRows
: Default 1

NBins
: Default 20

NBinsCats
: Default 1024

NBinsTopLevel
: Default 1024

HistogramType
: Default "AUTO"

CategoricalEncoding
: Default "AUTO"

Value

Saves to file and returned in list: VariableImportance.csv, Model, ValidationData.csv, EvaluationMetrics.csv, GridCollect, and GridList

Author(s)

Adrian Antico

See Also

Other Automated Supervised Learning - Multiclass Classification: AutoCatBoostMultiClass(), AutoH2oGAMMultiClass(), AutoH2oGBMMultiClass(), AutoH2oGLMMultiClass(), AutoH2oMLMultiClass(), AutoXGBoostMultiClass()

Examples

```
## Not run:
# Create some dummy correlated data
data <- AutoQuant::FakeDataGenerator(
  Correlation = 0.85,
  N = 1000L,
  ID = 2L,
  ZIP = 0L,
  AddDate = FALSE,
  Classification = FALSE,
  MultiClass = TRUE)

# Run function
TestModel <- AutoQuant::AutoH2oDRFMultiClass(
  OutputSelection = c("EvalMetrics","Score_TrainData"),
  data,
  TrainOnFull = FALSE,
  ValidationData = NULL,
  TestData = NULL,
  TargetColumnName = "Adrian",
  FeatureColNames = names(data)[!names(data) %in% c("IDcol_1", "IDcol_2","Adrian")],
  WeightsColumn = NULL,
  eval_metric = "logloss",
 MaxMem = {gc();paste0(as.character(floor(as.numeric(system("awk '/MemFree/ {print $2}' /proc/meminfo", inter
  NThreads = max(1, parallel::detectCores()-2),
  model_path = normalizePath("./"),
  metadata_path = file.path(normalizePath("./")),
  ModelID = "FirstModel",
  ReturnModelObjects = TRUE,
  SaveModelObjects = FALSE,
  IfSaveModel = "mojo",
  H2OShutdown = FALSE,
  H2OStartUp = TRUE,
  DebugMode = FALSE,

  # Grid Tuning Args
  GridStrategy = "RandomDiscrete",
  GridTune = FALSE,
  MaxModelsInGrid = 10,
  MaxRunTimeSecs = 60*60*24,
  StoppingRounds = 10,

  # ML args
  Trees = 50,
  MaxDepth = 20,
  SampleRate = 0.632,
```

```
  MTries = -1,
  ColSampleRatePerTree = 1,
  ColSampleRatePerTreeLevel = 1,
  MinRows = 1,
  NBins = 20,
  NBinsCats = 1024,
  NBinsTopLevel = 1024,
  HistogramType = "AUTO",
  CategoricalEncoding = "AUTO")

## End(Not run)
```

AutoH2oDRFRegression *AutoH2oDRFRegression*

Description

AutoH2oDRFRegression is an automated H2O modeling framework with grid-tuning and model evaluation that runs a variety of steps. First, the function will run a random grid tune over N number of models and find which model is the best (a default model is always included in that set). Once the model is identified and built, several other outputs are generated: validation data with predictions, evaluation plot, evaluation boxplot, evaluation metrics, variable importance, partial dependence calibration plots, partial dependence calibration box plots, and column names used in model fitting.

Usage

```
AutoH2oDRFRegression(
  OutputSelection = c("EvalMetrics", "Score_TrainData"),
  data = NULL,
  TrainOnFull = FALSE,
  ValidationData = NULL,
  TestData = NULL,
  TargetColumnName = NULL,
  FeatureColNames = NULL,
  WeightsColumn = NULL,
  MaxMem = {
     gc()

   paste0(as.character(floor(as.numeric(system("awk '/MemFree/ {print $2}' /proc/meminfo",
     intern = TRUE))/1e+06)), "G")
 },
  NThreads = max(1L, parallel::detectCores() - 2L),
  H2OShutdown = TRUE,
  H2OStartUp = TRUE,
  DebugMode = FALSE,
  ReturnModelObjects = TRUE,
  SaveModelObjects = FALSE,
  SaveInfoToPDF = FALSE,
  IfSaveModel = "mojo",
  model_path = NULL,
  metadata_path = NULL,
```

```
  ModelID = "FirstModel",
  TransformNumericColumns = NULL,
  Methods = c("Asinh", "Log", "LogPlus1", "Sqrt", "Asin", "Logit"),
  NumOfParDepPlots = 3,
  eval_metric = "RMSE",
  GridTune = FALSE,
  GridStrategy = "RandomDiscrete",
  MaxRunTimeSecs = 60 * 60 * 24,
  StoppingRounds = 10,
  MaxModelsInGrid = 2,
  Trees = 50,
  MaxDepth = 20,
  SampleRate = 0.632,
  MTries = -1,
  ColSampleRatePerTree = 1,
  ColSampleRatePerTreeLevel = 1,
  MinRows = 1,
  NBins = 20,
  NBinsCats = 1024,
  NBinsTopLevel = 1024,
  HistogramType = "AUTO",
  CategoricalEncoding = "AUTO"
)
```

Arguments

OutputSelection	You can select what type of output you want returned. Choose from "EvalMetrics", "Score_TrainData", "h2o.explain"
data	This is your data set for training and testing your model
TrainOnFull	Set to TRUE to train on full data
ValidationData	This is your holdout data set used in modeling either refine your hyperparameters.
TestData	This is your holdout data set. Catboost using both training and validation data in the training process so you should evaluate out of sample performance with this data set.
TargetColumnName	Either supply the target column name OR the column number where the target is located (but not mixed types).
FeatureColNames	Either supply the feature column names OR the column number where the target is located (but not mixed types)
WeightsColumn	Column name of a weights column
MaxMem	Set the maximum amount of memory you'd like to dedicate to the model run. E.g. "32G"
NThreads	Set the number of threads you want to dedicate to the model building
H2OShutdown	Set to TRUE to shutdown H2O inside the function
H2OStartUp	Defaults to TRUE which means H2O will be started inside the function
DebugMode	Set to TRUE to print steps to screen

`ReturnModelObjects`
: Set to TRUE to output all modeling objects (E.g. plots and evaluation metrics)

`SaveModelObjects`
: Set to TRUE to return all modeling objects to your environment

`SaveInfoToPDF`
: Set to TRUE to save insights to PDF

`IfSaveModel`
: Set to "mojo" to save a mojo file, otherwise "standard" to save a regular H2O model object

`model_path`
: A character string of your path file to where you want your output saved

`metadata_path`
: A character string of your path file to where you want your model evaluation output saved. If left NULL, all output will be saved to model_path.

`ModelID`
: A character string to name your model and output

`TransformNumericColumns`
: Set to NULL to do nothing; otherwise supply the column names of numeric variables you want transformed

`Methods`
: Choose from "YeoJohnson", "BoxCox", "Asinh", "Log", "LogPlus1", "Sqrt", "Asin", or "Logit". If more than one is selected, the one with the best normalization pearson statistic will be used. Identity is automatically selected and compared.

`NumOfParDepPlots`
: Tell the function the number of partial dependence calibration plots you want to create. Calibration boxplots will only be created for numerical features (not dummy variables)

`eval_metric`
: This is the metric used to identify best grid tuned model. Choose from "MSE", "RMSE", "MAE", "RMSLE"

`GridTune`
: Set to TRUE to run a grid tuning procedure. Set a number in MaxModelsInGrid to tell the procedure how many models you want to test.

`GridStrategy`
: Default "Cartesian"

`MaxRunTimeSecs`
: Default 86400

`StoppingRounds`
: Default 10

`MaxModelsInGrid`
: Number of models to test from grid options (1080 total possible options)

`Trees`
: The maximum number of trees you want in your models

`MaxDepth`
: Default 20

`SampleRate`
: Default 0.632

`MTries`
: Default -1 means it will default to number of features divided by 3

`ColSampleRatePerTree`
: Default 1

`ColSampleRatePerTreeLevel`
: Default 1

`MinRows`
: Default 1

`NBins`
: Default 20

`NBinsCats`
: Default 1024

`NBinsTopLevel`
: Default 1024

`HistogramType`
: Default "AUTO". Select from "AUTO", "UniformAdaptive", "Random", "QuantilesGlobal", "RoundRobin"

`CategoricalEncoding`
: Default "AUTO". Other options include "Enum", "OneHotInternal", "OneHotExplicit", "Binary", "Eigen", "LabelEncoder", "SortByResponse", "EnumLimite"

Value

Saves to file and returned in list: VariableImportance.csv, Model, ValidationData.csv, EvalutionPlot.png, EvalutionBoxPlot.png, EvaluationMetrics.csv, ParDepPlots.R a named list of features with partial dependence calibration plots, ParDepBoxPlots.R, GridCollect, GridList, and Transformation metadata

Author(s)

Adrian Antico

See Also

Other Automated Supervised Learning - Regression: AutoCatBoostRegression(), AutoH2oGAMRegression(), AutoH2oGBMRegression(), AutoH2oGLMRegression(), AutoH2oMLRegression(), AutoLightGBMRegression(), AutoXGBoostRegression()

Examples

```
## Not run:
# Create some dummy correlated data
data <- AutoQuant::FakeDataGenerator(
  Correlation = 0.85,
  N = 1000,
  ID = 2,
  ZIP = 0,
  AddDate = FALSE,
  Classification = FALSE,
  MultiClass = FALSE)

# Run function
TestModel <- AutoQuant::AutoH2oDRFRegression(

  # Compute management
 MaxMem = {gc();paste0(as.character(floor(as.numeric(system("awk '/MemFree/ {print $2}' /proc/meminfo", inter
  NThreads = max(1L, parallel::detectCores() - 2L),
  H2OShutdown = TRUE,
  H2OStartUp = TRUE,
  IfSaveModel = "mojo",

  # Model evaluation:
  eval_metric = "RMSE",
  NumOfParDepPlots = 3,

  # Metadata arguments
  OutputSelection = c("EvalMetrics","Score_TrainData"),
  model_path = normalizePath("./"),
  metadata_path = NULL,
  ModelID = "FirstModel",
  ReturnModelObjects = TRUE,
  SaveModelObjects = FALSE,
  SaveInfoToPDF = FALSE,
  DebugMode = FALSE,

  # Data Args
  data = data,
  TrainOnFull = FALSE,
```

```
  ValidationData = NULL,
  TestData = NULL,
  TargetColumnName = "Adrian",
  FeatureColNames = names(data)[!names(data) %in% c("IDcol_1", "IDcol_2","Adrian")],
  WeightsColumn = NULL,
  TransformNumericColumns = NULL,
  Methods = c("Asinh","Asin","Log","LogPlus1", "Sqrt","Logit"),

  # Grid Tuning Args
  GridStrategy = "RandomDiscrete",
  GridTune = FALSE,
  MaxModelsInGrid = 10,
  MaxRunTimeSecs = 60*60*24,
  StoppingRounds = 10,

  # ML Args
  Trees = 50,
  MaxDepth = 20,
  SampleRate = 0.632,
  MTries = -1,
  ColSampleRatePerTree = 1,
  ColSampleRatePerTreeLevel = 1,
  MinRows = 1,
  NBins = 20,
  NBinsCats = 1024,
  NBinsTopLevel = 1024,
  HistogramType = "AUTO",
  CategoricalEncoding = "AUTO")

## End(Not run)
```

`AutoH2oGAMClassifier` *AutoH2oGAMClassifier*

Description

AutoH2oGAMClassifier is an automated H2O modeling framework with grid-tuning and model evaluation that runs a variety of steps. First, a stratified sampling (by the target variable) is done to create train and validation sets. Then, the function will run a random grid tune over N number of models and find which model is the best (a default model is always included in that set). Once the model is identified and built, several other outputs are generated: validation data with predictions, evaluation plot, evaluation metrics, variable importance, partial dependence calibration plots, and column names used in model fitting.

Usage

```
AutoH2oGAMClassifier(
  OutputSelection = c("EvalMetrics", "Score_TrainData"),
  data = NULL,
  TrainOnFull = FALSE,
  ValidationData = NULL,
  TestData = NULL,
  TargetColumnName = NULL,
```

```
  FeatureColNames = NULL,
  WeightsColumn = NULL,
  GamColNames = NULL,
  Distribution = "binomial",
  Link = "logit",
  eval_metric = "auc",
  CostMatrixWeights = c(1, 0, 0, 1),
  MaxMem = {
     gc()

   paste0(as.character(floor(as.numeric(system("awk '/MemFree/ {print $2}' /proc/meminfo",
     intern = TRUE))/1e+06)), "G")
 },
  NThreads = max(1, parallel::detectCores() - 2),
  model_path = NULL,
  metadata_path = NULL,
  ModelID = "FirstModel",
  NumOfParDepPlots = 3,
  ReturnModelObjects = TRUE,
  SaveModelObjects = FALSE,
  SaveInfoToPDF = FALSE,
  IfSaveModel = "mojo",
  H2OShutdown = FALSE,
  H2OStartUp = TRUE,
  DebugMode = FALSE,
  GridTune = FALSE,
  GridStrategy = "Cartesian",
  StoppingRounds = 10,
  MaxRunTimeSecs = 3600 * 24 * 7,
  MaxModelsInGrid = 2,
  num_knots = NULL,
  keep_gam_cols = TRUE,
  Solver = "AUTO",
  Alpha = 0.5,
  Lambda = NULL,
  LambdaSearch = FALSE,
  NLambdas = -1,
  Standardize = TRUE,
  RemoveCollinearColumns = FALSE,
  InterceptInclude = TRUE,
  NonNegativeCoefficients = FALSE
)
```

Arguments

`OutputSelection`	You can select what type of output you want returned. Choose from c("EvalMetrics", "Score_TrainData")
`data`	This is your data set for training and testing your model
`TrainOnFull`	Set to TRUE to train on full data
`ValidationData`	This is your holdout data set used in modeling either refine your hyperparameters.

`TestData` This is your holdout data set. Catboost using both training and validation data in the training process so you should evaluate out of sample performance with this data set.

`TargetColumnName`
Either supply the target column name OR the column number where the target is located (but not mixed types). Note that the target column needs to be a 0 | 1 numeric variable.

`FeatureColNames`
Either supply the feature column names OR the column number where the target is located (but not mixed types)

`WeightsColumn` Weighted classification

`GamColNames` GAM column names. Up to 9 features

`Distribution` "binomial", "quasibinomial"

`Link` identity, logit, log, inverse, tweedie

`eval_metric` This is the metric used to identify best grid tuned model. Choose from "AUC" or "logloss"

`CostMatrixWeights`
A vector with 4 elements c(True Positive Cost, False Negative Cost, False Positive Cost, True Negative Cost). Default c(1,0,0,1),

`MaxMem` Set the maximum amount of memory you'd like to dedicate to the model run. E.g. "32G"

`NThreads` Set the number of threads you want to dedicate to the model building

`model_path` A character string of your path file to where you want your output saved

`metadata_path` A character string of your path file to where you want your model evaluation output saved. If left NULL, all output will be saved to model_path.

`ModelID` A character string to name your model and output

`NumOfParDepPlots`
Tell the function the number of partial dependence calibration plots you want to create.

`ReturnModelObjects`
Set to TRUE to output all modeling objects (E.g. plots and evaluation metrics)

`SaveModelObjects`
Set to TRUE to return all modeling objects to your environment

`SaveInfoToPDF` Set to TRUE to save modeling information to PDF. If model_path or metadata_path aren't defined then output will be saved to the working directory

`IfSaveModel` Set to "mojo" to save a mojo file, otherwise "standard" to save a regular H2O model object

`H2OShutdown` Set to TRUE to shutdown H2O after running the function

`H2OStartUp` Set to TRUE to start up H2O inside function

`DebugMode` Set to TRUE to get a print out of steps taken internally

`GridTune` Set to TRUE to run a grid tuning procedure. Set a number in MaxModelsInGrid to tell the procedure how many models you want to test.

`GridStrategy` "RandomDiscrete" or "Cartesian"

`StoppingRounds` Iterations in grid tuning

`MaxRunTimeSecs` Max run time in seconds

`MaxModelsInGrid`
: Number of models to test from grid options (1080 total possible options)

`num_knots`
: Numeric values for gam

`keep_gam_cols`
: Logical

`Solver`
: Default "AUTO". Options include "IRLSM", "L_BFGS", "COORDINATE_DESCENT_NAIVE", "COORDINATE_DESCENT", "GRADIENT_DESCENT_LH", "GRADIENT_DESCENT_SQERR

`Alpha`
: Gridable. Default 0.5 Otherwise supply a value between 0 and 1. 1 is equivalent to Lasso regression. 0 is equivalent to Ridge regression. Inbetween for a blend of the two.

`Lambda`
: Gridable. Default NULL. Regularization strength.

`LambdaSearch`
: Default FALSE.

`NLambdas`
: Default -1

`Standardize`
: Default TRUE. Standardize numerical columns

`RemoveCollinearColumns`
: Default FALSE. Removes some of the linearly dependent columns

`InterceptInclude`
: Default TRUE

`NonNegativeCoefficients`
: Default FALSE

Value

Saves to file and returned in list: VariableImportance.csv, Model, ValidationData.csv, Evalution-Plot.png, EvaluationMetrics.csv, ParDepPlots.R a named list of features with partial dependence calibration plots, GridCollect, and GridList

Author(s)

Adrian Antico

See Also

Other Automated Supervised Learning - Binary Classification: `AutoCatBoostClassifier()`, `AutoH2oDRFClassifier()`, `AutoH2oGBMClassifier()`, `AutoH2oGLMClassifier()`, `AutoH2oMLClassifier()`, `AutoLightGBMClassifier()`, `AutoXGBoostClassifier()`

Examples

```
# Create some dummy correlated data
data <- AutoQuant::FakeDataGenerator(
  Correlation = 0.85,
  N = 1000,
  ID = 2,
  ZIP = 0,
  AddDate = FALSE,
  Classification = TRUE,
  MultiClass = FALSE)

# Define GAM Columns to use - up to 9 are allowed
GamCols <- names(which(unlist(lapply(data, is.numeric))))
GamCols <- GamCols[!GamCols %in% c("Adrian","IDcol_1","IDcol_2")]
```

```
GamCols <- GamCols[1L:(min(9L,length(GamCols)))]

# Run function
TestModel <- AutoQuant::AutoH2oGAMClassifier(

  # Compute management
 MaxMem = {gc();paste0(as.character(floor(as.numeric(system("awk '/MemFree/ {print $2}' /proc/meminfo", inter
  NThreads = max(1, parallel::detectCores()-2),
  H2OShutdown = TRUE,
  H2OStartUp = TRUE,
  IfSaveModel = "mojo",

  # Model evaluation args
  CostMatrixWeights = c(1,0,0,1),
  eval_metric = "auc",
  NumOfParDepPlots = 3,

  # Metadata arguments
  OutputSelection = c("EvalMetrics", "Score_TrainData"),
  model_path = NULL,
  metadata_path = NULL,
  ModelID = "FirstModel",
  ReturnModelObjects = TRUE,
  SaveModelObjects = FALSE,
  SaveInfoToPDF = FALSE,
  DebugMode = FALSE,

  # Data args
  data = data,
  TrainOnFull = FALSE,
  ValidationData = NULL,
  TestData = NULL,
  TargetColumnName = "Adrian",
  FeatureColNames = names(data)[!names(data) %in% c("IDcol_1", "IDcol_2","Adrian")],
  WeightsColumn = NULL,
  GamColNames = GamCols,

  # ML args
  num_knots = NULL,
  keep_gam_cols = TRUE,
  GridTune = FALSE,
  GridStrategy = "Cartesian",
  StoppingRounds = 10,
  MaxRunTimeSecs = 3600 * 24 * 7,
  MaxModelsInGrid = 10,
  Distribution = "binomial",
  Link = "logit",
  Solver = "AUTO",
  Alpha = 0.5,
  Lambda = NULL,
  LambdaSearch = FALSE,
  NLambdas = -1,
  Standardize = TRUE,
  RemoveCollinearColumns = FALSE,
  InterceptInclude = TRUE,
  NonNegativeCoefficients = FALSE)
```

AutoH2oGAMMultiClass *AutoH2oGAMMultiClass*

Description

AutoH2oGAMMultiClass is an automated H2O modeling framework with grid-tuning and model evaluation that runs a variety of steps. First, a stratified sampling (by the target variable) is done to create train and validation sets. Then, the function will run a random grid tune over N number of models and find which model is the best (a default model is always included in that set). Once the model is identified and built, several other outputs are generated: validation data with predictions, evaluation metrics, confusion matrix, and variable importance.

Usage

```
AutoH2oGAMMultiClass(
  OutputSelection = c("EvalMetrics", "Score_TrainData"),
  data = NULL,
  TrainOnFull = FALSE,
  ValidationData = NULL,
  TestData = NULL,
  TargetColumnName = NULL,
  FeatureColNames = NULL,
  WeightsColumn = NULL,
  GamColNames = NULL,
  eval_metric = "logloss",
  MaxMem = {
     gc()

   paste0(as.character(floor(as.numeric(system("awk '/MemFree/ {print $2}' /proc/meminfo",
     intern = TRUE))/1e+06)), "G")
 },
  NThreads = max(1, parallel::detectCores() - 2),
  model_path = NULL,
  metadata_path = NULL,
  ModelID = "FirstModel",
  ReturnModelObjects = TRUE,
  SaveModelObjects = FALSE,
  IfSaveModel = "mojo",
  H2OShutdown = FALSE,
  H2OStartUp = TRUE,
  DebugMode = FALSE,
  GridTune = FALSE,
  GridStrategy = "Cartesian",
  StoppingRounds = 10,
  MaxRunTimeSecs = 3600 * 24 * 7,
  MaxModelsInGrid = 2,
  Distribution = "multinomial",
  Link = "Family_Default",
  num_knots = NULL,
  keep_gam_cols = TRUE,
  Solver = "AUTO",
```

```
  Alpha = 0.5,
  Lambda = NULL,
  LambdaSearch = FALSE,
  NLambdas = -1,
  Standardize = TRUE,
  RemoveCollinearColumns = FALSE,
  InterceptInclude = TRUE,
  NonNegativeCoefficients = FALSE
)
```

Arguments

OutputSelection	You can select what type of output you want returned. Choose from c("EvalMetrics", "Score_TrainData")
data	This is your data set for training and testing your model
TrainOnFull	Set to TRUE to train on full data
ValidationData	This is your holdout data set used in modeling either refine your hyperparameters.
TestData	This is your holdout data set. Catboost using both training and validation data in the training process so you should evaluate out of sample performance with this data set.
TargetColumnName	Either supply the target column name OR the column number where the target is located (but not mixed types).
FeatureColNames	Either supply the feature column names OR the column number where the target is located (but not mixed types)
WeightsColumn	Weighted classification
GamColNames	GAM column names. Up to 9 features
eval_metric	This is the metric used to identify best grid tuned model. Choose from "logloss", "r2", "RMSE", "MSE"
MaxMem	Set the maximum amount of memory you'd like to dedicate to the model run. E.g. "32G"
NThreads	Set the number of threads you want to dedicate to the model building
model_path	A character string of your path file to where you want your output saved
metadata_path	A character string of your path file to where you want your model evaluation output saved. If left NULL, all output will be saved to model_path.
ModelID	A character string to name your model and output
ReturnModelObjects	Set to TRUE to output all modeling objects (E.g. plots and evaluation metrics)
SaveModelObjects	Set to TRUE to return all modeling objects to your environment
IfSaveModel	Set to "mojo" to save a mojo file, otherwise "standard" to save a regular H2O model object
H2OShutdown	Set to TRUE to have H2O shutdown after running this function
H2OStartUp	Set to TRUE to start up H2O inside function

DebugMode	Set to TRUE to print steps to screen
GridTune	Set to TRUE to run a grid tuning procedure. Set a number in MaxModelsInGrid to tell the procedure how many models you want to test.
GridStrategy	"RandomDiscrete" or "Cartesian"
StoppingRounds	Iterations in grid tuning
MaxRunTimeSecs	Max run time in seconds
MaxModelsInGrid	Number of models to test from grid options (1080 total possible options)
num_knots	Numeric values for gam
keep_gam_cols	Logical
Solver	Default "AUTO". Options include "IRLSM", "L_BFGS", "COORDINATE_DESCENT_NAIVE", "COORDINATE_DESCENT", "GRADIENT_DESCENT_LH", "GRADIENT_DESCENT_SQERR
Alpha	Gridable. Default 0.5 Otherwise supply a value between 0 and 1. 1 is equivalent to Lasso regression. 0 is equivalent to Ridge regression. Inbetween for a blend of the two.
Lambda	Gridable. Default NULL. Regularization strength.
LambdaSearch	Default FALSE.
NLambdas	Default -1
Standardize	Default TRUE. Standardize numerical columns
RemoveCollinearColumns	Default FALSE. Removes some of the linearly dependent columns
InterceptInclude	Default TRUE
NonNegativeCoefficients	Default FALSE

Value

Saves to file and returned in list: VariableImportance.csv, Model, ValidationData.csv, EvaluationMetrics.csv, GridCollect, and GridList

Author(s)

Adrian Antico

See Also

Other Automated Supervised Learning - Multiclass Classification: AutoCatBoostMultiClass(), AutoH2oDRFMultiClass(), AutoH2oGBMMultiClass(), AutoH2oGLMMultiClass(), AutoH2oMLMultiClass(), AutoXGBoostMultiClass()

Examples

```
# Create some dummy correlated data with numeric and categorical features
data <- AutoQuant::FakeDataGenerator(
  Correlation = 0.85,
  N = 1000L,
  ID = 2L,
  ZIP = 0L,
  AddDate = FALSE,
```

```
  Classification = FALSE,
  MultiClass = TRUE)

# Define GAM Columns to use - up to 9 are allowed
GamCols <- names(which(unlist(lapply(data, is.numeric))))
GamCols <- GamCols[!GamCols %in% c("Adrian","IDcol_1","IDcol_2")]
GamCols <- GamCols[1L:(min(9L,length(GamCols)))]

# Run function
TestModel <- AutoQuant::AutoH2oGAMMultiClass(
  OutputSelection = c("EvalMetrics", "Score_TrainData"),
  data,
  TrainOnFull = FALSE,
  ValidationData = NULL,
  TestData = NULL,
  TargetColumnName = "Adrian",
  FeatureColNames = names(data)[!names(data) %in% c("IDcol_1", "IDcol_2","Adrian")],
  WeightsColumn = NULL,
  GamColNames = GamCols,
  eval_metric = "logloss",
 MaxMem = {gc();paste0(as.character(floor(as.numeric(system("awk '/MemFree/ {print $2}' /proc/meminfo", inter
  NThreads = max(1, parallel::detectCores()-2),
  model_path = normalizePath("./"),
  metadata_path = NULL,
  ModelID = "FirstModel",
  ReturnModelObjects = TRUE,
  SaveModelObjects = FALSE,
  IfSaveModel = "mojo",
  H2OShutdown = FALSE,
  H2OStartUp = TRUE,
  DebugMode = FALSE,

  # ML args
  num_knots = NULL,
  keep_gam_cols = TRUE,
  GridTune = FALSE,
  GridStrategy = "Cartesian",
  StoppingRounds = 10,
  MaxRunTimeSecs = 3600 * 24 * 7,
  MaxModelsInGrid = 10,
  Distribution = "multinomial",
  Link = "Family_Default",
  Solver = "AUTO",
  Alpha = 0.5,
  Lambda = NULL,
  LambdaSearch = FALSE,
  NLambdas = -1,
  Standardize = TRUE,
  RemoveCollinearColumns = FALSE,
  InterceptInclude = TRUE,
  NonNegativeCoefficients = FALSE)
```

AutoH2oGAMRegression *AutoH2oGAMRegression*

Description

AutoH2oGAMRegression is an automated H2O modeling framework with grid-tuning and model evaluation that runs a variety of steps. First, the function will run a random grid tune over N number of models and find which model is the best (a default model is always included in that set). Once the model is identified and built, several other outputs are generated: validation data with predictions, evaluation plot, evaluation boxplot, evaluation metrics, variable importance, partial dependence calibration plots, partial dependence calibration box plots, and column names used in model fitting.

Usage

```
AutoH2oGAMRegression(
  OutputSelection = c("EvalMetrics", "Score_TrainData"),
  data = NULL,
  TrainOnFull = FALSE,
  ValidationData = NULL,
  TestData = NULL,
  TargetColumnName = NULL,
  FeatureColNames = NULL,
  InteractionColNumbers = NULL,
  WeightsColumn = NULL,
  GamColNames = NULL,
  Distribution = "gaussian",
  Link = "identity",
  TweedieLinkPower = NULL,
  TweedieVariancePower = NULL,
  TransformNumericColumns = NULL,
  Methods = c("BoxCox", "Asinh", "Log", "LogPlus1", "Sqrt", "Asin", "Logit"),
  eval_metric = "RMSE",
  MaxMem = {
     gc()

   paste0(as.character(floor(as.numeric(system("awk '/MemFree/ {print $2}' /proc/meminfo",
     intern = TRUE))/1e+06)), "G")
 },
  NThreads = max(1, parallel::detectCores() - 2),
  model_path = NULL,
  metadata_path = NULL,
  ModelID = "FirstModel",
  NumOfParDepPlots = 3,
  ReturnModelObjects = TRUE,
  SaveModelObjects = FALSE,
  SaveInfoToPDF = FALSE,
  IfSaveModel = "mojo",
  H2OShutdown = TRUE,
  H2OStartUp = TRUE,
  GridTune = FALSE,
  GridStrategy = "Cartesian",
  StoppingRounds = 10,
  MaxRunTimeSecs = 3600 * 24 * 7,
  MaxModelsInGrid = 2,
  num_knots = NULL,
  keep_gam_cols = TRUE,
```

```
  Solver = "AUTO",
  Alpha = 0.5,
  Lambda = NULL,
  LambdaSearch = FALSE,
  NLambdas = -1,
  Standardize = TRUE,
  RemoveCollinearColumns = FALSE,
  InterceptInclude = TRUE,
  NonNegativeCoefficients = FALSE,
  DebugMode = FALSE
)
```

Arguments

OutputSelection	You can select what type of output you want returned. Choose from c("EvalMetrics", "Score_TrainData")
data	This is your data set for training and testing your model
TrainOnFull	Set to TRUE to train on full data
ValidationData	This is your holdout data set used in modeling either refine your hyperparameters.
TestData	This is your holdout data set. Catboost using both training and validation data in the training process so you should evaluate out of sample performance with this data set.
TargetColumnName	Either supply the target column name OR the column number where the target is located (but not mixed types).
FeatureColNames	Either supply the feature column names OR the column number where the target is located (but not mixed types)
InteractionColNumbers	Column numbers of the features you want to be pairwise interacted
WeightsColumn	Column name of a weights column
GamColNames	GAM column names. Up to 9 features
Distribution	: "AUTO", "gaussian", "binomial", "quasi-binomial", "ordinal", "multinomial", "poisson", "gamma", "tweedie", "negative-binomial", "fractionalbinomial"
Link	"family_default", "identity", "logit", "log", "inverse", "tweedie","ologit"
TweedieLinkPower	See h2o docs for background
TweedieVariancePower	See h2o docs for background
TransformNumericColumns	Set to NULL to do nothing; otherwise supply the column names of numeric variables you want transformed
Methods	Choose from "BoxCox", "Asinh", "Log", "LogPlus1", "Sqrt", "Asin", or "Logit". If more than one is selected, the one with the best normalization pearson statistic will be used. Identity is automatically selected and compared.
eval_metric	This is the metric used to identify best grid tuned model. Choose from "MSE", "RMSE", "MAE", "RMSLE"

`MaxMem` Set the maximum amount of memory you'd like to dedicate to the model run. E.g. "32G"

`NThreads` Set the number of threads you want to dedicate to the model building

`model_path` A character string of your path file to where you want your output saved

`metadata_path` A character string of your path file to where you want your model evaluation output saved. If left NULL, all output will be saved to model_path.

`ModelID` A character string to name your model and output

`NumOfParDepPlots`
Tell the function the number of partial dependence calibration plots you want to create. Calibration boxplots will only be created for numerical features (not dummy variables)

`ReturnModelObjects`
Set to TRUE to output all modeling objects (E.g. plots and evaluation metrics)

`SaveModelObjects`
Set to TRUE to return all modeling objects to your environment

`SaveInfoToPDF` Set to TRUE to save insights to PDF

`IfSaveModel` Set to "mojo" to save a mojo file, otherwise "standard" to save a regular H2O model object

`H2OShutdown` Set to TRUE to shutdown H2O inside the function

`H2OStartUp` Defaults to TRUE which means H2O will be started inside the function

`GridTune` Set to TRUE to run a grid tuning procedure. Set a number in MaxModelsInGrid to tell the procedure how many models you want to test.

`GridStrategy` "RandomDiscrete" or "Cartesian"

`StoppingRounds` Iterations in grid tuning

`MaxRunTimeSecs` Max run time in seconds

`MaxModelsInGrid`
Number of models to test from grid options (1080 total possible options)

`num_knots` Numeric values for gam

`keep_gam_cols` Logical

`Solver` Default "AUTO". Options include "IRLSM", "L_BFGS", "COORDINATE_DESCENT_NAIVE", "COORDINATE_DESCENT", "GRADIENT_DESCENT_LH", "GRADIENT_DESCENT_SQERR

`Alpha` Gridable. Default 0.5 Otherwise supply a value between 0 and 1. 1 is equivalent to Lasso regression. 0 is equivalent to Ridge regression. Inbetween for a blend of the two.

`Lambda` Gridable. Default NULL. Regularization strength.

`LambdaSearch` Default FALSE.

`NLambdas` Default -1

`Standardize` Default TRUE. Standardize numerical columns

`RemoveCollinearColumns`
Default FALSE. Removes some of the linearly dependent columns

`InterceptInclude`
Default TRUE

`NonNegativeCoefficients`
Default FALSE

`DebugMode` Set to TRUE to get a printout of steps taken

Value

Saves to file and returned in list: VariableImportance.csv, Model, ValidationData.csv, EvalutionPlot.png, EvalutionBoxPlot.png, EvaluationMetrics.csv, ParDepPlots.R a named list of features with partial dependence calibration plots, ParDepBoxPlots.R, GridCollect, GridList, and Transformation metadata

Author(s)

Adrian Antico

See Also

Other Automated Supervised Learning - Regression: AutoCatBoostRegression(), AutoH2oDRFRegression(), AutoH2oGBMRegression(), AutoH2oGLMRegression(), AutoH2oMLRegression(), AutoLightGBMRegression(), AutoXGBoostRegression()

Examples

```
# Create some dummy correlated data
data <- AutoQuant::FakeDataGenerator(
  Correlation = 0.85,
  N = 1000,
  ID = 2,
  ZIP = 0,
  AddDate = FALSE,
  Classification = FALSE,
  MultiClass = FALSE)

# Define GAM Columns to use - up to 9 are allowed
GamCols <- names(which(unlist(lapply(data, is.numeric))))
GamCols <- GamCols[!GamCols %in% c("Adrian","IDcol_1","IDcol_2")]
GamCols <- GamCols[1L:(min(9L,length(GamCols)))]

# Run function
TestModel <- AutoQuant::AutoH2oGAMRegression(

 # Compute management
 MaxMem = {gc();paste0(as.character(floor(as.numeric(system("awk '/MemFree/ {print $2}' /proc/meminfo", inter
 NThreads = max(1, parallel::detectCores()-2),
 H2OShutdown = TRUE,
 H2OStartUp = TRUE,
 IfSaveModel = "mojo",

 # Model evaluation
 eval_metric = "RMSE",
 NumOfParDepPlots = 3,

 # Metadata arguments
 OutputSelection = c("EvalMetrics", "Score_TrainData"),
 model_path = NULL,
 metadata_path = NULL,
 ModelID = "FirstModel",
 ReturnModelObjects = TRUE,
 SaveModelObjects = FALSE,
 SaveInfoToPDF = FALSE,
```

```
# Data arguments:
data = data,
TrainOnFull = FALSE,
ValidationData = NULL,
TestData = NULL,
TargetColumnName = "Adrian",
FeatureColNames = names(data)[!names(data) %in%
                                c("IDcol_1", "IDcol_2","Adrian")],
InteractionColNumbers = NULL,
WeightsColumn = NULL,
GamColNames = GamCols,
TransformNumericColumns = NULL,
Methods = c("BoxCox", "Asinh", "Asin", "Log",
            "LogPlus1", "Sqrt", "Logit"),

# Model args
num_knots = NULL,
keep_gam_cols = TRUE,
GridTune = FALSE,
GridStrategy = "Cartesian",
StoppingRounds = 10,
MaxRunTimeSecs = 3600 * 24 * 7,
MaxModelsInGrid = 10,
Distribution = "gaussian",
Link = "Family_Default",
TweedieLinkPower = NULL,
TweedieVariancePower = NULL,
Solver = "AUTO",
Alpha = 0.5,
Lambda = NULL,
LambdaSearch = FALSE,
NLambdas = -1,
Standardize = TRUE,
RemoveCollinearColumns = FALSE,
InterceptInclude = TRUE,
NonNegativeCoefficients = FALSE,
DebugMode = FALSE)
```

AutoH2oGBMClassifier *AutoH2oGBMClassifier*

Description

AutoH2oGBMClassifier is an automated H2O modeling framework with grid-tuning and model evaluation that runs a variety of steps. First, a stratified sampling (by the target variable) is done to create train and validation sets. Then, the function will run a random grid tune over N number of models and find which model is the best (a default model is always included in that set). Once the model is identified and built, several other outputs are generated: validation data with predictions, evaluation plot, evaluation metrics, variable importance, partial dependence calibration plots, and column names used in model fitting.

Usage

```
AutoH2oGBMClassifier(
  OutputSelection = c("EvalMetrics", "Score_TrainData"),
  data = NULL,
  TrainOnFull = FALSE,
  ValidationData = NULL,
  TestData = NULL,
  TargetColumnName = NULL,
  FeatureColNames = NULL,
  WeightsColumn = NULL,
  MaxMem = {
     gc()

   paste0(as.character(floor(as.numeric(system("awk '/MemFree/ {print $2}' /proc/meminfo",
    intern = TRUE))/1e+06)), "G")
 },
  NThreads = max(1L, parallel::detectCores() - 2L),
  model_path = NULL,
  metadata_path = NULL,
  ModelID = "FirstModel",
  NumOfParDepPlots = 3L,
  ReturnModelObjects = TRUE,
  SaveModelObjects = FALSE,
  SaveInfoToPDF = FALSE,
  IfSaveModel = "mojo",
  H2OShutdown = FALSE,
  H2OStartUp = TRUE,
  DebugMode = FALSE,
  GridStrategy = "Cartesian",
  MaxRunTimeSecs = 60 * 60 * 24,
  StoppingRounds = 10,
  MaxModelsInGrid = 2,
  eval_metric = "auc",
  CostMatrixWeights = c(1, 0, 0, 1),
  Trees = 50L,
  GridTune = FALSE,
  LearnRate = 0.1,
  LearnRateAnnealing = 1,
  Distribution = "bernoulli",
  MaxDepth = 20,
  SampleRate = 0.632,
  ColSampleRate = 1,
  ColSampleRatePerTree = 1,
  ColSampleRatePerTreeLevel = 1,
  MinRows = 1,
  NBins = 20,
  NBinsCats = 1024,
  NBinsTopLevel = 1024,
  HistogramType = "AUTO",
  CategoricalEncoding = "AUTO"
)
```

Arguments

OutputSelection	You can select what type of output you want returned. Choose from c("EvalMetrics", "Score_TrainData", "h2o.explain")
data	This is your data set for training and testing your model
TrainOnFull	Set to TRUE to train on full data
ValidationData	This is your holdout data set used in modeling either refine your hyperparameters.
TestData	This is your holdout data set. Catboost using both training and validation data in the training process so you should evaluate out of sample performance with this data set.
TargetColumnName	Either supply the target column name OR the column number where the target is located (but not mixed types).
FeatureColNames	Either supply the feature column names OR the column number where the target is located (but not mixed types)
WeightsColumn	Column name of a weights column
MaxMem	Set the maximum amount of memory you'd like to dedicate to the model run. E.g. "32G"
NThreads	Set to the mamimum amount of threads you want to use for this function
model_path	A character string of your path file to where you want your output saved
metadata_path	A character string of your path file to where you want your model evaluation output saved. If left NULL, all output will be saved to model_path.
ModelID	A character string to name your model and output
NumOfParDepPlots	Tell the function the number of partial dependence calibration plots you want to create. Calibration boxplots will only be created for numerical features (not dummy variables)
ReturnModelObjects	Set to TRUE to output all modeling objects (E.g. plots and evaluation metrics)
SaveModelObjects	Set to TRUE to return all modeling objects to your environment
SaveInfoToPDF	Set to TRUE to save modeling information to PDF. If model_path or metadata_path aren't defined then output will be saved to the working directory
IfSaveModel	Set to "mojo" to save a mojo file, otherwise "standard" to save a regular H2O model object
H2OShutdown	Set to TRUE to shutdown H2O inside the function
H2OStartUp	Defaults to TRUE which means H2O will be started inside the function
DebugMode	Set to TRUE to get a printout of the steps taken internally
GridStrategy	Default "Cartesian"
MaxRunTimeSecs	Default 60*60*24
StoppingRounds	Number of runs
MaxModelsInGrid	Number of models to test from grid options (1080 total possible options)

`eval_metric` This is the metric used to identify best grid tuned model. Choose from "auc","logloss","aucpr", "lift_top_group","misclassification","mean_per_class_error"

`CostMatrixWeights`
A vector with 4 elements c(True Positive Cost, False Negative Cost, False Positive Cost, True Negative Cost). Default c(1,0,0,1),

`Trees` The maximum number of trees you want in your models

`GridTune` Set to TRUE to run a grid tuning procedure. Set a number in MaxModelsInGrid to tell the procedure how many models you want to test.

`LearnRate` Default 0.10

`LearnRateAnnealing`
Default 1

`Distribution` Choose from "AUTO", "bernoulli", and "quasibinomial"

`MaxDepth` Default 20

`SampleRate` Default 0.632

`ColSampleRate` Default 1

`ColSampleRatePerTree`
Default 1

`ColSampleRatePerTreeLevel`
Default 1

`MinRows` Default 1

`NBins` Default 20

`NBinsCats` Default 1024

`NBinsTopLevel` Default 1024

`HistogramType` Default "AUTO"

`CategoricalEncoding`
Default "AUTO"

Value

Saves to file and returned in list: VariableImportance.csv, Model, ValidationData.csv, EvalutionPlot.png, EvaluationMetrics.csv, ParDepPlots.R a named list of features with partial dependence calibration plots, GridCollect, and GridList

Author(s)

Adrian Antico

See Also

Other Automated Supervised Learning - Binary Classification: `AutoCatBoostClassifier()`, `AutoH2oDRFClassifier()`, `AutoH2oGAMClassifier()`, `AutoH2oGLMClassifier()`, `AutoH2oMLClassifier()`, `AutoLightGBMClassifier()`, `AutoXGBoostClassifier()`

Examples

```
## Not run:
# Create some dummy correlated data
data <- AutoQuant::FakeDataGenerator(
  Correlation = 0.85,
```

```
  N = 1000L,
  ID = 2L,
  ZIP = 0L,
  AddDate = FALSE,
  Classification = TRUE,
  MultiClass = FALSE)

TestModel <- AutoQuant::AutoH2oGBMClassifier(

  # Compute management
 MaxMem = {gc();paste0(as.character(floor(as.numeric(system("awk '/MemFree/ {print $2}' /proc/meminfo", int
  NThreads = max(1, parallel::detectCores()-2),
  H2OShutdown = TRUE,
  H2OStartUp = TRUE,
  IfSaveModel = "mojo",

  # Model evaluation
  CostMatrixWeights = c(1,0,0,1),
  eval_metric = "auc",
  NumOfParDepPlots = 3,

  # Metadata arguments
  OutputSelection = c("EvalMetrics", "Score_TrainData"),
  model_path = normalizePath("./"),
  metadata_path = file.path(normalizePath("./")),
  ModelID = "FirstModel",
  ReturnModelObjects = TRUE,
  SaveModelObjects = FALSE,
  SaveInfoToPDF = FALSE,
  DebugMode = FALSE,

  # Data arguments
  data = data,
  TrainOnFull = FALSE,
  ValidationData = NULL,
  TestData = NULL,
  TargetColumnName = "Adrian",
  FeatureColNames = names(data)[!names(data) %in% c("IDcol_1", "IDcol_2","Adrian")],
  WeightsColumn = NULL,

  # ML grid tuning args
  GridTune = FALSE,
  GridStrategy = "Cartesian",
  MaxRunTimeSecs = 60*60*24,
  StoppingRounds = 10,
  MaxModelsInGrid = 2,

  # Model args
  Trees = 50,
  LearnRate = 0.10,
  LearnRateAnnealing = 1,
  Distribution = "bernoulli",
  MaxDepth = 20,
  SampleRate = 0.632,
  ColSampleRate = 1,
  ColSampleRatePerTree = 1,
  ColSampleRatePerTreeLevel  = 1,
```

```
    MinRows = 1,
    NBins = 20,
    NBinsCats = 1024,
    NBinsTopLevel = 1024,
    HistogramType = "AUTO",
    CategoricalEncoding = "AUTO")

## End(Not run)
```

AutoH2oGBMHurdleModel *AutoH2oGBMHurdleModel*

Description

AutoH2oGBMHurdleModel for hurdle modeing

Usage

```
AutoH2oGBMHurdleModel(
  data,
  ValidationData = NULL,
  TestData = NULL,
  Buckets = 0L,
  TargetColumnName = NULL,
  FeatureColNames = NULL,
  TransformNumericColumns = NULL,
  Distribution = "gaussian",
  SplitRatios = c(0.7, 0.2, 0.1),
  ModelID = "ModelTest",
  Paths = NULL,
  MetaDataPaths = NULL,
  SaveModelObjects = TRUE,
  IfSaveModel = "mojo",
  MaxMem = {
     gc()

   paste0(as.character(floor(as.numeric(system("awk '/MemFree/ {print $2}' /proc/meminfo",
     intern = TRUE))/1e+06)), "G")
 },
  NThreads = max(1L, parallel::detectCores() - 2L),
  Trees = 1000L,
  GridTune = TRUE,
  MaxModelsInGrid = 1L,
  NumOfParDepPlots = 10L,
  PassInGrid = NULL
)
```

Arguments

data	Source training data. Do not include a column that has the class labels for the buckets as they are created internally.

`ValidationData` Source validation data. Do not include a column that has the class labels for the buckets as they are created internally.

`TestData` Souce test data. Do not include a column that has the class labels for the buckets as they are created internally.

`Buckets` A numeric vector of the buckets used for subsetting the data. NOTE: the final Bucket value will first create a subset of data that is less than the value and a second one thereafter for data greater than the bucket value.

`TargetColumnName`
Supply the column name or number for the target variable

`FeatureColNames`
Supply the column names or number of the features (not included the PrimaryDateColumn)

`TransformNumericColumns`
Transform numeric column inside the AutoCatBoostRegression() function

`Distribution` Set to the distribution of choice based on H2O regression documents.

`SplitRatios` Supply vector of partition ratios. For example, c(0.70,0.20,0,10).

`ModelID` Define a character name for your models

`Paths` The path to your folder where you want your model information saved

`MetaDataPaths` A character string of your path file to where you want your model evaluation output saved. If left NULL, all output will be saved to Paths.

`SaveModelObjects`
Set to TRUE to save the model objects to file in the folders listed in Paths

`IfSaveModel` Save as "mojo" or "standard"

`MaxMem` Set the maximum memory your system can provide

`NThreads` Set the number of threads you want to dedicate to the model building

`Trees` Default 1000

`GridTune` Set to TRUE if you want to grid tune the models

`MaxModelsInGrid`
Set to a numeric value for the number of models to try in grid tune

`NumOfParDepPlots`
Set to pull back N number of partial dependence calibration plots.

`PassInGrid` Pass in a grid for changing up the parameter settings for catboost

Value

Returns AutoXGBoostRegression() model objects: VariableImportance.csv, Model, ValidationData.csv, EvalutionPlot.png, EvalutionBoxPlot.png, EvaluationMetrics.csv, ParDepPlots.R a named list of features with partial dependence calibration plots, ParDepBoxPlots.R, GridCollect, and the grid used

Author(s)

Adrian Antico

See Also

Other Supervised Learning - Hurdle Modeling: `AutoH2oDRFHurdleModel()`

Examples

```
Output <- AutoQuant::AutoH2oGBMHurdleModel(
  data,
  ValidationData = NULL,
  TestData = NULL,
  Buckets = 1L,
  TargetColumnName = "Target_Variable",
  FeatureColNames = 4L:ncol(data),
  TransformNumericColumns = NULL,
  Distribution = "gaussian",
  SplitRatios = c(0.7, 0.2, 0.1),
 MaxMem = {gc();paste0(as.character(floor(as.numeric(system("awk '/MemFree/ {print $2}' /proc/meminfo", inter
  NThreads = max(1L, parallel::detectCores()-2L),
  ModelID = "ModelID",
  Paths = normalizePath("./"),
  MetaDataPaths = NULL,
  SaveModelObjects = TRUE,
  IfSaveModel = "mojo",
  Trees = 1000L,
  GridTune = FALSE,
  MaxModelsInGrid = 1L,
  NumOfParDepPlots = 10L,
  PassInGrid = NULL)
```

AutoH2oGBMMultiClass *AutoH2oGBMMultiClass*

Description

AutoH2oGBMMultiClass is an automated H2O modeling framework with grid-tuning and model evaluation that runs a variety of steps. First, a stratified sampling (by the target variable) is done to create train and validation sets. Then, the function will run a random grid tune over N number of models and find which model is the best (a default model is always included in that set). Once the model is identified and built, several other outputs are generated: validation data with predictions, evaluation metrics, confusion matrix, and variable importance.

Usage

```
AutoH2oGBMMultiClass(
  OutputSelection = c("EvalMetrics", "Score_TrainData"),
  data = NULL,
  TrainOnFull = FALSE,
  ValidationData = NULL,
  TestData = NULL,
  TargetColumnName = NULL,
  FeatureColNames = NULL,
  WeightsColumn = NULL,
  MaxMem = {
     gc()

   paste0(as.character(floor(as.numeric(system("awk '/MemFree/ {print $2}' /proc/meminfo",
```

```
    intern = TRUE))/1e+06)), "G")
 },
  NThreads = max(1L, parallel::detectCores() - 2L),
  model_path = NULL,
  metadata_path = NULL,
  ModelID = "FirstModel",
  NumOfParDepPlots = 3L,
  ReturnModelObjects = TRUE,
  SaveModelObjects = FALSE,
  IfSaveModel = "mojo",
  H2OShutdown = TRUE,
  H2OStartUp = TRUE,
  DebugMode = FALSE,
  GridTune = FALSE,
  GridStrategy = "Cartesian",
  MaxRunTimeSecs = 60 * 60 * 24,
  StoppingRounds = 10,
  MaxModelsInGrid = 2,
  eval_metric = "auc",
  Trees = 50L,
  LearnRate = 0.1,
  LearnRateAnnealing = 1,
  Distribution = "multinomial",
  MaxDepth = 20,
  SampleRate = 0.632,
  MTries = -1,
  ColSampleRate = 1,
  ColSampleRatePerTree = 1,
  ColSampleRatePerTreeLevel = 1,
  MinRows = 1,
  NBins = 20,
  NBinsCats = 1024,
  NBinsTopLevel = 1024,
  HistogramType = "AUTO",
  CategoricalEncoding = "AUTO"
)
```

Arguments

OutputSelection	You can select what type of output you want returned. Choose from c("EvalMetrics", "Score_TrainData", "h2o.explain")
data	This is your data set for training and testing your model
TrainOnFull	Set to TRUE to train on full data
ValidationData	This is your holdout data set used in modeling either refine your hyperparameters.
TestData	This is your holdout data set. Catboost using both training and validation data in the training process so you should evaluate out of sample performance with this data set.
TargetColumnName	Either supply the target column name OR the column number where the target is located (but not mixed types).

`FeatureColNames`
: Either supply the feature column names OR the column number where the target is located (but not mixed types)

`WeightsColumn`
: Column name of a weights column

`MaxMem`
: Set the maximum amount of memory you'd like to dedicate to the model run. E.g. "32G"

`NThreads`
: Set to the mamimum amount of threads you want to use for this function

`model_path`
: A character string of your path file to where you want your output saved

`metadata_path`
: A character string of your path file to where you want your model evaluation output saved. If left NULL, all output will be saved to model_path.

`ModelID`
: A character string to name your model and output

`NumOfParDepPlots`
: Tell the function the number of partial dependence calibration plots you want to create. Calibration boxplots will only be created for numerical features (not dummy variables)

`ReturnModelObjects`
: Set to TRUE to output all modeling objects (E.g. plots and evaluation metrics)

`SaveModelObjects`
: Set to TRUE to return all modeling objects to your environment

`IfSaveModel`
: Set to "mojo" to save a mojo file, otherwise "standard" to save a regular H2O model object

`H2OShutdown`
: Set to TRUE to shutdown H2O inside the function

`H2OStartUp`
: Defaults to TRUE which means H2O will be started inside the function

`DebugMode`
: Set to TRUE to print steps

`GridTune`
: Set to TRUE to run a grid tuning procedure. Set a number in MaxModelsInGrid to tell the procedure how many models you want to test.

`GridStrategy`
: Default "Cartesian"

`MaxRunTimeSecs`
: Default 60*60*24

`StoppingRounds`
: Number of runs

`MaxModelsInGrid`
: Number of models to test from grid options (1080 total possible options)

`eval_metric`
: This is the metric used to identify best grid tuned model. Choose from "auc", "logloss"

`Trees`
: The maximum number of trees you want in your models

`LearnRate`
: Default 0.10

`LearnRateAnnealing`
: Default 1

`Distribution`
: Choose from "multinomial". Placeholder in more options get added

`MaxDepth`
: Default 20

`SampleRate`
: Default 0.632

`ColSampleRate`
: Default 1

`ColSampleRatePerTree`
: Default 1

`ColSampleRatePerTreeLevel`
: Default 1

MinRows	Default 1
NBins	Default 20
NBinsCats	Default 1024
NBinsTopLevel	Default 1024
HistogramType	Default "AUTO"
CategoricalEncoding	Default "AUTO"
SaveInfoToPDF	Set to TRUE to save insights to PDF

Value

Saves to file and returned in list: VariableImportance.csv, Model, ValidationData.csv, EvaluationMetrics.csv, GridCollect, and GridList

Author(s)

Adrian Antico

See Also

Other Automated Supervised Learning - Multiclass Classification: AutoCatBoostMultiClass(), AutoH2oDRFMultiClass(), AutoH2oGAMMultiClass(), AutoH2oGLMMultiClass(), AutoH2oMLMultiClass(), AutoXGBoostMultiClass()

Examples

```
# Create some dummy correlated data
data <- AutoQuant::FakeDataGenerator(
  Correlation = 0.85,
  N = 1000,
  ID = 2,
  ZIP = 0,
  AddDate = FALSE,
  Classification = FALSE,
  MultiClass = TRUE)

# Run function
TestModel <- AutoQuant::AutoH2oGBMMultiClass(
  OutputSelection = c("EvalMetrics", "Score_TrainData"),
  data,
  TrainOnFull = FALSE,
  ValidationData = NULL,
  TestData = NULL,
  TargetColumnName = "Adrian",
  FeatureColNames = names(data)[!names(data) %in% c("IDcol_1", "IDcol_2","Adrian")],
  WeightsColumn = NULL,
  eval_metric = "logloss",
 MaxMem = {gc();paste0(as.character(floor(as.numeric(system("awk '/MemFree/ {print $2}' /proc/meminfo", inter
  NThreads = max(1, parallel::detectCores()-2),
  model_path = normalizePath("./"),
  metadata_path = file.path(normalizePath("./")),
  ModelID = "FirstModel",
  ReturnModelObjects = TRUE,
  SaveModelObjects = FALSE,
```

```
  IfSaveModel = "mojo",
  H2OShutdown = TRUE,
  H2OStartUp = TRUE,
  DebugMode = FALSE,

  # Model args
  GridTune = FALSE,
  GridStrategy = "Cartesian",
  MaxRunTimeSecs = 60*60*24,
  StoppingRounds = 10,
  MaxModelsInGrid = 2,
  Trees = 50,
  LearnRate = 0.10,
  LearnRateAnnealing = 1,
  eval_metric = "RMSE",
  Distribution = "multinomial",
  MaxDepth = 20,
  SampleRate = 0.632,
  ColSampleRate = 1,
  ColSampleRatePerTree = 1,
  ColSampleRatePerTreeLevel  = 1,
  MinRows = 1,
  NBins = 20,
  NBinsCats = 1024,
  NBinsTopLevel = 1024,
  HistogramType = "AUTO",
  CategoricalEncoding = "AUTO")
```

`AutoH2oGBMRegression` *AutoH2oGBMRegression*

Description

AutoH2oGBMRegression is an automated H2O modeling framework with grid-tuning and model evaluation that runs a variety of steps. First, the function will run a random grid tune over N number of models and find which model is the best (a default model is always included in that set). Once the model is identified and built, several other outputs are generated: validation data with predictions, evaluation plot, evaluation boxplot, evaluation metrics, variable importance, partial dependence calibration plots, partial dependence calibration box plots, and column names used in model fitting.

Usage

```
AutoH2oGBMRegression(
  OutputSelection = c("EvalMetrics", "Score_TrainData"),
  data = NULL,
  TrainOnFull = FALSE,
  ValidationData = NULL,
  TestData = NULL,
  TargetColumnName = NULL,
  FeatureColNames = NULL,
  WeightsColumn = NULL,
  TransformNumericColumns = NULL,
```

```
  Methods = c("Asinh", "Log", "LogPlus1", "Sqrt", "Asin", "Logit"),
  MaxMem = {
     gc()

   paste0(as.character(floor(as.numeric(system("awk '/MemFree/ {print $2}' /proc/meminfo",
     intern = TRUE))/1e+06)), "G")
 },
  NThreads = max(1, parallel::detectCores() - 2),
  model_path = NULL,
  metadata_path = NULL,
  ModelID = "FirstModel",
  NumOfParDepPlots = 3,
  ReturnModelObjects = TRUE,
  SaveModelObjects = FALSE,
  SaveInfoToPDF = FALSE,
  IfSaveModel = "mojo",
  H2OShutdown = TRUE,
  H2OStartUp = TRUE,
  DebugMode = FALSE,
  GridTune = FALSE,
  GridStrategy = "Cartesian",
  MaxRunTimeSecs = 60 * 60 * 24,
  StoppingRounds = 10,
  MaxModelsInGrid = 2,
  eval_metric = "RMSE",
  Trees = 50,
  LearnRate = 0.1,
  LearnRateAnnealing = 1,
  Alpha = NULL,
  Distribution = "poisson",
  MaxDepth = 20,
  SampleRate = 0.632,
  MTries = -1,
  ColSampleRate = 1,
  ColSampleRatePerTree = 1,
  ColSampleRatePerTreeLevel = 1,
  MinRows = 1,
  NBins = 20,
  NBinsCats = 1024,
  NBinsTopLevel = 1024,
  HistogramType = "AUTO",
  CategoricalEncoding = "AUTO"
)
```

Arguments

OutputSelection	You can select what type of output you want returned. Choose from c("EvalMetrics", "Score_TrainData", "h2o.explain")
data	This is your data set for training and testing your model
TrainOnFull	Set to TRUE to train on full data

`ValidationData` This is your holdout data set used in modeling either refine your hyperparameters.

`TestData` This is your holdout data set. Catboost using both training and validation data in the training process so you should evaluate out of sample performance with this data set.

`TargetColumnName`
Either supply the target column name OR the column number where the target is located (but not mixed types).

`FeatureColNames`
Either supply the feature column names OR the column number where the target is located (but not mixed types)

`WeightsColumn` Column name of a weights column

`TransformNumericColumns`
Set to NULL to do nothing; otherwise supply the column names of numeric variables you want transformed

`Methods` Choose from "YeoJohnson", "BoxCox", "Asinh", "Log", "LogPlus1", "Sqrt", "Asin", or "Logit". If more than one is selected, the one with the best normalization pearson statistic will be used. Identity is automatically selected and compared.

`MaxMem` Set the maximum amount of memory you'd like to dedicate to the model run. E.g. "32G"

`NThreads` Set to the mamimum amount of threads you want to use for this function

`model_path` A character string of your path file to where you want your output saved

`metadata_path` A character string of your path file to where you want your model evaluation output saved. If left NULL, all output will be saved to model_path.

`ModelID` A character string to name your model and output

`NumOfParDepPlots`
Tell the function the number of partial dependence calibration plots you want to create. Calibration boxplots will only be created for numerical features (not dummy variables)

`ReturnModelObjects`
Set to TRUE to output all modeling objects (E.g. plots and evaluation metrics)

`SaveModelObjects`
Set to TRUE to return all modeling objects to your environment

`SaveInfoToPDF` Set to TRUE to save insights to PDF

`IfSaveModel` Set to "mojo" to save a mojo file, otherwise "standard" to save a regular H2O model object

`H2OShutdown` Set to TRUE to shutdown H2O inside the function

`H2OStartUp` Defaults to TRUE which means H2O will be started inside the function

`DebugMode` Set to TRUE to print steps to screen

`GridTune` Set to TRUE to run a grid tuning procedure. Set a number in MaxModelsInGrid to tell the procedure how many models you want to test.

`GridStrategy` Default "Cartesian"

`MaxRunTimeSecs` Default 60*60*24

`StoppingRounds` Number of runs

`MaxModelsInGrid`
: Number of models to test from grid options (1080 total possible options)

`eval_metric`
: This is the metric used to identify best grid tuned model. Choose from "MSE", "RMSE", "MAE", "RMSLE"

`Trees`
: The maximum number of trees you want in your models

`LearnRate`
: Default 0.10

`LearnRateAnnealing`
: Default 1

`Alpha`
: This is the quantile value you want to use for quantile regression. Must be a decimal between 0 and 1.

`Distribution`
: Choose from gaussian", "poisson", "gamma", "tweedie", "laplace", "quantile", "huber"

`MaxDepth`
: Default 20

`SampleRate`
: Default 0.632

`ColSampleRate`
: Default 1

`ColSampleRatePerTree`
: Default 1

`ColSampleRatePerTreeLevel`
: Default 1

`MinRows`
: Default 1

`NBins`
: Default 20

`NBinsCats`
: Default 1024

`NBinsTopLevel`
: Default 1024

`HistogramType`
: Default "AUTO"

`CategoricalEncoding`
: Default "AUTO"

Value

Saves to file and returned in list: VariableImportance.csv, Model, ValidationData.csv, EvalutionPlot.png, EvalutionBoxPlot.png, EvaluationMetrics.csv, ParDepPlots.R a named list of features with partial dependence calibration plots, ParDepBoxPlots.R, GridCollect, GridList, and metadata

Author(s)

Adrian Antico

See Also

Other Automated Supervised Learning - Regression: `AutoCatBoostRegression()`, `AutoH2oDRFRegression()`, `AutoH2oGAMRegression()`, `AutoH2oGLMRegression()`, `AutoH2oMLRegression()`, `AutoLightGBMRegression()`, `AutoXGBoostRegression()`

Examples

```
# Create some dummy correlated data
data <- AutoQuant::FakeDataGenerator(
  Correlation = 0.85,
  N = 1000,
  ID = 2,
```

```
  ZIP = 0,
  AddDate = FALSE,
  Classification = FALSE,
  MultiClass = FALSE)

# Run function
TestModel <- AutoQuant::AutoH2oGBMRegression(

  # Compute management
 MaxMem = {gc();paste0(as.character(floor(as.numeric(system("awk '/MemFree/ {print $2}' /proc/meminfo", inter
  NThreads = max(1, parallel::detectCores()-2),
  H2OShutdown = TRUE,
  H2OStartUp = TRUE,
  IfSaveModel = "mojo",

  # Model evaluation
  NumOfParDepPlots = 3,

  # Metadata arguments
  OutputSelection = c("EvalMetrics", "PDFs", "Score_TrainData"),
  model_path = normalizePath("./"),
  metadata_path = file.path(normalizePath("./")),
  ModelID = "FirstModel",
  ReturnModelObjects = TRUE,
  SaveModelObjects = FALSE,
  SaveInfoToPDF = FALSE,
  DebugMode = FALSE,

  # Data arguments
  data = data,
  TrainOnFull = FALSE,
  ValidationData = NULL,
  TestData = NULL,
  TargetColumnName = "Adrian",
  FeatureColNames = names(data)[!names(data) %in% c("IDcol_1", "IDcol_2","Adrian")],
  WeightsColumn = NULL,
  TransformNumericColumns = NULL,
  Methods = c("Asinh", "Asin", "Log", "LogPlus1", "Sqrt", "Logit"),

  # ML grid tuning args
  GridTune = FALSE,
  GridStrategy = "Cartesian",
  MaxRunTimeSecs = 60*60*24,
  StoppingRounds = 10,
  MaxModelsInGrid = 2,

  # Model args
  Trees = 50,
  LearnRate = 0.10,
  LearnRateAnnealing = 1,
  eval_metric = "RMSE",
  Alpha = NULL,
  Distribution = "poisson",
  MaxDepth = 20,
  SampleRate = 0.632,
  ColSampleRate = 1,
  ColSampleRatePerTree = 1,
```

```
  ColSampleRatePerTreeLevel  = 1,
  MinRows = 1,
  NBins = 20,
  NBinsCats = 1024,
  NBinsTopLevel = 1024,
  HistogramType = "AUTO",
  CategoricalEncoding = "AUTO")
```

AutoH2oGLMClassifier *AutoH2oGLMClassifier*

Description

AutoH2oGLMClassifier is an automated H2O modeling framework with grid-tuning and model evaluation that runs a variety of steps. First, a stratified sampling (by the target variable) is done to create train and validation sets. Then, the function will run a random grid tune over N number of models and find which model is the best (a default model is always included in that set). Once the model is identified and built, several other outputs are generated: validation data with predictions, evaluation plot, evaluation metrics, variable importance, partial dependence calibration plots, and column names used in model fitting.

Usage

```
AutoH2oGLMClassifier(
  OutputSelection = c("EvalMetrics", "Score_TrainData"),
  data = NULL,
  TrainOnFull = FALSE,
  ValidationData = NULL,
  TestData = NULL,
  TargetColumnName = NULL,
  FeatureColNames = NULL,
  RandomColNumbers = NULL,
  InteractionColNumbers = NULL,
  WeightsColumn = NULL,
  MaxMem = {
     gc()

   paste0(as.character(floor(as.numeric(system("awk '/MemFree/ {print $2}' /proc/meminfo",
     intern = TRUE))/1e+06)), "G")
 },
  NThreads = max(1, parallel::detectCores() - 2),
  ModelID = "FirstModel",
  ReturnModelObjects = TRUE,
  model_path = NULL,
  metadata_path = NULL,
  SaveModelObjects = FALSE,
  SaveInfoToPDF = FALSE,
  IfSaveModel = "mojo",
  H2OShutdown = TRUE,
  H2OStartUp = TRUE,
  DebugMode = FALSE,
```

```
  MaxModelsInGrid = 2,
  NumOfParDepPlots = 3,
  GridTune = FALSE,
  GridStrategy = "Cartesian",
  StoppingRounds = 10,
  MaxRunTimeSecs = 3600 * 24 * 7,
  Distribution = "binomial",
  Link = "logit",
  eval_metric = "auc",
  CostMatrixWeights = c(1, 0, 0, 1),
  RandomDistribution = NULL,
  RandomLink = NULL,
  Solver = "AUTO",
  Alpha = 0.5,
  Lambda = NULL,
  LambdaSearch = FALSE,
  NLambdas = -1,
  Standardize = TRUE,
  RemoveCollinearColumns = FALSE,
  InterceptInclude = TRUE,
  NonNegativeCoefficients = FALSE
)
```

Arguments

OutputSelection	You can select what type of output you want returned. Choose from c("EvalMetrics", "Score_TrainData")
data	This is your data set for training and testing your model
TrainOnFull	Set to TRUE to train on full data
ValidationData	This is your holdout data set used in modeling either refine your hyperparameters.
TestData	This is your holdout data set. Catboost using both training and validation data in the training process so you should evaluate out of sample performance with this data set.
TargetColumnName	Either supply the target column name OR the column number where the target is located (but not mixed types).
FeatureColNames	Either supply the feature column names OR the column number where the target is located (but not mixed types)
RandomColNumbers	Random effects column number indicies. You can also pass character names of the columns.
InteractionColNumbers	Column numbers of the features you want to be pairwise interacted
WeightsColumn	Column name of a weights column
MaxMem	Set the maximum amount of memory you'd like to dedicate to the model run. E.g. "32G"
NThreads	Set the number of threads you want to dedicate to the model building

ModelID A character string to name your model and output

ReturnModelObjects
Set to TRUE to output all modeling objects (E.g. plots and evaluation metrics)

model_path A character string of your path file to where you want your output saved

metadata_path A character string of your path file to where you want your model evaluation output saved. If left NULL, all output will be saved to model_path.

SaveModelObjects
Set to TRUE to return all modeling objects to your environment

SaveInfoToPDF Set to TRUE to save modeling information to PDF. If model_path or metadata_path aren't defined then output will be saved to the working directory

IfSaveModel Set to "mojo" to save a mojo file, otherwise "standard" to save a regular H2O model object

H2OShutdown Set to TRUE to shutdown H2O inside the function

H2OStartUp Defaults to TRUE which means H2O will be started inside the function

DebugMode Set to TRUE to print steps to screen

MaxModelsInGrid
Number of models to test from grid options (1080 total possible options)

NumOfParDepPlots
Tell the function the number of partial dependence calibration plots you want to create. Calibration boxplots will only be created for numerical features (not dummy variables)

GridTune Set to TRUE to run a grid tuning procedure. Set a number in MaxModelsInGrid to tell the procedure how many models you want to test.

GridStrategy "RandomDiscrete" or "Cartesian"

StoppingRounds Iterations in grid tuning

MaxRunTimeSecs Max run time in seconds

Distribution "binomial", "fractionalbinomial", "quasibinomial"

Link identity, logit, log, inverse, tweedie

eval_metric This is the metric used to identify best grid tuned model. Choose from "auc"

CostMatrixWeights
A vector with 4 elements c(True Positive Cost, False Negative Cost, False Positive Cost, True Negative Cost). Default c(1,0,0,1),

RandomDistribution
Random effects family. Defaults NULL, otherwise it will run a hierarchical glm

RandomLink Random effects link. Defaults NULL, otherwise it will run a hierarchical glm

Solver Default "AUTO". Options include "IRLSM", "L_BFGS", "COORDINATE_DESCENT_NAIVE", "COORDINATE_DESCENT", "GRADIENT_DESCENT_LH", "GRADIENT_DESCENT_SQERR

Alpha Default 0.5 Otherwise supply a value between 0 and 1. 1 is equivalent to Lasso regression. 0 is equivalent to Ridge regression. Inbetween for a blend of the two.

Lambda Default NULL. Regularization strength.

LambdaSearch Default FALSE.

NLambdas Default -1

Standardize Default TRUE. Standardize numerical columns

RemoveCollinearColumns
: Default FALSE. Removes some of the linearly dependent columns

InterceptInclude
: Default TRUE

NonNegativeCoefficients
: Default FALSE

Value

Saves to file and returned in list: VariableImportance.csv, Model, ValidationData.csv, EvalutionPlot.png, EvaluationMetrics.csv, ParDepPlots.R a named list of features with partial dependence calibration plots, GridCollect, and GridList

Author(s)

Adrian Antico

See Also

Other Automated Supervised Learning - Binary Classification: AutoCatBoostClassifier(), AutoH2oDRFClassifier(), AutoH2oGAMClassifier(), AutoH2oGBMClassifier(), AutoH2oMLClassifier(), AutoLightGBMClassifier(), AutoXGBoostClassifier()

Examples

```
# Create some dummy correlated data with numeric and categorical features
data <- AutoQuant::FakeDataGenerator(
  Correlation = 0.85,
  N = 1000L,
  ID = 2L,
  ZIP = 0L,
  AddDate = FALSE,
  Classification = TRUE,
  MultiClass = FALSE)

# Run function
TestModel <- AutoQuant::AutoH2oGLMClassifier(

    # Compute management
   MaxMem = {gc();paste0(as.character(floor(as.numeric(system("awk '/MemFree/ {print $2}' /proc/meminfo", int
    NThreads = max(1, parallel::detectCores()-2),
    H2OShutdown = TRUE,
    H2OStartUp = TRUE,
    IfSaveModel = "mojo",

    # Model evaluation args
    CostMatrixWeights = c(1,0,0,1),
    eval_metric = "auc",
    NumOfParDepPlots = 3,

    # Metadata args
    OutputSelection = c("EvalMetrics", "Score_TrainData"),
    model_path = NULL,
    metadata_path = NULL,
    ModelID = "FirstModel",
    ReturnModelObjects = TRUE,
```

```
  SaveModelObjects = FALSE,
  SaveInfoToPDF = FALSE,
  DebugMode = FALSE,

  # Data args
  data = data,
  TrainOnFull = FALSE,
  ValidationData = NULL,
  TestData = NULL,
  TargetColumnName = "Adrian",
  FeatureColNames = names(data)[!names(data) %in%
    c("IDcol_1", "IDcol_2","Adrian")],
  RandomColNumbers = NULL,
  InteractionColNumbers = NULL,
  WeightsColumn = NULL,

  # ML args
  GridTune = FALSE,
  GridStrategy = "Cartesian",
  StoppingRounds = 10,
  MaxRunTimeSecs = 3600 * 24 * 7,
  MaxModelsInGrid = 10,
  Distribution = "binomial",
  Link = "logit",
  RandomDistribution = NULL,
  RandomLink = NULL,
  Solver = "AUTO",
  Alpha = 0.5,
  Lambda = NULL,
  LambdaSearch = FALSE,
  NLambdas = -1,
  Standardize = TRUE,
  RemoveCollinearColumns = FALSE,
  InterceptInclude = TRUE,
  NonNegativeCoefficients = FALSE)
```

AutoH2oGLMMultiClass *AutoH2oGLMMultiClass*

Description

AutoH2oGLMMultiClass is an automated H2O modeling framework with grid-tuning and model evaluation that runs a variety of steps. First, a stratified sampling (by the target variable) is done to create train and validation sets. Then, the function will run a random grid tune over N number of models and find which model is the best (a default model is always included in that set). Once the model is identified and built, several other outputs are generated: validation data with predictions, evaluation metrics, confusion matrix, and variable importance.

Usage

```
AutoH2oGLMMultiClass(
  OutputSelection = c("EvalMetrics", "Score_TrainData"),
  data = NULL,
```

```
  TrainOnFull = FALSE,
  ValidationData = NULL,
  TestData = NULL,
  TargetColumnName = NULL,
  FeatureColNames = NULL,
  RandomColNumbers = NULL,
  InteractionColNumbers = NULL,
  WeightsColumn = NULL,
  MaxMem = {
     gc()

   paste0(as.character(floor(as.numeric(system("awk '/MemFree/ {print $2}' /proc/meminfo",
     intern = TRUE))/1e+06)), "G")
 },
  NThreads = max(1, parallel::detectCores() - 2),
  ModelID = "FirstModel",
  ReturnModelObjects = TRUE,
  model_path = NULL,
  metadata_path = NULL,
  DebugMode = FALSE,
  SaveModelObjects = FALSE,
  SaveInfoToPDF = FALSE,
  IfSaveModel = "mojo",
  H2OShutdown = TRUE,
  H2OStartUp = TRUE,
  MaxModelsInGrid = 2,
  NumOfParDepPlots = 3,
  GridTune = FALSE,
  GridStrategy = "Cartesian",
  StoppingRounds = 10,
  MaxRunTimeSecs = 3600 * 24 * 7,
  Distribution = "multinomial",
  Link = "family_default",
  eval_metric = "logloss",
  RandomDistribution = NULL,
  RandomLink = NULL,
  Solver = "AUTO",
  Alpha = 0.5,
  Lambda = NULL,
  LambdaSearch = FALSE,
  NLambdas = -1,
  Standardize = TRUE,
  RemoveCollinearColumns = FALSE,
  InterceptInclude = TRUE,
  NonNegativeCoefficients = FALSE
)
```

Arguments

OutputSelection	You can select what type of output you want returned. Choose from c("EvalMetrics", "Score_TrainData")
data	This is your data set for training and testing your model

`TrainOnFull` Set to TRUE to train on full data

`ValidationData` This is your holdout data set used in modeling either refine your hyperparameters.

`TestData` This is your holdout data set. Catboost using both training and validation data in the training process so you should evaluate out of sample performance with this data set.

`TargetColumnName`
Either supply the target column name OR the column number where the target is located (but not mixed types).

`FeatureColNames`
Either supply the feature column names OR the column number where the target is located (but not mixed types)

`RandomColNumbers`
Random effects column number indicies. You can also pass character names of the columns.

`InteractionColNumbers`
Column numbers of the features you want to be pairwise interacted

`WeightsColumn` Column name of a weights column

`MaxMem` Set the maximum amount of memory you'd like to dedicate to the model run. E.g. "32G"

`NThreads` Set the number of threads you want to dedicate to the model building

`ModelID` A character string to name your model and output

`ReturnModelObjects`
Set to TRUE to output all modeling objects (E.g. plots and evaluation metrics)

`model_path` A character string of your path file to where you want your output saved

`metadata_path` A character string of your path file to where you want your model evaluation output saved. If left NULL, all output will be saved to model_path.

`DebugMode` Set to TRUE to see a printout of each step

`SaveModelObjects`
Set to TRUE to return all modeling objects to your environment

`SaveInfoToPDF` Set to TRUE to save insights to PDF

`IfSaveModel` Set to "mojo" to save a mojo file, otherwise "standard" to save a regular H2O model object

`H2OShutdown` Set to TRUE to shutdown H2O inside the function

`H2OStartUp` Defaults to TRUE which means H2O will be started inside the function

`MaxModelsInGrid`
Number of models to test from grid options (1080 total possible options)

`NumOfParDepPlots`
Tell the function the number of partial dependence calibration plots you want to create. Calibration boxplots will only be created for numerical features (not dummy variables)

`GridTune` Set to TRUE to run a grid tuning procedure. Set a number in MaxModelsInGrid to tell the procedure how many models you want to test.

`GridStrategy` "RandomDiscrete" or "Cartesian"

`StoppingRounds` Iterations in grid tuning

`MaxRunTimeSecs` Max run time in seconds

`Distribution` "multinomial"

`Link` "family_default"

`eval_metric` This is the metric used to identify best grid tuned model. Choose from "logloss"

`RandomDistribution`
Random effects family. Defaults NULL, otherwise it will run a hierarchical glm

`RandomLink` Random effects link. Defaults NULL, otherwise it will run a hierarchical glm

`Solver` Default "AUTO". Options include "IRLSM", "L_BFGS", "COORDINATE_DESCENT_NAIVE", "COORDINATE_DESCENT", "GRADIENT_DESCENT_LH", "GRADIENT_DESCENT_SQERR

`Alpha` Default 0.5 Otherwise supply a value between 0 and 1. 1 is equivalent to Lasso regression. 0 is equivalent to Ridge regression. Inbetween for a blend of the two.

`Lambda` Default NULL. Regularization strength.

`LambdaSearch` Default FALSE.

`NLambdas` Default -1

`Standardize` Default TRUE. Standardize numerical columns

`RemoveCollinearColumns`
Default FALSE. Removes some of the linearly dependent columns

`InterceptInclude`
Default TRUE

`NonNegativeCoefficients`
Default FALSE

Value

Saves to file and returned in list: VariableImportance.csv, Model, ValidationData.csv, EvaluationMetrics.csv, GridCollect, and GridList

Author(s)

Adrian Antico

See Also

Other Automated Supervised Learning - Multiclass Classification: `AutoCatBoostMultiClass()`, `AutoH2oDRFMultiClass()`, `AutoH2oGAMMultiClass()`, `AutoH2oGBMMultiClass()`, `AutoH2oMLMultiClass()`, `AutoXGBoostMultiClass()`

Examples

```
# Create some dummy correlated data with numeric and categorical features
data <- AutoQuant::FakeDataGenerator(
  Correlation = 0.85,
  N = 1000L,
  ID = 2L,
  ZIP = 0L,
  AddDate = FALSE,
  Classification = FALSE,
  MultiClass = TRUE)

# Run function
TestModel <- AutoQuant::AutoH2oGLMMultiClass(
```

```
  # Compute management
  OutputSelection = c("EvalMetrics", "Score_TrainData"),
 MaxMem = {gc();paste0(as.character(floor(as.numeric(system("awk '/MemFree/ {print $2}' /proc/meminfo", inter
  NThreads = max(1, parallel::detectCores()-2),
  H2OShutdown = TRUE,
  H2OStartUp = TRUE,
  IfSaveModel = "mojo",

  # Model evaluation:
  eval_metric = "logloss",
  NumOfParDepPlots = 3,

  # Metadata arguments:
  model_path = NULL,
  metadata_path = NULL,
  ModelID = "FirstModel",
  ReturnModelObjects = TRUE,
  SaveModelObjects = FALSE,
  SaveInfoToPDF = FALSE,
  DebugMode = FALSE,

  # Data arguments:
  data = data,
  TrainOnFull = FALSE,
  ValidationData = NULL,
  TestData = NULL,
  TargetColumnName = "Adrian",
  FeatureColNames = names(data)[!names(data) %in% c("IDcol_1", "IDcol_2","Adrian")],
  RandomColNumbers = NULL,
  InteractionColNumbers = NULL,
  WeightsColumn = NULL,

  # Model args
  GridTune = FALSE,
  GridStrategy = "Cartesian",
  StoppingRounds = 10,
  MaxRunTimeSecs = 3600 * 24 * 7,
  MaxModelsInGrid = 10,
  Distribution = "multinomial",
  Link = "family_default",
  RandomDistribution = NULL,
  RandomLink = NULL,
  Solver = "AUTO",
  Alpha = 0.5,
  Lambda = NULL,
  LambdaSearch = FALSE,
  NLambdas = -1,
  Standardize = TRUE,
  RemoveCollinearColumns = FALSE,
  InterceptInclude = TRUE,
  NonNegativeCoefficients = FALSE)
```

AutoH2oGLMRegression *AutoH2oGLMRegression*

Description

AutoH2oGLMis an automated H2O modeling framework with grid-tuning and model evaluation that runs a variety of steps. First, the function will run a random grid tune over N number of models and find which model is the best (a default model is always included in that set). Once the model is identified and built, several other outputs are generated: validation data with predictions, evaluation plot, evaluation boxplot, evaluation metrics, variable importance, partial dependence calibration plots, partial dependence calibration box plots, and column names used in model fitting.

Usage

```
AutoH2oGLMRegression(
  OutputSelection = c("EvalMetrics", "Score_TrainData"),
  data = NULL,
  TrainOnFull = FALSE,
  ValidationData = NULL,
  TestData = NULL,
  TargetColumnName = NULL,
  FeatureColNames = NULL,
  RandomColNumbers = NULL,
  InteractionColNumbers = NULL,
  WeightsColumn = NULL,
  MaxMem = {
     gc()

   paste0(as.character(floor(as.numeric(system("awk '/MemFree/ {print $2}' /proc/meminfo",
     intern = TRUE))/1e+06)), "G")
 },
  NThreads = max(1, parallel::detectCores() - 2),
  ModelID = "FirstModel",
  ReturnModelObjects = TRUE,
  model_path = NULL,
  metadata_path = NULL,
  SaveModelObjects = FALSE,
  SaveInfoToPDF = FALSE,
  IfSaveModel = "mojo",
  H2OShutdown = TRUE,
  H2OStartUp = TRUE,
  DebugMode = FALSE,
  TransformNumericColumns = NULL,
  Methods = c("BoxCox", "Asinh", "Log", "LogPlus1", "Sqrt", "Asin", "Logit"),
  NumOfParDepPlots = 3,
  GridTune = FALSE,
  GridStrategy = "Cartesian",
  StoppingRounds = 10,
  MaxRunTimeSecs = 3600 * 24 * 7,
  MaxModelsInGrid = 2,
  Distribution = "gaussian",
  Link = "identity",
  TweedieLinkPower = NULL,
  TweedieVariancePower = NULL,
  eval_metric = "RMSE",
  RandomDistribution = NULL,
```

```
  RandomLink = NULL,
  Solver = "AUTO",
  Alpha = 0.5,
  Lambda = NULL,
  LambdaSearch = FALSE,
  NLambdas = -1,
  Standardize = TRUE,
  RemoveCollinearColumns = FALSE,
  InterceptInclude = TRUE,
  NonNegativeCoefficients = FALSE
)
```

Arguments

OutputSelection	You can select what type of output you want returned. Choose from "EvalMetrics", "Score_TrainData", "h2o.explain"
data	This is your data set for training and testing your model
TrainOnFull	Set to TRUE to train on full data
ValidationData	This is your holdout data set used in modeling either refine your hyperparameters.
TestData	This is your holdout data set. Catboost using both training and validation data in the training process so you should evaluate out of sample performance with this data set.
TargetColumnName	Either supply the target column name OR the column number where the target is located (but not mixed types).
FeatureColNames	Either supply the feature column names OR the column number where the target is located (but not mixed types)
RandomColNumbers	Random effects column number indicies. You can also pass character names of the columns.
InteractionColNumbers	Column numbers of the features you want to be pairwise interacted
WeightsColumn	Column name of a weights column
MaxMem	Set the maximum amount of memory you'd like to dedicate to the model run. E.g. "32G"
NThreads	Set the number of threads you want to dedicate to the model building
ModelID	A character string to name your model and output
ReturnModelObjects	Set to TRUE to output all modeling objects (E.g. plots and evaluation metrics)
model_path	A character string of your path file to where you want your output saved
metadata_path	A character string of your path file to where you want your model evaluation output saved. If left NULL, all output will be saved to model_path.
SaveModelObjects	Set to TRUE to return all modeling objects to your environment
SaveInfoToPDF	Set to TRUE to save insights to PDF

IfSaveModel Set to "mojo" to save a mojo file, otherwise "standard" to save a regular H2O model object

H2OShutdown Set to TRUE to shutdown H2O inside the function

H2OStartUp Defaults to TRUE which means H2O will be started inside the function

DebugMode Set to TRUE to print out steps to screen

TransformNumericColumns
Set to NULL to do nothing; otherwise supply the column names of numeric variables you want transformed

Methods Choose from "YeoJohnson", "BoxCox", "Asinh", "Log", "LogPlus1", "Sqrt", "Asin", or "Logit". If more than one is selected, the one with the best normalization pearson statistic will be used. Identity is automatically selected and compared.

NumOfParDepPlots
Tell the function the number of partial dependence calibration plots you want to create. Calibration boxplots will only be created for numerical features (not dummy variables)

GridTune Set to TRUE to run a grid tuning procedure. Set a number in MaxModelsInGrid to tell the procedure how many models you want to test.

GridStrategy "RandomDiscrete" or "Cartesian"

StoppingRounds Iterations in grid tuning

MaxRunTimeSecs Max run time in seconds

MaxModelsInGrid
Number of models to test from grid options (1080 total possible options)

Distribution "AUTO", "gaussian", "poisson", "gamma", "tweedie", "negativebinomial"

Link "family_default", "identity", "log", "inverse", "tweedie"

TweedieLinkPower
1, 2, 3 for Poisson, Gamma, and Gaussian

TweedieVariancePower
See h2o docs for background

eval_metric This is the metric used to identify best grid tuned model. Choose from "MSE", "RMSE", "MAE", "RMSLE"

RandomDistribution
Random effects family. Defaults NULL, otherwise it will run a hierarchical glm

RandomLink Random effects link. Defaults NULL, otherwise it will run a hierarchical glm

Solver Default "AUTO". Options include "IRLSM", "L_BFGS", "COORDINATE_DESCENT_NAIVE", "COORDINATE_DESCENT", "GRADIENT_DESCENT_LH", "GRADIENT_DESCENT_SQERR

Alpha Default 0.5 Otherwise supply a value between 0 and 1. 1 is equivalent to Lasso regression. 0 is equivalent to Ridge regression. Inbetween for a blend of the two.

Lambda Default NULL. Regularization strength.

LambdaSearch Default FALSE.

NLambdas Default -1

Standardize Default TRUE. Standardize numerical columns

RemoveCollinearColumns
Default FALSE. Removes some of the linearly dependent columns

InterceptInclude
Default TRUE

NonNegativeCoefficients
Default FALSE

Value

Saves to file and returned in list: VariableImportance.csv, Model, ValidationData.csv, EvalutionPlot.png, EvalutionBoxPlot.png, EvaluationMetrics.csv, ParDepPlots.R a named list of features with partial dependence calibration plots, ParDepBoxPlots.R, GridCollect, GridList, and Transformation metadata

Author(s)

Adrian Antico

See Also

Other Automated Supervised Learning - Regression: AutoCatBoostRegression(), AutoH2oDRFRegression(), AutoH2oGAMRegression(), AutoH2oGBMRegression(), AutoH2oMLRegression(), AutoLightGBMRegression(), AutoXGBoostRegression()

Examples

```
# Create some dummy correlated data
data <- AutoQuant::FakeDataGenerator(
  Correlation = 0.85,
  N = 1000,
  ID = 2,
  ZIP = 0,
  AddDate = FALSE,
  Classification = FALSE,
  MultiClass = FALSE)

# Run function
TestModel <- AutoQuant::AutoH2oGLMRegression(

  # Compute management
 MaxMem = {gc();paste0(as.character(floor(as.numeric(system("awk '/MemFree/ {print $2}' /proc/meminfo", inter
  NThreads = max(1, parallel::detectCores()-2),
  H2OShutdown = TRUE,
  H2OStartUp = TRUE,
  IfSaveModel = "mojo",

  # Model evaluation:
  eval_metric = "RMSE",
  NumOfParDepPlots = 3,

  # Metadata arguments
  OutputSelection = c("EvalMetrics", "Score_TrainData"),
  model_path = NULL,
  metadata_path = NULL,
  ModelID = "FirstModel",
  ReturnModelObjects = TRUE,
  SaveModelObjects = FALSE,
  SaveInfoToPDF = FALSE,
  DebugMode = FALSE,

  # Data arguments:
  data = data,
  TrainOnFull = FALSE,
  ValidationData = NULL,
```

```
  TestData = NULL,
  TargetColumnName = "Adrian",
  FeatureColNames = names(data)[!names(data) %in%
    c("IDcol_1", "IDcol_2","Adrian")],
  RandomColNumbers = NULL,
  InteractionColNumbers = NULL,
  WeightsColumn = NULL,
  TransformNumericColumns = NULL,
  Methods = c("Asinh", "Asin", "Log", "LogPlus1", "Sqrt", "Logit"),

  # Model args
  GridTune = FALSE,
  GridStrategy = "Cartesian",
  StoppingRounds = 10,
  MaxRunTimeSecs = 3600 * 24 * 7,
  MaxModelsInGrid = 10,
  Distribution = "gaussian",
  Link = "identity",
  TweedieLinkPower = NULL,
  TweedieVariancePower = NULL,
  RandomDistribution = NULL,
  RandomLink = NULL,
  Solver = "AUTO",
  Alpha = 0.5,
  Lambda = NULL,
  LambdaSearch = FALSE,
  NLambdas = -1,
  Standardize = TRUE,
  RemoveCollinearColumns = FALSE,
  InterceptInclude = TRUE,
  NonNegativeCoefficients = FALSE)
```

AutoH2oMLClassifier *AutoH2oMLClassifier*

Description

AutoH2oMLClassifier is an automated H2O modeling framework with grid-tuning and model evaluation that runs a variety of steps. First, a stratified sampling (by the target variable) is done to create train and validation sets. Then, the function will run a random grid tune over N number of models and find which model is the best (a default model is always included in that set). Once the model is identified and built, several other outputs are generated: validation data with predictions, evaluation plot, evaluation metrics, variable importance, partial dependence calibration plots, and column names used in model fitting.

Usage

```
AutoH2oMLClassifier(
  OutputSelection = c("EvalMetrics", "Score_TrainData"),
  data = NULL,
  TrainOnFull = FALSE,
  ValidationData = NULL,
  TestData = NULL,
```

```
  TargetColumnName = NULL,
  FeatureColNames = NULL,
  ExcludeAlgos = NULL,
  eval_metric = "auc",
  CostMatrixWeights = c(1, 0, 0, 1),
  MaxMem = {
     gc()

   paste0(as.character(floor(as.numeric(system("awk '/MemFree/ {print $2}' /proc/meminfo",
     intern = TRUE))/1e+06)), "G")
 },
  NThreads = max(1, parallel::detectCores() - 2),
  MaxModelsInGrid = 2,
  model_path = NULL,
  metadata_path = NULL,
  ModelID = "FirstModel",
  NumOfParDepPlots = 3,
  ReturnModelObjects = TRUE,
  SaveModelObjects = FALSE,
  SaveInfoToPDF = TRUE,
  IfSaveModel = "mojo",
  H2OShutdown = TRUE,
  H2OStartUp = TRUE,
  DebugMode = FALSE
)
```

Arguments

OutputSelection	You can select what type of output you want returned. Choose from c("EvalMetrics", "Score_TrainData")
data	This is your data set for training and testing your model
TrainOnFull	Set to TRUE to train on full data
ValidationData	This is your holdout data set used in modeling either refine your hyperparameters.
TestData	This is your holdout data set. Catboost using both training and validation data in the training process so you should evaluate out of sample performance with this data set.
TargetColumnName	Either supply the target column name OR the column number where the target is located (but not mixed types). Note that the target column needs to be a 0 | 1 numeric variable.
FeatureColNames	Either supply the feature column names OR the column number where the target is located (but not mixed types)
ExcludeAlgos	"DRF","GLM","XGBoost","GBM","DeepLearning" and "Stacke-dEnsemble"
eval_metric	This is the metric used to identify best grid tuned model. Choose from "AUC" or "logloss"
CostMatrixWeights	A vector with 4 elements c(True Positive Cost, False Negative Cost, False Positive Cost, True Negative Cost). Default c(1,0,0,1),

MaxMem	Set the maximum amount of memory you'd like to dedicate to the model run. E.g. "32G"
NThreads	Set the number of threads you want to dedicate to the model building
MaxModelsInGrid	Number of models to test from grid options (1080 total possible options)
model_path	A character string of your path file to where you want your output saved
metadata_path	A character string of your path file to where you want your model evaluation output saved. If left NULL, all output will be saved to model_path.
ModelID	A character string to name your model and output
NumOfParDepPlots	Tell the function the number of partial dependence calibration plots you want to create.
ReturnModelObjects	Set to TRUE to output all modeling objects (E.g. plots and evaluation metrics)
SaveModelObjects	Set to TRUE to return all modeling objects to your environment
SaveInfoToPDF	Set to TRUE to print model insights to PDF
IfSaveModel	Set to "mojo" to save a mojo file, otherwise "standard" to save a regular H2O model object
H2OShutdown	Set to TRUE to shutdown H2O after running the function
H2OStartUp	Set to FALSE
DebugMode	Set to TRUE to print out steps taken

Value

Saves to file and returned in list: VariableImportance.csv, Model, ValidationData.csv, Evalution-Plot.png, EvaluationMetrics.csv, ParDepPlots.R a named list of features with partial dependence calibration plots, GridCollect, and GridList

Author(s)

Adrian Antico

See Also

Other Automated Supervised Learning - Binary Classification: AutoCatBoostClassifier(), AutoH2oDRFClassifier(), AutoH2oGAMClassifier(), AutoH2oGBMClassifier(), AutoH2oGLMClassifier(), AutoLightGBMClassifier(), AutoXGBoostClassifier()

Examples

```
# Create some dummy correlated data with numeric and categorical features
data <- AutoQuant::FakeDataGenerator(
  Correlation = 0.85,
  N = 1000L,
  ID = 2L,
  ZIP = 0L,
  AddDate = FALSE,
  Classification = TRUE,
  MultiClass = FALSE)
```

```
TestModel <- AutoQuant::AutoH2oMLClassifier(
  OutputSelection = c("EvalMetrics", "Score_TrainData"),
  data,
  TrainOnFull = FALSE,
  ValidationData = NULL,
  TestData = NULL,
  TargetColumnName = "Adrian",
  FeatureColNames = names(data)[!names(data) %in% c("IDcol_1", "IDcol_2","Adrian")],
  ExcludeAlgos = NULL,
  eval_metric = "auc",
  CostMatrixWeights = c(1,0,0,1),
 MaxMem = {gc();paste0(as.character(floor(as.numeric(system("awk '/MemFree/ {print $2}' /proc/meminfo", inter
  NThreads = max(1, parallel::detectCores()-2),
  MaxModelsInGrid = 10,
  model_path = normalizePath("./"),
  metadata_path = normalizePath("./"),
  ModelID = "FirstModel",
  NumOfParDepPlots = 3,
  ReturnModelObjects = TRUE,
  SaveModelObjects = FALSE,
  SaveInfoToPDF = TRUE,
  IfSaveModel = "mojo",
  H2OShutdown = TRUE,
  H2OStartUp = TRUE,
  DebugMode = FALSE)
```

AutoH2oMLMultiClass *AutoH2oMLMultiClass*

Description

AutoH2oDRFMultiClass is an automated H2O modeling framework with grid-tuning and model evaluation that runs a variety of steps. First, a stratified sampling (by the target variable) is done to create train and validation sets. Then, the function will run a random grid tune over N number of models and find which model is the best (a default model is always included in that set). Once the model is identified and built, several other outputs are generated: validation data with predictions, evaluation metrics, confusion matrix, and variable importance.

Usage

```
AutoH2oMLMultiClass(
  OutputSelection = c("EvalMetrics", "Score_TrainData"),
  data = NULL,
  TrainOnFull = FALSE,
  ValidationData = NULL,
  TestData = NULL,
  TargetColumnName = NULL,
  FeatureColNames = NULL,
  ExcludeAlgos = NULL,
  eval_metric = "logloss",
  MaxMem = {
     gc()
```

```
  paste0(as.character(floor(as.numeric(system("awk '/MemFree/ {print $2}' /proc/meminfo",
    intern = TRUE))/1e+06)), "G")
 },
 NThreads = max(1, parallel::detectCores() - 2),
 MaxModelsInGrid = 2,
 model_path = NULL,
 metadata_path = NULL,
 ModelID = "FirstModel",
 ReturnModelObjects = TRUE,
 SaveModelObjects = FALSE,
 SaveInfoToPDF = TRUE,
 IfSaveModel = "mojo",
 H2OShutdown = TRUE,
 H2OStartUp = TRUE,
 DebugMode = FALSE
)
```

Arguments

OutputSelection	You can select what type of output you want returned. Choose from c("EvalMetrics", "Score_TrainData")
data	This is your data set for training and testing your model
TrainOnFull	Set to TRUE to train on full data
ValidationData	This is your holdout data set used in modeling either refine your hyperparameters.
TestData	This is your holdout data set. Catboost using both training and validation data in the training process so you should evaluate out of sample performance with this data set.
TargetColumnName	Either supply the target column name OR the column number where the target is located (but not mixed types).
FeatureColNames	Either supply the feature column names OR the column number where the target is located (but not mixed types)
ExcludeAlgos	"DRF","GLM","XGBoost","GBM","DeepLearning" and "Stacke-dEnsemble"
eval_metric	This is the metric used to identify best grid tuned model. Choose from "logloss", "r2", "RMSE", "MSE"
MaxMem	Set the maximum amount of memory you'd like to dedicate to the model run. E.g. "32G"
NThreads	Set the number of threads you want to dedicate to the model building
MaxModelsInGrid	Number of models to test from grid options (1080 total possible options)
model_path	A character string of your path file to where you want your output saved
metadata_path	A character string of your path file to where you want your model evaluation output saved. If left NULL, all output will be saved to model_path.
ModelID	A character string to name your model and output

ReturnModelObjects
: Set to TRUE to output all modeling objects (E.g. plots and evaluation metrics)

SaveModelObjects
: Set to TRUE to return all modeling objects to your environment

SaveInfoToPDF
: Set to TRUE to print model insights to PDF

IfSaveModel
: Set to "mojo" to save a mojo file, otherwise "standard" to save a regular H2O model object

H2OShutdown
: Set to TRUE to have H2O shutdown after running this function

H2OStartUp
: Set to FALSE

DebugMode
: Set to TRUE to get a print out of steps taken internally

Value

Saves to file and returned in list: VariableImportance.csv, Model, ValidationData.csv, EvaluationMetrics.csv, GridCollect, and GridList

Author(s)

Adrian Antico

See Also

Other Automated Supervised Learning - Multiclass Classification: AutoCatBoostMultiClass(), AutoH2oDRFMultiClass(), AutoH2oGAMMultiClass(), AutoH2oGBMMultiClass(), AutoH2oGLMMultiClass(), AutoXGBoostMultiClass()

Examples

```
# Create some dummy correlated data with numeric and categorical features
data <- AutoQuant::FakeDataGenerator(
  Correlation = 0.85,
  N = 1000,
  ID = 2,
  ZIP = 0,
  AddDate = FALSE,
  Classification = FALSE,
  MultiClass = TRUE)

# Run function
TestModel <- AutoQuant::AutoH2oMLMultiClass(
  OutputSelection = c("EvalMetrics", "Score_TrainData"),
  data,
  TrainOnFull = FALSE,
  ValidationData = NULL,
  TestData = NULL,
  TargetColumnName = "Adrian",
  FeatureColNames = names(data)[!names(data) %in% c("IDcol_1", "IDcol_2","Adrian")],
  ExcludeAlgos = NULL,
  eval_metric = "logloss",
 MaxMem = {gc();paste0(as.character(floor(as.numeric(system("awk '/MemFree/ {print $2}' /proc/meminfo", inter
  NThreads = max(1, parallel::detectCores()-2),
  MaxModelsInGrid = 10,
  model_path = normalizePath("./"),
  metadata_path = normalizePath("./"),
```

```
  ModelID = "FirstModel",
  ReturnModelObjects = TRUE,
  SaveModelObjects = FALSE,
  SaveInfoToPDF = TRUE,
  IfSaveModel = "mojo",
  H2OShutdown = TRUE,
  H2OStartUp = TRUE,
  DebugMode = FALSE)
```

AutoH2oMLRegression *AutoH2oMLRegression*

Description

AutoH2oMLRegression is an automated H2O modeling framework with grid-tuning and model evaluation that runs a variety of steps. First, the function will run a random grid tune over N number of models and find which model is the best (a default model is always included in that set). Once the model is identified and built, several other outputs are generated: validation data with predictions, evaluation plot, evaluation boxplot, evaluation metrics, variable importance, partial dependence calibration plots, partial dependence calibration box plots, and column names used in model fitting.

Usage

```
AutoH2oMLRegression(
  OutputSelection = c("EvalMetrics", "Score_TrainData"),
  data = NULL,
  TrainOnFull = FALSE,
  ValidationData = NULL,
  TestData = NULL,
  TargetColumnName = NULL,
  FeatureColNames = NULL,
  ExcludeAlgos = NULL,
  TransformNumericColumns = NULL,
  Methods = c("BoxCox", "Asinh", "Log", "LogPlus1", "Sqrt", "Asin", "Logit"),
  eval_metric = "RMSE",
  MaxMem = {
     gc()

   paste0(as.character(floor(as.numeric(system("awk '/MemFree/ {print $2}' /proc/meminfo",
     intern = TRUE))/1e+06)), "G")
 },
  NThreads = max(1, parallel::detectCores() - 2),
  model_path = NULL,
  metadata_path = NULL,
  ModelID = "FirstModel",
  NumOfParDepPlots = 3,
  ReturnModelObjects = TRUE,
  SaveModelObjects = FALSE,
  SaveInfoToPDF = TRUE,
  IfSaveModel = "mojo",
```

```
  H2OShutdown = TRUE,
  H2OStartUp = TRUE,
  DebugMode = FALSE
)
```

Arguments

OutputSelection	You can select what type of output you want returned. Choose from c("EvalMetrics", "Score_TrainData")
data	This is your data set for training and testing your model
TrainOnFull	Set to TRUE to train on full data
ValidationData	This is your holdout data set used in modeling either refine your hyperparameters.
TestData	This is your holdout data set. Catboost using both training and validation data in the training process so you should evaluate out of sample performance with this data set.
TargetColumnName	Either supply the target column name OR the column number where the target is located (but not mixed types).
FeatureColNames	Either supply the feature column names OR the column number where the target is located (but not mixed types)
ExcludeAlgos	"DRF","GLM","XGBoost","GBM","DeepLearning" and "Stacke-dEnsemble"
TransformNumericColumns	Set to NULL to do nothing; otherwise supply the column names of numeric variables you want transformed
Methods	Choose from "YeoJohnson", "BoxCox", "Asinh", "Log", "LogPlus1", "Sqrt", "Asin", or "Logit". If more than one is selected, the one with the best normalization pearson statistic will be used. Identity is automatically selected and compared.
eval_metric	This is the metric used to identify best grid tuned model. Choose from "MSE", "RMSE", "MAE", "RMSLE"
MaxMem	Set the maximum amount of memory you'd like to dedicate to the model run. E.g. "32G"
NThreads	Set the number of threads you want to dedicate to the model building
model_path	A character string of your path file to where you want your output saved
metadata_path	A character string of your path file to where you want your model evaluation output saved. If left NULL, all output will be saved to model_path.
ModelID	A character string to name your model and output
NumOfParDepPlots	Tell the function the number of partial dependence calibration plots you want to create. Calibration boxplots will only be created for numerical features (not dummy variables)
ReturnModelObjects	Set to TRUE to output all modeling objects (E.g. plots and evaluation metrics)
SaveModelObjects	Set to TRUE to return all modeling objects to your environment

SaveInfoToPDF	Set to TRUE to save insights to PDF
IfSaveModel	Set to "mojo" to save a mojo file, otherwise "standard" to save a regular H2O model object
H2OShutdown	Set to TRUE to shutdown H2O inside the function
H2OStartUp	Defaults to TRUE which means H2O will be started inside the function
DebugMode	Set to TRUE to print to screen steps taken internally

Value

Saves to file and returned in list: VariableImportance.csv, Model, ValidationData.csv, EvalutionPlot.png, EvalutionBoxPlot.png, EvaluationMetrics.csv, ParDepPlots.R a named list of features with partial dependence calibration plots, ParDepBoxPlots.R, GridCollect, GridList, and Transformation metadata

Author(s)

Adrian Antico

See Also

Other Automated Supervised Learning - Regression: AutoCatBoostRegression(), AutoH2oDRFRegression(), AutoH2oGAMRegression(), AutoH2oGBMRegression(), AutoH2oGLMRegression(), AutoLightGBMRegression(), AutoXGBoostRegression()

Examples

```
# Create some dummy correlated data
data <- AutoQuant::FakeDataGenerator(
  Correlation = 0.85,
  N = 1000,
  ID = 2,
  ZIP = 0,
  AddDate = FALSE,
  Classification = FALSE,
  MultiClass = FALSE)

# Run function
TestModel <- AutoQuant::AutoH2oMLRegression(

  # Compute management
 MaxMem = {gc();paste0(as.character(floor(as.numeric(system("awk '/MemFree/ {print $2}' /proc/meminfo", inter
  NThreads = max(1, parallel::detectCores()-2),
  H2OShutdown = TRUE,
  H2OStartUp = TRUE,
  IfSaveModel = "mojo",

  # Model evaluation
  eval_metric = "RMSE",
  NumOfParDepPlots = 3,

  # Metadata arguments
  OutputSelection = c("EvalMetrics", "Score_TrainData"),
  model_path = NULL,
  metadata_path = NULL,
  ModelID = "FirstModel",
```

```
  ReturnModelObjects = TRUE,
  SaveModelObjects = FALSE,
  SaveInfoToPDF = TRUE,
  DebugMode = FALSE,

  # Data arguments
  TrainOnFull = FALSE,
  ValidationData = NULL,
  TestData = NULL,
  TargetColumnName = "Adrian",
  FeatureColNames = names(data)[!names(data) %in% c("IDcol_1", "IDcol_2","Adrian")],
  TransformNumericColumns = NULL,
  Methods = c("BoxCox", "Asinh", "Asin", "Log", "LogPlus1", "Sqrt", "Logit"),

  # Model args
  ExcludeAlgos = NULL)
```

AutoH2OMLScoring *AutoH2OMLScoring*

Description

AutoH2OMLScoring is an automated scoring function that compliments the AutoH2oGBM__() and AutoH2oDRF__() models training functions. This function requires you to supply features for scoring. It will run ModelDataPrep()to prepare your features for H2O data conversion and scoring.

Usage

```
AutoH2OMLScoring(
  ScoringData = NULL,
  ModelObject = NULL,
  ModelType = "mojo",
  H2OShutdown = TRUE,
  H2OStartUp = TRUE,
  MaxMem = {
     gc()

   paste0(as.character(floor(as.numeric(system("awk '/MemFree/ {print $2}' /proc/meminfo",
     intern = TRUE))/1e+06)), "G")
 },
  NThreads = max(1, parallel::detectCores() - 2),
  JavaOptions = "-Xmx1g -XX:ReservedCodeCacheSize=256m",
  ModelPath = NULL,
  ModelID = NULL,
  ReturnFeatures = TRUE,
  TransformNumeric = FALSE,
  BackTransNumeric = FALSE,
  TargetColumnName = NULL,
  TransformationObject = NULL,
  TransID = NULL,
  TransPath = NULL,
```

```
  MDP_Impute = TRUE,
  MDP_CharToFactor = TRUE,
  MDP_RemoveDates = TRUE,
  MDP_MissFactor = "0",
  MDP_MissNum = -1
)
```

Arguments

ScoringData	This is your data.table of features for scoring. Can be a single row or batch.
ModelObject	Supply a model object from AutoH2oDRF__()
ModelType	Set to either "mojo" or "standard" depending on which version you saved
H2OShutdown	Set to TRUE to shutdown H2O inside the function.
H2OStartUp	Defaults to TRUE which means H2O will be started inside the function
MaxMem	Set to you dedicated amount of memory. E.g. "28G"
NThreads	Default set to max(1, parallel::detectCores()-2)
JavaOptions	Change the default to your machines specification if needed. Default is '-Xmx1g -XX:ReservedCodeCacheSize=256m',
ModelPath	Supply your path file used in the AutoH2o__() function
ModelID	Supply the model ID used in the AutoH2o__() function
ReturnFeatures	Set to TRUE to return your features with the predicted values.
TransformNumeric	Set to TRUE if you have features that were transformed automatically from an Auto__Regression() model AND you haven't already transformed them.
BackTransNumeric	Set to TRUE to generate back-transformed predicted values. Also, if you return features, those will also be back-transformed.
TargetColumnName	Input your target column name used in training if you are utilizing the transformation service
TransformationObject	Set to NULL if you didn't use transformations or if you want the function to pull from the file output from the Auto__Regression() function. You can also supply the transformation data.table object with the transformation details versus having it pulled from file.
TransID	Set to the ID used for saving the transformation data.table object or set it to the ModelID if you are pulling from file from a build with Auto__Regression().
TransPath	Set the path file to the folder where your transformation data.table detail object is stored. If you used the Auto__Regression() to build, set it to the same path as ModelPath.
MDP_Impute	Set to TRUE if you did so for modeling and didn't do so before supplying ScoringData in this function
MDP_CharToFactor	Set to TRUE to turn your character columns to factors if you didn't do so to your ScoringData that you are supplying to this function
MDP_RemoveDates	Set to TRUE if you have date of timestamp columns in your ScoringData

MDP_MissFactor If you set MDP_Impute to TRUE, supply the character values to replace missing values with

MDP_MissNum If you set MDP_Impute to TRUE, supply a numeric value to replace missing values with

Value

A data.table of predicted values with the option to return model features as well.

Author(s)

Adrian Antico

See Also

Other Automated Model Scoring: AutoCatBoostScoring(), AutoLightGBMScoring(), AutoXGBoostScoring()

Examples

```
## Not run:
Preds <- AutoH2OMLScoring(
  ScoringData = data,
  ModelObject = NULL,
  ModelType = "mojo",
  H2OShutdown = TRUE,
  H2OStartUp = TRUE,
 MaxMem = {gc();paste0(as.character(floor(as.numeric(system("awk '/MemFree/ {print $2}' /proc/meminfo", inter
  NThreads = max(1, parallel::detectCores()-2),
  JavaOptions = '-Xmx1g -XX:ReservedCodeCacheSize=256m',
  ModelPath = normalizePath("./"),
  ModelID = "ModelTest",
  ReturnFeatures = TRUE,
  TransformNumeric = FALSE,
  BackTransNumeric = FALSE,
  TargetColumnName = NULL,
  TransformationObject = NULL,
  TransID = NULL,
  TransPath = NULL,
  MDP_Impute = TRUE,
  MDP_CharToFactor = TRUE,
  MDP_RemoveDates = TRUE,
  MDP_MissFactor = "0",
  MDP_MissNum = -1)

## End(Not run)
```

AutoHierarchicalFourier

AutoHierarchicalFourier

Description

AutoHierarchicalFourier reverses the difference

Usage

```
AutoHierarchicalFourier(
  datax = data,
  xRegs = names(XREGS),
  FourierTermS = FourierTerms,
  TimeUniT = TimeUnit,
  FC_PeriodS = FC_Periods,
  TargetColumN = TargetColumn,
  DateColumN = DateColumnName,
  HierarchGroups = NULL,
  IndependentGroups = NULL
)
```

Arguments

datax	data
xRegs	The XREGS
FourierTermS	Number of fourier pairs
TimeUniT	Time unit
FC_PeriodS	Number of forecast periods
TargetColumN	Target column name
DateColumN	Date column name
HierarchGroups	Character vector of categorical columns to fully interact
IndependentGroups	Character vector of categorical columns to run independently

Author(s)

Adrian Antico

See Also

Other Feature Engineering: AutoDataPartition(), AutoDiffLagN(), AutoInteraction(), AutoLagRollMode(), AutoLagRollStatsScoring(), AutoLagRollStats(), AutoTransformationCreate(), AutoTransformationScore(), AutoWord2VecModeler(), AutoWord2VecScoring(), CategoricalEncoding(), CreateCalendarVariables(), CreateHolidayVariables(), DummifyDT(), H2OAutoencoderScoring(), H2OAutoencoder(), ModelDataPrep(), PercRankScoring(), PercRank(), StandardizeScoring(), Standardize(), TimeSeriesFillRoll(), TimeSeriesFill()

AutoInteraction *AutoInteraction*

Description

AutoInteraction creates interaction variables from your numerical features in your data. Supply a set of column names to utilize and set the interaction level. Supply a character vector of columns to exclude and the function will ignore those features.

Usage

```
AutoInteraction(
  data = NULL,
  NumericVars = NULL,
  InteractionDepth = 2,
  Center = TRUE,
  Scale = TRUE,
  SkipCols = NULL,
  Scoring = FALSE,
  File = NULL
)
```

Arguments

data	Source data.table
InteractionDepth	The max K in N choose K. If NULL, K will loop through 1 to length(NumVars). Default is 2 for pairwise interactions
Center	TRUE to center the data
Scale	TRUE to scale the data
SkipCols	Use this to exclude features from being created. An example could be, you build a model with all variables and then use the varaible importance list to determine which features aren't necessary and pass that set of features into this argument as a character vector.
Scoring	Defaults to FALSE. Set to TRUE for generating these columns in a model scoring setting
File	When Scoring is set to TRUE you have to supply either the .Rdata list with lookup values for recreating features or a pathfile to the .Rdata file with the lookup values. If you didn't center or scale the data then this argument can be ignored.
NumVars	Names of numeric columns (if NULL, all numeric and integer columns will be used)

Author(s)

Adrian Antico

See Also

Other Feature Engineering: AutoDataPartition(), AutoDiffLagN(), AutoHierarchicalFourier(), AutoLagRollMode(), AutoLagRollStatsScoring(), AutoLagRollStats(), AutoTransformationCreate(), AutoTransformationScore(), AutoWord2VecModeler(), AutoWord2VecScoring(), CategoricalEncoding(), CreateCalendarVariables(), CreateHolidayVariables(), DummifyDT(), H2OAutoencoderScoring(), H2OAutoencoder(), ModelDataPrep(), PercRankScoring(), PercRank(), StandardizeScoring(), Standardize(), TimeSeriesFillRoll(), TimeSeriesFill()

Examples

```
## Not run:

########################################
```

```
# Feature Engineering for Model Training
########################################

# Create fake data
data <- AutoQuant::FakeDataGenerator(
  Correlation = 0.70,
  N = 50000,
  ID = 2L,
  FactorCount = 2L,
  AddDate = TRUE,
  ZIP = 0L,
  TimeSeries = FALSE,
  ChainLadderData = FALSE,
  Classification = FALSE,
  MultiClass = FALSE)

# Print number of columns
print(ncol(data))

# Store names of numeric and integer cols
Cols <-names(data)[c(which(unlist(lapply(data, is.numeric))),
                     which(unlist(lapply(data, is.integer))))]

# Model Training Feature Engineering
system.time(data <- AutoQuant::AutoInteraction(
  data = data,
  NumericVars = Cols,
  InteractionDepth = 4,
  Center = TRUE,
  Scale = TRUE,
  SkipCols = NULL,
  Scoring = FALSE,
  File = getwd()))

# user  system elapsed
# 0.30    0.11    0.41

# Print number of columns
print(ncol(data))

########################################
# Feature Engineering for Model Scoring
########################################

# Create fake data
data <- AutoQuant::FakeDataGenerator(
  Correlation = 0.70,
  N = 1000,
  ID = 2L,
  FactorCount = 2L,
  AddDate = TRUE,
  ZIP = 0L,
  TimeSeries = FALSE,
  ChainLadderData = FALSE,
  Classification = FALSE,
  MultiClass = FALSE)
```

```
# Print number of columns
print(ncol(data))

# Reduce to single row to mock a scoring scenario
data <- data[1L]

# Model Scoring Feature Engineering
system.time(data <- AutoQuant::AutoInteraction(
  data = data,
  NumericVars = names(data)[
    c(which(unlist(lapply(data, is.numeric))),
      which(unlist(lapply(data, is.integer))))],
  InteractionDepth = 4,
  Center = TRUE,
  Scale = TRUE,
  SkipCols = NULL,
  Scoring = TRUE,
  File = file.path(getwd(), "Standardize.Rdata")))

# user  system elapsed
# 0.19    0.00    0.19

# Print number of columns
print(ncol(data))

## End(Not run)
```

AutoLagRollMode *AutoLagRollMode*

Description

Create lags and rolling modes for categorical variables.

Usage

```
AutoLagRollMode(
  data,
  Lags = 1,
  ModePeriods = 0,
  Targets = NULL,
  GroupingVars = NULL,
  SortDateName = NULL,
  WindowingLag = 0,
  Type = c("Lag"),
  SimpleImpute = TRUE,
  Debug = FALSE
)
```

Arguments

data	A data.table you want to run the function on

Lags	A numeric vector of the specific lags you want to have generated. You must include 1 if WindowingLag = 1.
ModePeriods	A numberic vector of window sizes
Targets	A character vector of the column names for the reference column in which you will build your lags and rolling stats
GroupingVars	A character vector of categorical variable names you will build your lags and rolling stats by
SortDateName	The column name of your date column used to sort events over time
WindowingLag	Set to 0 to build rolling stats off of target columns directly or set to 1 to build the rolling stats off of the lag-1 target
Type	List either "Lag" if you want features built on historical values or "Lead" if you want features built on future values
SimpleImpute	Set to TRUE for factor level imputation of "0" and numeric imputation of -1
Debug	= FALSE

Value

data.table of original data plus created lags, rolling stats, and time between event lags and rolling stats

Author(s)

Adrian Antico

See Also

Other Feature Engineering: AutoDataPartition(), AutoDiffLagN(), AutoHierarchicalFourier(), AutoInteraction(), AutoLagRollStatsScoring(), AutoLagRollStats(), AutoTransformationCreate(), AutoTransformationScore(), AutoWord2VecModeler(), AutoWord2VecScoring(), CategoricalEncoding(), CreateCalendarVariables(), CreateHolidayVariables(), DummifyDT(), H2OAutoencoderScoring(), H2OAutoencoder(), ModelDataPrep(), PercRankScoring(), PercRank(), StandardizeScoring(), Standardize(), TimeSeriesFillRoll(), TimeSeriesFill()

Examples

```
## Not run:
# NO GROUPING CASE: Create fake Panel Data----
Count <- 1L
for(Level in LETTERS) {
  datatemp <- AutoQuant::FakeDataGenerator(
    Correlation = 0.75,
    N = 25000L,
    ID = 0L,
    ZIP = 0L,
    FactorCount = 2L,
    AddDate = TRUE,
    Classification = FALSE,
    MultiClass = FALSE)
  datatemp[, Factor1 := eval(Level)]
  if(Count == 1L) {
    data <- data.table::copy(datatemp)
  } else {
```

```
    data <- data.table::rbindlist(
      list(data, data.table::copy(datatemp)))
  }
  Count <- Count + 1L
}

# NO GROUPING CASE: Create rolling modes for categorical features
data <- AutoQuant::AutoLagRollMode(
  data,
  Lags           = seq(1,5,1),
  ModePeriods    = seq(2,5,1),
  Targets        = c("Factor_1"),
  GroupingVars   = NULL,
  SortDateName   = "DateTime",
  WindowingLag   = 1,
  Type           = "Lag",
  SimpleImpute   = TRUE)

# GROUPING CASE: Create fake Panel Data----
Count <- 1L
for(Level in LETTERS) {
  datatemp <- AutoQuant::FakeDataGenerator(
    Correlation = 0.75,
    N = 25000L,
    ID = 0L,
    ZIP = 0L,
    FactorCount = 2L,
    AddDate = TRUE,
    Classification = FALSE,
    MultiClass = FALSE)
  datatemp[, Factor1 := eval(Level)]
  if(Count == 1L) {
    data <- data.table::copy(datatemp)
  } else {
    data <- data.table::rbindlist(
      list(data, data.table::copy(datatemp)))
  }
  Count <- Count + 1L
}

# GROUPING CASE: Create rolling modes for categorical features
data <- AutoQuant::AutoLagRollMode(
  data,
  Lags           = seq(1,5,1),
  ModePeriods    = seq(2,5,1),
  Targets        = c("Factor_1"),
  GroupingVars   = "Factor_2",
  SortDateName   = "DateTime",
  WindowingLag   = 1,
  Type           = "Lag",
  SimpleImpute   = TRUE)

## End(Not run)
```

AutoLagRollStats *AutoLagRollStats*

Description

AutoLagRollStats Builds lags and a large variety of rolling statistics with options to generate them for hierarchical categorical interactions.

Usage

```
AutoLagRollStats(
  data,
  Targets = NULL,
  HierarchyGroups = NULL,
  IndependentGroups = NULL,
  DateColumn = NULL,
  TimeUnit = NULL,
  TimeUnitAgg = NULL,
  TimeGroups = NULL,
  TimeBetween = NULL,
  RollOnLag1 = TRUE,
  Type = "Lag",
  SimpleImpute = TRUE,
  Lags = NULL,
  MA_RollWindows = NULL,
  SD_RollWindows = NULL,
  Skew_RollWindows = NULL,
  Kurt_RollWindows = NULL,
  Quantile_RollWindows = NULL,
  Quantiles_Selected = NULL,
  ShortName = TRUE,
  Debug = FALSE
)
```

Arguments

data	A data.table you want to run the function on
Targets	A character vector of the column names for the reference column in which you will build your lags and rolling stats
HierarchyGroups	A vector of categorical column names that you want to have generate all lags and rolling stats done for the individual columns and their full set of interactions.
IndependentGroups	A vector of categorical column names that you want to have run independently of each other. This will mean that no interaction will be done.
DateColumn	The column name of your date column used to sort events over time
TimeUnit	List the time aggregation level for the time between events features, such as "hour", "day", "weeks", "months", "quarter", or "year"
TimeUnitAgg	List the time aggregation of your data that you want to use as a base time unit for your features. E.g. "raw" or "day"
TimeGroups	A vector of TimeUnits indicators to specify any time-aggregated GDL features you want to have returned. E.g. c("raw" (no aggregation is done),"hour","day","week","month","quarter","year")
TimeBetween	Specify a desired name for features created for time between events. Set to NULL if you don't want time between events features created.

RollOnLag1 Set to FALSE to build rolling stats off of target columns directly or set to TRUE to build the rolling stats off of the lag-1 target

Type List either "Lag" if you want features built on historical values or "Lead" if you want features built on future values

SimpleImpute Set to TRUE for factor level imputation of "0" and numeric imputation of -1

Lags A numeric vector of the specific lags you want to have generated. You must include 1 if WindowingLag = 1.

MA_RollWindows A numeric vector of the specific rolling statistics window sizes you want to utilize in the calculations.

SD_RollWindows A numeric vector of Standard Deviation rolling statistics window sizes you want to utilize in the calculations.

Skew_RollWindows
A numeric vector of Skewness rolling statistics window sizes you want to utilize in the calculations.

Kurt_RollWindows
A numeric vector of Kurtosis rolling statistics window sizes you want to utilize in the calculations.

Quantile_RollWindows
A numeric vector of Quantile rolling statistics window sizes you want to utilize in the calculations.

Quantiles_Selected
Select from the following c("q5", "q10", "q15", "q20", "q25", "q30", "q35", "q40", "q45", "q50", "q55", "q60"," q65", "q70", "q75", "q80", "q85", "q90", "q95")

ShortName Default TRUE. If FALSE, Group Variable names will be added to the rolling stat and lag names. If you plan on have multiple versions of lags and rollings stats by different group variables then set this to FALSE.

Debug Set to TRUE to get a print of which steps are running

Value

data.table of original data plus created lags, rolling stats, and time between event lags and rolling stats

Author(s)

Adrian Antico

See Also

Other Feature Engineering: AutoDataPartition(), AutoDiffLagN(), AutoHierarchicalFourier(), AutoInteraction(), AutoLagRollMode(), AutoLagRollStatsScoring(), AutoTransformationCreate(), AutoTransformationScore(), AutoWord2VecModeler(), AutoWord2VecScoring(), CategoricalEncoding(), CreateCalendarVariables(), CreateHolidayVariables(), DummifyDT(), H2OAutoencoderScoring(), H2OAutoencoder(), ModelDataPrep(), PercRankScoring(), PercRank(), StandardizeScoring(), Standardize(), TimeSeriesFillRoll(), TimeSeriesFill()

Examples

```
## Not run:
# Create fake Panel Data----
Count <- 1L
for(Level in LETTERS) {
  datatemp <- AutoQuant::FakeDataGenerator(
    Correlation = 0.75,
    N = 25000L,
    ID = 0L,
    ZIP = 0L,
    FactorCount = 0L,
    AddDate = TRUE,
    Classification = FALSE,
    MultiClass = FALSE)
  datatemp[, Factor1 := eval(Level)]
  if(Count == 1L) {
    data <- data.table::copy(datatemp)
  } else {
    data <- data.table::rbindlist(
      list(data, data.table::copy(datatemp)))
  }
  Count <- Count + 1L
}

# Add scoring records
data <- AutoQuant::AutoLagRollStats(
  data                 = data,
  DateColumn           = "DateTime",
  Targets              = "Adrian",
  HierarchyGroups      = NULL,
  IndependentGroups    = c("Factor1"),
  TimeUnitAgg          = "days",
  TimeGroups           = c("days","weeks","months","quarters"),
  TimeBetween          = NULL,
  TimeUnit             = "days",
  RollOnLag1           = TRUE,
  Type                 = "Lag",
  SimpleImpute         = TRUE,
 Lags           = list("days" = c(seq(1,5,1)), "weeks" = c(seq(1,3,1)), "months" = c(seq(1,2,1)), "quarters" =
 MA_RollWindows     = list("days" = c(seq(1,5,1)), "weeks" = c(seq(1,3,1)), "months" = c(seq(1,2,1)), "quarter
 SD_RollWindows     = list("days" = c(seq(1,5,1)), "weeks" = c(seq(1,3,1)), "months" = c(seq(1,2,1)), "quarter
 Skew_RollWindows    = list("days" = c(seq(1,5,1)), "weeks" = c(seq(1,3,1)), "months" = c(seq(1,2,1)), "quarte
 Kurt_RollWindows    = list("days" = c(seq(1,5,1)), "weeks" = c(seq(1,3,1)), "months" = c(seq(1,2,1)), "quarte
 Quantile_RollWindows = list("days" = c(seq(1,5,1)), "weeks" = c(seq(1,3,1)), "months" = c(seq(1,2,1)), "quart
  Quantiles_Selected   = c('q5','q50'),
  Debug                = FALSE)

## End(Not run)
```

AutoLagRollStatsScoring

AutoLagRollStatsScoring

Description

AutoLagRollStatsScoring Builds lags and a large variety of rolling statistics with options to generate them for hierarchical categorical interactions.

Usage

```
AutoLagRollStatsScoring(
  data,
  RowNumsID = "temp",
  RowNumsKeep = 1,
  Targets = NULL,
  HierarchyGroups = NULL,
  IndependentGroups = NULL,
  DateColumn = NULL,
  TimeUnit = "day",
  TimeUnitAgg = "day",
  TimeGroups = "day",
  TimeBetween = NULL,
  RollOnLag1 = 1,
  Type = "Lag",
  SimpleImpute = TRUE,
  Lags = NULL,
  MA_RollWindows = NULL,
  SD_RollWindows = NULL,
  Skew_RollWindows = NULL,
  Kurt_RollWindows = NULL,
  Quantile_RollWindows = NULL,
  Quantiles_Selected = NULL,
  ShortName = TRUE,
  Debug = FALSE
)
```

Arguments

data	A data.table you want to run the function on
RowNumsID	The name of your column used to id the records so you can specify which rows to keep
RowNumsKeep	The RowNumsID numbers that you want to keep
Targets	A character vector of the column names for the reference column in which you will build your lags and rolling stats
HierarchyGroups	A vector of categorical column names that you want to have generate all lags and rolling stats done for the individual columns and their full set of interactions.
IndependentGroups	Only supply if you do not want HierarchyGroups. A vector of categorical column names that you want to have run independently of each other. This will mean that no interaction will be done.
DateColumn	The column name of your date column used to sort events over time
TimeUnit	List the time aggregation level for the time between events features, such as "hour", "day", "weeks", "months", "quarter", or "year"

TimeUnitAgg	List the time aggregation of your data that you want to use as a base time unit for your features. E.g. "day",
TimeGroups	A vector of TimeUnits indicators to specify any time-aggregated GDL features you want to have returned. E.g. c("hour", "day","week","month","quarter","year"). STILL NEED TO ADD these '1min', '5min', '10min', '15min', '30min', '45min'
TimeBetween	Specify a desired name for features created for time between events. Set to NULL if you don't want time between events features created.
RollOnLag1	Set to FALSE to build rolling stats off of target columns directly or set to TRUE to build the rolling stats off of the lag-1 target
Type	List either "Lag" if you want features built on historical values or "Lead" if you want features built on future values
SimpleImpute	Set to TRUE for factor level imputation of "0" and numeric imputation of -1
Lags	A numeric vector of the specific lags you want to have generated. You must include 1 if WindowingLag = 1.
MA_RollWindows	A numeric vector of the specific rolling statistics window sizes you want to utilize in the calculations.
SD_RollWindows	A numeric vector of Standard Deviation rolling statistics window sizes you want to utilize in the calculations.
Skew_RollWindows	A numeric vector of Skewness rolling statistics window sizes you want to utilize in the calculations.
Kurt_RollWindows	A numeric vector of Kurtosis rolling statistics window sizes you want to utilize in the calculations.
Quantile_RollWindows	A numeric vector of Quantile rolling statistics window sizes you want to utilize in the calculations.
Quantiles_Selected	Select from the following c("q5", "q10", "q15", "q20", "q25", "q30", "q35", "q40", "q45", "q50", "q55", "q60"," q65", "q70", "q75", "q80", "q85", "q90", "q95")
ShortName	Default TRUE. If FALSE, Group Variable names will be added to the rolling stat and lag names. If you plan on have multiple versions of lags and rollings stats by different group variables then set this to FALSE.
Debug	Set to TRUE to get a print out of which step you are on

Value

data.table of original data plus created lags, rolling stats, and time between event lags and rolling stats

Author(s)

Adrian Antico

See Also

Other Feature Engineering: AutoDataPartition(), AutoDiffLagN(), AutoHierarchicalFourier(), AutoInteraction(), AutoLagRollMode(), AutoLagRollStats(), AutoTransformationCreate(), AutoTransformationScore(), AutoWord2VecModeler(), AutoWord2VecScoring(), CategoricalEncoding(),

CreateCalendarVariables(), CreateHolidayVariables(), DummifyDT(), H2OAutoencoderScoring(), H2OAutoencoder(), ModelDataPrep(), PercRankScoring(), PercRank(), StandardizeScoring(), Standardize(), TimeSeriesFillRoll(), TimeSeriesFill()

Examples

```
# Create fake Panel Data----
Count <- 1L
for(Level in LETTERS) {
  datatemp <- AutoQuant::FakeDataGenerator(
    Correlation = 0.75,
    N = 25000L,
    ID = 0L,
    ZIP = 0L,
    FactorCount = 0L,
    AddDate = TRUE,
    Classification = FALSE,
    MultiClass = FALSE)
  datatemp[, Factor1 := eval(Level)]
  if(Count == 1L) {
    data1 <- data.table::copy(datatemp)
  } else {
    data1 <- data.table::rbindlist(
      list(data1, data.table::copy(datatemp)))
  }
  Count <- Count + 1L
}

# Create ID columns to know which records to score
data1[, ID := .N:1L, by = "Factor1"]
data.table::set(data1, i = which(data1[["ID"]] == 2L), j = "ID", value = 1L)

# Score records
data1 <- AutoQuant::AutoLagRollStatsScoring(

  # Data
  data                = data1,
  RowNumsID           = "ID",
  RowNumsKeep         = 1,
  DateColumn          = "DateTime",
  Targets             = "Adrian",
  HierarchyGroups     = NULL,
  IndependentGroups   = c("Factor1"),

  # Services
  TimeBetween         = NULL,
  TimeGroups          = c("days","weeks","months","quarters"),
  TimeUnit            = "day",
  TimeUnitAgg         = "day",
  RollOnLag1          = TRUE,
  Type                = "Lag",
  SimpleImpute        = TRUE,

  # Calculated Columns
 Lags           = list("days" = c(seq(1,5,1)), "weeks" = c(seq(1,3,1)), "months" = c(seq(1,2,1)), "quarters" =
 MA_RollWindows     = list("days" = c(seq(1,5,1)), "weeks" = c(seq(1,3,1)), "months" = c(seq(1,2,1)), "quarter
 SD_RollWindows     = list("days" = c(seq(1,5,1)), "weeks" = c(seq(1,3,1)), "months" = c(seq(1,2,1)), "quarter
```

```
Skew_RollWindows    = list("days" = c(seq(1,5,1)), "weeks" = c(seq(1,3,1)), "months" = c(seq(1,2,1)), "quarte
Kurt_RollWindows    = list("days" = c(seq(1,5,1)), "weeks" = c(seq(1,3,1)), "months" = c(seq(1,2,1)), "quarte
Quantile_RollWindows = list("days" = c(seq(1,5,1)), "weeks" = c(seq(1,3,1)), "months" = c(seq(1,2,1)), "quart
 Quantiles_Selected   = c('q5','q50'),
 Debug                 = FALSE)
```

AutoLightGBMCARMA *AutoLightGBMCARMA*

Description

AutoLightGBMCARMA Mutlivariate Forecasting with calendar variables, Holiday counts, holiday lags, holiday moving averages, differencing, transformations, interaction-based categorical encoding using target variable and features to generate various time-based aggregated lags, moving averages, moving standard deviations, moving skewness, moving kurtosis, moving quantiles, parallelized interaction-based fourier pairs by grouping variables, and Trend Variables.

Usage

```
AutoLightGBMCARMA(
  data = NULL,
  XREGS = NULL,
  TimeWeights = NULL,
  NonNegativePred = FALSE,
  RoundPreds = FALSE,
  TrainOnFull = FALSE,
  TargetColumnName = NULL,
  DateColumnName = NULL,
  HierarchGroups = NULL,
  GroupVariables = NULL,
  FC_Periods = 1,
  NThreads = max(1, parallel::detectCores() - 2L),
  SaveDataPath = NULL,
  TimeUnit = NULL,
  TimeGroups = NULL,
  TargetTransformation = FALSE,
  Methods = c("Asinh", "Log", "LogPlus1", "Sqrt"),
  EncodingMethod = "target_encoding",
  AnomalyDetection = NULL,
  Lags = NULL,
  MA_Periods = NULL,
  SD_Periods = NULL,
  Skew_Periods = NULL,
  Kurt_Periods = NULL,
  Quantile_Periods = NULL,
  Quantiles_Selected = c("q5", "q95"),
  Difference = TRUE,
  FourierTerms = 0,
  CalendarVariables = NULL,
  HolidayVariable = NULL,
```

```
  HolidayLookback = NULL,
  HolidayLags = 1L,
  HolidayMovingAverages = 3L,
  TimeTrendVariable = FALSE,
  DataTruncate = FALSE,
  ZeroPadSeries = "maxmax",
  SplitRatios = c(0.95, 0.05),
  PartitionType = "random",
  Timer = TRUE,
  SaveModel = FALSE,
  ArgsList = NULL,
  DebugMode = FALSE,
  ModelID = "FC001",
  GridTune = FALSE,
  GridEvalMetric = "mae",
  ModelCount = 30L,
  MaxRunsWithoutNewWinner = 20L,
  MaxRunMinutes = 24L * 60L,
  Device_Type = "cpu",
  LossFunction = "regression",
  EvalMetric = "mae",
  Input_Model = NULL,
  Task = "train",
  Boosting = "gbdt",
  LinearTree = FALSE,
  Trees = 500L,
  ETA = 0.5,
  Num_Leaves = 31,
  Deterministic = TRUE,
  Force_Col_Wise = FALSE,
  Force_Row_Wise = FALSE,
  Max_Depth = 6,
  Min_Data_In_Leaf = 20,
  Min_Sum_Hessian_In_Leaf = 0.001,
  Bagging_Freq = 1,
  Bagging_Fraction = 0.7,
  Feature_Fraction = 1,
  Feature_Fraction_Bynode = 1,
  Lambda_L1 = 4,
  Lambda_L2 = 4,
  Extra_Trees = FALSE,
  Early_Stopping_Round = 10,
  First_Metric_Only = TRUE,
  Max_Delta_Step = 0,
  Linear_Lambda = 0,
  Min_Gain_To_Split = 0,
  Drop_Rate_Dart = 0.1,
  Max_Drop_Dart = 50,
  Skip_Drop_Dart = 0.5,
  Uniform_Drop_Dart = FALSE,
  Top_Rate_Goss = FALSE,
  Other_Rate_Goss = FALSE,
```

```
  Monotone_Constraints = NULL,
  Monotone_Constraints_method = "advanced",
  Monotone_Penalty = 0,
  Forcedsplits_Filename = NULL,
  Refit_Decay_Rate = 0.9,
  Path_Smooth = 0,
  Max_Bin = 255,
  Min_Data_In_Bin = 3,
  Data_Random_Seed = 1,
  Is_Enable_Sparse = TRUE,
  Enable_Bundle = TRUE,
  Use_Missing = TRUE,
  Zero_As_Missing = FALSE,
  Two_Round = FALSE,
  Convert_Model = NULL,
  Convert_Model_Language = "cpp",
  Boost_From_Average = TRUE,
  Alpha = 0.9,
  Fair_C = 1,
  Poisson_Max_Delta_Step = 0.7,
  Tweedie_Variance_Power = 1.5,
  Lambdarank_Truncation_Level = 30,
  Is_Provide_Training_Metric = TRUE,
  Eval_At = c(1, 2, 3, 4, 5),
  Num_Machines = 1,
  Gpu_Platform_Id = -1,
  Gpu_Device_Id = -1,
  Gpu_Use_Dp = TRUE,
  Num_Gpu = 1,
  TVT = NULL
)
```

Arguments

data	Supply your full series data set here
XREGS	Additional data to use for model development and forecasting. Data needs to be a complete series which means both the historical and forward looking values over the specified forecast window needs to be supplied.
TimeWeights	Supply a value that will be multiplied by he time trend value
NonNegativePred	TRUE or FALSE
RoundPreds	Rounding predictions to an integer value. TRUE or FALSE. Defaults to FALSE
TrainOnFull	Set to TRUE to train on full data
TargetColumnName	List the column name of your target variables column. E.g. 'Target'
DateColumnName	List the column name of your date column. E.g. 'DateTime'
HierarchGroups	= NULL Character vector or NULL with names of the columns that form the interaction hierarchy
GroupVariables	Defaults to NULL. Use NULL when you have a single series. Add in GroupVariables when you have a series for every level of a group or multiple groups.

`FC_Periods` Set the number of periods you want to have forecasts for. E.g. 52 for weekly data to forecast a year ahead

`NThreads` Set the maximum number of threads you'd like to dedicate to the model run. E.g. 8

`SaveDataPath` Path to save modeling data

`TimeUnit` List the time unit your data is aggregated by. E.g. '1min', '5min', '10min', '15min', '30min', 'hour', 'day', 'week', 'month', 'quarter', 'year'

`TimeGroups` Select time aggregations for adding various time aggregated GDL features.

`TargetTransformation`
Run AutoTransformationCreate() to find best transformation for the target variable. Tests YeoJohnson, BoxCox, and Asigh (also Asin and Logit for proportion target variables).

`Methods` Choose from 'YeoJohnson', 'BoxCox', 'Asinh', 'Log', 'LogPlus1', 'Sqrt', 'Asin', or 'Logit'. If more than one is selected, the one with the best normalization pearson statistic will be used. Identity is automatically selected and compared.

`EncodingMethod` Choose from 'binary', 'm_estimator', 'credibility', 'woe', 'target_encoding', 'poly_encode', 'backward_difference', 'helmert'

`AnomalyDetection`
NULL for not using the service. Other, provide a list, e.g. AnomalyDetection = list('tstat_high' = 4, tstat_low = -4)

`Lags` Select the periods for all lag variables you want to create. E.g. c(1:5,52) or list('day' = c(1:10), 'weeks' = c(1:4))

`MA_Periods` Select the periods for all moving average variables you want to create. E.g. c(1:5,52) or list('day' = c(2:10), 'weeks' = c(2:4))

`SD_Periods` Select the periods for all moving standard deviation variables you want to create. E.g. c(1:5,52) or list('day' = c(2:10), 'weeks' = c(2:4))

`Skew_Periods` Select the periods for all moving skewness variables you want to create. E.g. c(1:5,52) or list('day' = c(2:10), 'weeks' = c(2:4))

`Kurt_Periods` Select the periods for all moving kurtosis variables you want to create. E.g. c(1:5,52) or list('day' = c(2:10), 'weeks' = c(2:4))

`Quantile_Periods`
Select the periods for all moving quantiles variables you want to create. E.g. c(1:5,52) or list('day' = c(2:10), 'weeks' = c(2:4))

`Quantiles_Selected`
Select from the following c('q5','q10','q15','q20','q25','q30','q35','q40','q45','q50','q55','q60','q6

`Difference` Set to TRUE to put the I in ARIMA

`FourierTerms` Set to the max number of pairs

`CalendarVariables`
NULL, or select from 'second', 'minute', 'hour', 'wday', 'mday', 'yday', 'week', 'wom', 'isoweek', 'month', 'quarter', 'year'

`HolidayVariable`
NULL, or select from 'USPublicHolidays', 'EasterGroup', 'ChristmasGroup', 'OtherEcclesticalFeasts'

`HolidayLookback`
Number of days in range to compute number of holidays from a given date in the data. If NULL, the number of days are computed for you.

`HolidayLags` Number of lags for the holiday counts

HolidayMovingAverages
: Number of moving averages for holiday counts

TimeTrendVariable
: Set to TRUE to have a time trend variable added to the model. Time trend is numeric variable indicating the numeric value of each record in the time series (by group). Time trend starts at 1 for the earliest point in time and increments by one for each success time point.

DataTruncate
: Set to TRUE to remove records with missing values from the lags and moving average features created

ZeroPadSeries
: NULL to do nothing. Otherwise, set to 'maxmax', 'minmax', 'maxmin', 'minmin'. See TimeSeriesFill for explanations of each type

SplitRatios
: E.g c(0.7,0.2,0.1) for train, validation, and test sets

PartitionType
: Select 'random' for random data partitioning 'time' for partitioning by time frames

Timer
: Setting to TRUE prints out the forecast number while it is building

SaveModel
: Logical. If TRUE, output ArgsList will have a named element 'Model' with the CatBoost model object

ArgsList
: ArgsList is for scoring. Must contain named element 'Model' with a catboost model object

DebugMode
: Setting to TRUE generates printout of all header code comments during run time of function

ModelID
: Something to name your model if you want it saved

GridTune
: Set to TRUE to run a grid tune

GridEvalMetric
: This is the metric used to find the threshold 'poisson', 'mae', 'mape', 'mse', 'msle', 'kl', 'cs', 'r2'

ModelCount
: Set the number of models to try in the grid tune

MaxRunsWithoutNewWinner
: Number of consecutive runs without a new winner in order to terminate procedure

MaxRunMinutes
: Default 24L*60L

Device_Type
: = 'CPU'

LossFunction
: = 'regression' (or 'mean_squared_error'), 'regression_l1' (or 'mean_absolute_error'), 'mae' (or 'mean_absolute_percentage_error'), 'huber', 'fair', 'poisson', 'quantile', 'gamma', 'tweedie'

EvalMetric
: = 'mae'

Input_Model
: = NULL

Task
: = 'train'

Boosting
: = 'gbdt'

LinearTree
: = FALSE

Trees
: = 1000

ETA
: = 0.10

Num_Leaves
: = 31

Deterministic
: = TRUE

Learning Parameters # https://lightgbm.readthedocs.io/en/latest/Parameters.html#learning-control-parameters

Force_Col_Wise = FALSE

Force_Row_Wise = FALSE

Max_Depth = 6

Min_Data_In_Leaf = 20

Min_Sum_Hessian_In_Leaf = 0.001

Bagging_Freq = 1.0

Bagging_Fraction = 1.0

Feature_Fraction = 1.0

Feature_Fraction_Bynode = 1.0

Lambda_L1 = 0.0

Lambda_L2 = 0.0

Extra_Trees = FALSE

Early_Stopping_Round = 10

First_Metric_Only = TRUE

Max_Delta_Step = 0.0

Linear_Lambda = 0.0

Min_Gain_To_Split = 0

Drop_Rate_Dart = 0.10

Max_Drop_Dart = 50

Skip_Drop_Dart = 0.50

Uniform_Drop_Dart = FALSE

Top_Rate_Goss = FALSE

Other_Rate_Goss = FALSE

Monotone_Constraints = NULL

Monotone_Constraints_method = 'advanced'

Monotone_Penalty = 0.0

Forcedsplits_Filename = NULL

Refit_Decay_Rate = 0.90

Path_Smooth = 0.0

IO Dataset Parameters # https://lightgbm.readthedocs.io/en/latest/Parameters.html#io-parameters

Max_Bin = 255

```
Min_Data_In_Bin
                = 3
Data_Random_Seed
                = 1
Is_Enable_Sparse
                = TRUE
Enable_Bundle   = TRUE
Use_Missing     = TRUE
Zero_As_Missing
                = FALSE
Two_Round       = FALSE
                # Convert Parameters
Convert_Model   = NULL
Convert_Model_Language
                = 'cpp'
                # Objective Parameters # https://lightgbm.readthedocs.io/en/latest/Parameters.html#objective-
                parameters
Boost_From_Average
                = TRUE
Alpha           = 0.90
Fair_C          = 1.0
Poisson_Max_Delta_Step
                = 0.70
Tweedie_Variance_Power
                = 1.5
Lambdarank_Truncation_Level
                = 30
                # Metric Parameters (metric is in Core) # https://lightgbm.readthedocs.io/en/latest/Parameters.html#m
                parameters
Is_Provide_Training_Metric
                = TRUE,
Eval_At         = c(1,2,3,4,5)
                # Network Parameters # https://lightgbm.readthedocs.io/en/latest/Parameters.html#network-
                parameters
Num_Machines    = 1
                # GPU Parameters
Gpu_Platform_Id
                = -1
Gpu_Device_Id   = -1
Gpu_Use_Dp      = TRUE
Num_Gpu         = 1
TVT             Passthrough
                # ML Args begin
TreeMethod      Choose from 'hist', 'gpu_hist'
#               https://lightgbm.readthedocs.io/en/latest/Parameters.html#gpu-parameters
```

Value

See examples

Author(s)

Adrian Antico

See Also

Other Automated Panel Data Forecasting: AutoCatBoostCARMA(), AutoH2OCARMA(), AutoXGBoostCARMA()

Examples

```
## Not run:

# Load data
data <- data.table::fread('https://www.dropbox.com/s/2str3ek4f4cheqi/walmart_train.csv?dl=1')

# Ensure series have no missing dates (also remove series with more than 25% missing values)
data <- AutoQuant::TimeSeriesFill(
  data,
  DateColumnName = 'Date',
  GroupVariables = c('Store','Dept'),
  TimeUnit = 'weeks',
  FillType = 'maxmax',
  MaxMissingPercent = 0.25,
  SimpleImpute = TRUE)

# Set negative numbers to 0
data <- data[, Weekly_Sales := data.table::fifelse(Weekly_Sales < 0, 0, Weekly_Sales)]

# Remove IsHoliday column
data[, IsHoliday := NULL]

# Create xregs (this is the include the categorical variables instead of utilizing only the interaction of them)
xregs <- data[, .SD, .SDcols = c('Date', 'Store', 'Dept')]

# Change data types
data[, ':=' (Store = as.character(Store), Dept = as.character(Dept))]
xregs[, ':=' (Store = as.character(Store), Dept = as.character(Dept))]

# Build forecast
Results <- AutoLightGBMCARMA(

  # Data Artifacts
  data = data,
  NonNegativePred = FALSE,
  RoundPreds = FALSE,
  TargetColumnName = 'Weekly_Sales',
  DateColumnName = 'Date',
  HierarchGroups = NULL,
  GroupVariables = c('Store','Dept'),
  TimeUnit = 'weeks',
  TimeGroups = c('weeks','months'),

  # Data Wrangling Features
```

```
EncodingMethod = 'binary',
ZeroPadSeries = NULL,
DataTruncate = FALSE,
SplitRatios = c(1 - 10 / 138, 10 / 138),
PartitionType = 'timeseries',
AnomalyDetection = NULL,

# Productionize
FC_Periods = 0,
TrainOnFull = FALSE,
NThreads = 8,
Timer = TRUE,
DebugMode = FALSE,
SaveDataPath = NULL,
SaveModel = FALSE,
ArgsList = NULL,

# Target Transformations
TargetTransformation = TRUE,
Methods = c('BoxCox', 'Asinh', 'Asin', 'Log',
            'LogPlus1', 'Sqrt', 'Logit','YeoJohnson'),
Difference = FALSE,

# Features
Lags = list('weeks' = seq(1L, 10L, 1L),
            'months' = seq(1L, 5L, 1L)),
MA_Periods = list('weeks' = seq(5L, 20L, 5L),
                  'months' = seq(2L, 10L, 2L)),
SD_Periods = NULL,
Skew_Periods = NULL,
Kurt_Periods = NULL,
Quantile_Periods = NULL,
Quantiles_Selected = c('q5','q95'),
XREGS = xregs,
FourierTerms = 4,
CalendarVariables = c('week', 'wom', 'month', 'quarter'),
HolidayVariable = c('USPublicHolidays','EasterGroup',
  'ChristmasGroup','OtherEcclesticalFeasts'),
HolidayLookback = NULL,
HolidayLags = 1,
HolidayMovingAverages = 1:2,
TimeTrendVariable = TRUE,

# ML eval args
TreeMethod = 'hist',
EvalMetric = 'RMSE',
LossFunction = 'reg:squarederror',

# Grid tuning args
GridTune = FALSE,
GridEvalMetric = 'mae',
ModelCount = 30L,
MaxRunsWithoutNewWinner = 20L,
MaxRunMinutes = 24L*60L,

# LightGBM Args
Device_Type = TaskType,
```

```
  LossFunction = 'regression',
  EvalMetric = 'MAE',
  Input_Model = NULL,
  Task = 'train',
  Boosting = 'gbdt',
  LinearTree = FALSE,
  Trees = 1000,
  ETA = 0.10,
  Num_Leaves = 31,
  Deterministic = TRUE,

  # Learning Parameters
  # https://lightgbm.readthedocs.io/en/latest/Parameters.html#learning-control-parameters
  Force_Col_Wise = FALSE,
  Force_Row_Wise = FALSE,
  Max_Depth = 6,
  Min_Data_In_Leaf = 20,
  Min_Sum_Hessian_In_Leaf = 0.001,
  Bagging_Freq = 1.0,
  Bagging_Fraction = 1.0,
  Feature_Fraction = 1.0,
  Feature_Fraction_Bynode = 1.0,
  Lambda_L1 = 0.0,
  Lambda_L2 = 0.0,
  Extra_Trees = FALSE,
  Early_Stopping_Round = 10,
  First_Metric_Only = TRUE,
  Max_Delta_Step = 0.0,
  Linear_Lambda = 0.0,
  Min_Gain_To_Split = 0,
  Drop_Rate_Dart = 0.10,
  Max_Drop_Dart = 50,
  Skip_Drop_Dart = 0.50,
  Uniform_Drop_Dart = FALSE,
  Top_Rate_Goss = FALSE,
  Other_Rate_Goss = FALSE,
  Monotone_Constraints = NULL,
  Monotone_Constraints_Method = 'advanced',
  Monotone_Penalty = 0.0,
  Forcedsplits_Filename = NULL, # use for AutoStack option; .json file
  Refit_Decay_Rate = 0.90,
  Path_Smooth = 0.0,

  # IO Dataset Parameters
  # https://lightgbm.readthedocs.io/en/latest/Parameters.html#io-parameters
  Max_Bin = 255,
  Min_Data_In_Bin = 3,
  Data_Random_Seed = 1,
  Is_Enable_Sparse = TRUE,
  Enable_Bundle = TRUE,
  Use_Missing = TRUE,
  Zero_As_Missing = FALSE,
  Two_Round = FALSE,

  # Convert Parameters
  Convert_Model = NULL,
  Convert_Model_Language = 'cpp',
```

```
  # Objective Parameters
  # https://lightgbm.readthedocs.io/en/latest/Parameters.html#objective-parameters
  Boost_From_Average = TRUE,
  Alpha = 0.90,
  Fair_C = 1.0,
  Poisson_Max_Delta_Step = 0.70,
  Tweedie_Variance_Power = 1.5,
  Lambdarank_Truncation_Level = 30,

  # Metric Parameters (metric is in Core)
  # https://lightgbm.readthedocs.io/en/latest/Parameters.html#metric-parameters
  Is_Provide_Training_Metric = TRUE,
  Eval_At = c(1,2,3,4,5),

  # Network Parameters
  # https://lightgbm.readthedocs.io/en/latest/Parameters.html#network-parameters
  Num_Machines = 1,

  # GPU Parameters
  # https://lightgbm.readthedocs.io/en/latest/Parameters.html#gpu-parameters
  Gpu_Platform_Id = -1,
  Gpu_Device_Id = -1,
  Gpu_Use_Dp = TRUE,
  Num_Gpu = 1)

UpdateMetrics <- print(
  Results$ModelInformation$EvaluationMetrics[
    Metric == 'MSE', MetricValue := sqrt(MetricValue)])
print(UpdateMetrics)
Results$ModelInformation$EvaluationMetricsByGroup[order(-R2_Metric)]
Results$ModelInformation$EvaluationMetricsByGroup[order(MAE_Metric)]
Results$ModelInformation$EvaluationMetricsByGroup[order(MSE_Metric)]
Results$ModelInformation$EvaluationMetricsByGroup[order(MAPE_Metric)]

## End(Not run)
```

`AutoLightGBMClassifier`

AutoLightGBMClassifier

Description

AutoLightGBMClassifier is an automated lightgbm modeling framework with grid-tuning and model evaluation that runs a variety of steps. First, the function will run a random grid tune over N number of models and find which model is the best (a default model is always included in that set). Once the model is identified and built, several other outputs are generated: validation data with predictions, evaluation plot, evaluation boxplot, evaluation metrics, variable importance, partial dependence calibration plots, partial dependence calibration box plots, and column names used in model fitting.

Usage

```
AutoLightGBMClassifier(
  data = NULL,
```

```
  TrainOnFull = FALSE,
  ValidationData = NULL,
  TestData = NULL,
  TargetColumnName = NULL,
  FeatureColNames = NULL,
  PrimaryDateColumn = NULL,
  IDcols = NULL,
  WeightsColumnName = NULL,
  CostMatrixWeights = c(1, 0, 0, 1),
  EncodingMethod = "credibility",
 OutputSelection = c("Importances", "EvalPlots", "EvalMetrics", "Score_TrainData"),
  model_path = NULL,
  metadata_path = NULL,
  DebugMode = FALSE,
  SaveInfoToPDF = FALSE,
  ModelID = "TestModel",
  ReturnFactorLevels = TRUE,
  ReturnModelObjects = TRUE,
  SaveModelObjects = FALSE,
  NumOfParDepPlots = 3L,
  Verbose = 0L,
  GridTune = FALSE,
  grid_eval_metric = "Utility",
  BaselineComparison = "default",
  MaxModelsInGrid = 10L,
  MaxRunsWithoutNewWinner = 20L,
  MaxRunMinutes = 24L * 60L,
  PassInGrid = NULL,
  input_model = NULL,
  task = "train",
  device_type = "CPU",
  NThreads = parallel::detectCores()/2,
  objective = "binary",
  metric = "binary_logloss",
  boosting = "gbdt",
  LinearTree = FALSE,
  Trees = 50L,
  eta = NULL,
  num_leaves = 31,
  deterministic = TRUE,
  force_col_wise = FALSE,
  force_row_wise = FALSE,
  max_depth = NULL,
  min_data_in_leaf = 20,
  min_sum_hessian_in_leaf = 0.001,
  bagging_freq = 0,
  bagging_fraction = 1,
  feature_fraction = 1,
  feature_fraction_bynode = 1,
  extra_trees = FALSE,
  early_stopping_round = 10,
  first_metric_only = TRUE,
```

```
  max_delta_step = 0,
  lambda_l1 = 0,
  lambda_l2 = 0,
  linear_lambda = 0,
  min_gain_to_split = 0,
  drop_rate_dart = 0.1,
  max_drop_dart = 50,
  skip_drop_dart = 0.5,
  uniform_drop_dart = FALSE,
  top_rate_goss = FALSE,
  other_rate_goss = FALSE,
  monotone_constraints = NULL,
  monotone_constraints_method = "advanced",
  monotone_penalty = 0,
  forcedsplits_filename = NULL,
  refit_decay_rate = 0.9,
  path_smooth = 0,
  max_bin = 255,
  min_data_in_bin = 3,
  data_random_seed = 1,
  is_enable_sparse = TRUE,
  enable_bundle = TRUE,
  use_missing = TRUE,
  zero_as_missing = FALSE,
  two_round = FALSE,
  convert_model = NULL,
  convert_model_language = "cpp",
  boost_from_average = TRUE,
  is_unbalance = FALSE,
  scale_pos_weight = 1,
  is_provide_training_metric = TRUE,
  eval_at = c(1, 2, 3, 4, 5),
  num_machines = 1,
  gpu_platform_id = -1,
  gpu_device_id = -1,
  gpu_use_dp = TRUE,
  num_gpu = 1
)
```

Arguments

data	This is your data set for training and testing your model
TrainOnFull	Set to TRUE to train on full data
ValidationData	This is your holdout data set used in modeling either refine your hyperparameters.
TestData	This is your holdout data set.
TargetColumnName	Either supply the target column name OR the column number where the target is located (but not mixed types).
FeatureColNames	Either supply the feature column names OR the column number where the target is located (but not mixed types)

PrimaryDateColumn
: Supply a date or datetime column for catboost to utilize time as its basis for handling categorical features, instead of random shuffling

IDcols
: A vector of column names or column numbers to keep in your data but not include in the modeling.

WeightsColumnName
: Supply a column name for your weights column. Leave NULL otherwise

CostMatrixWeights
: = c(1,0,0,1)

EncodingMethod
: Choose from 'binary', 'm_estimator', 'credibility', 'woe', 'target_encoding', 'poly_encode', 'backward_difference', 'helmert'

OutputSelection
: You can select what type of output you want returned. Choose from c("Importances", "EvalPlots", "EvalMetrics", "Score_TrainData")

model_path
: A character string of your path file to where you want your output saved

metadata_path
: A character string of your path file to where you want your model evaluation output saved. If left NULL, all output will be saved to model_path.

DebugMode
: Set to TRUE to get a print out of the steps taken throughout the function

SaveInfoToPDF
: Set to TRUE to save model insights to pdf

ModelID
: A character string to name your model and output

ReturnFactorLevels
: Set to TRUE to have the factor levels returned with the other model objects

ReturnModelObjects
: Set to TRUE to output all modeling objects (E.g. plots and evaluation metrics)

SaveModelObjects
: Set to TRUE to return all modeling objects to your environment

NumOfParDepPlots
: Tell the function the number of partial dependence calibration plots you want to create.

Verbose
: Set to 0 if you want to suppress model evaluation updates in training

GridTune
: Set to TRUE to run a grid tuning procedure. Set a number in MaxModelsInGrid to tell the procedure how many models you want to test.

grid_eval_metric
: "mae", "mape", "rmse", "r2". Case sensitive

BaselineComparison
: Set to either "default" or "best". Default is to compare each successive model build to the baseline model using max trees (from function args). Best makes the comparison to the current best model.

  # Core parameters https://lightgbm.readthedocs.io/en/latest/Parameters.html#core-parameter

MaxModelsInGrid
: Number of models to test from grid options (243 total possible options)

MaxRunsWithoutNewWinner
: Runs without new winner to end procedure

MaxRunMinutes
: In minutes

PassInGrid
: Default is NULL. Provide a data.table of grid options from a previous run.

input_model
: = NULL, # continue training a model that is stored to fil

task	'train' or 'refit'
device_type	'cpu' or 'gpu'
NThreads	only list up to number of cores, not threads. parallel::detectCores() / 2
objective	'binary'
metric	'binary_logloss', 'average_precision', 'auc', 'map', 'binary_error', 'auc_mu'
boosting	'gbdt', 'rf', 'dart', 'goss'
LinearTree	FALSE
Trees	50L
eta	NULL
num_leaves	31
deterministic	TRUE
	# Learning Parameters https://lightgbm.readthedocs.io/en/latest/Parameters.html#learning-control-parameter
force_col_wise	FALSE
force_row_wise	FALSE
max_depth	NULL
min_data_in_leaf	20
min_sum_hessian_in_leaf	0.001
bagging_freq	0
bagging_fraction	1.0
feature_fraction	1.0
feature_fraction_bynode	1.0
extra_trees	FALSE
early_stopping_round	10
first_metric_only	TRUE
max_delta_step	0.0
lambda_l1	0.0
lambda_l2	0.0
linear_lambda	0.0
min_gain_to_split	0
drop_rate_dart	0.10
max_drop_dart	50
skip_drop_dart	0.50
uniform_drop_dart	FALSE
top_rate_goss	FALSE

other_rate_goss
: FALSE

monotone_constraints
: "gbdt_prediction.cpp"

monotone_constraints_method
: 'advanced'

monotone_penalty
: 0.0

forcedsplits_filename
: NULL # use for AutoStack option; .json fil

refit_decay_rate
: 0.90

path_smooth
: 0.0

: # IO Dataset Parameters https://lightgbm.readthedocs.io/en/latest/Parameters.html#io-parameters

max_bin
: 255

min_data_in_bin
: 3

data_random_seed
: 1

is_enable_sparse
: TRUE

enable_bundle
: TRUE

use_missing
: TRUE

zero_as_missing
: FALSE

two_round
: FALSE

: # Convert Parameters # https://lightgbm.readthedocs.io/en/latest/Parameters.html#convert-parameters

convert_model
: 'gbdt_prediction.cpp'

convert_model_language
: 'cpp'

: # Objective Parameters https://lightgbm.readthedocs.io/en/latest/Parameters.html#objective-parameters

boost_from_average
: TRUE

is_unbalance
: FALSE

scale_pos_weight
: 1.0

: # Metric Parameters (metric is in Core)

is_provide_training_metric
: TRUE

eval_at
: c(1,2,3,4,5)

: # Network Parameter

num_machines
: 1

: # GPU Parameter

gpu_platform_id
: -1

gpu_device_id	-1
gpu_use_dp	TRUE
num_gpu	1

Value

Saves to file and returned in list: VariableImportance.csv, Model, ValidationData.csv, EvalutionPlot.png, EvalutionBoxPlot.png, EvaluationMetrics.csv, ParDepPlots.R a named list of features with partial dependence calibration plots, ParDepBoxPlots.R, GridCollect, and GridList

Author(s)

Adrian Antico

See Also

Other Automated Supervised Learning - Binary Classification: AutoCatBoostClassifier(), AutoH2oDRFClassifier(), AutoH2oGAMClassifier(), AutoH2oGBMClassifier(), AutoH2oGLMClassifier(), AutoH2oMLClassifier(), AutoXGBoostClassifier()

Examples

```
## Not run:
# Create some dummy correlated data
data <- AutoQuant::FakeDataGenerator(
  Correlation = 0.85,
  N = 1000,
  ID = 2,
  ZIP = 0,
  AddDate = FALSE,
  Classification = TRUE,
  MultiClass = FALSE)

# Run function
TestModel <- AutoQuant::AutoLightGBMClassifier(

  # Metadata args
  OutputSelection = c('Importances','EvalPlots','EvalMetrics','Score_TrainData'),
  model_path = normalizePath("./"),
  metadata_path = NULL,
  ModelID = "Test_Model_1",
  NumOfParDepPlots = 3L,
  EncodingMethod = "credibility",
  ReturnFactorLevels = TRUE,
  ReturnModelObjects = TRUE,
  SaveModelObjects = FALSE,
  SaveInfoToPDF = FALSE,
  DebugMode = FALSE,

  # Data args
  data = data,
  TrainOnFull = FALSE,
  ValidationData = NULL,
  TestData = NULL,
  TargetColumnName = "Adrian",
  FeatureColNames = names(data)[!names(data) %in% c("IDcol_1", "IDcol_2","Adrian")],
```

```
  PrimaryDateColumn = NULL,
  WeightsColumnName = NULL,
  CostMatrixWeights = c(1,0,0,1),
  IDcols = c("IDcol_1","IDcol_2"),

  # Grid parameters
  GridTune = FALSE,
  grid_eval_metric = 'Utility',
  BaselineComparison = 'default',
  MaxModelsInGrid = 10L,
  MaxRunsWithoutNewWinner = 20L,
  MaxRunMinutes = 24L*60L,
  PassInGrid = NULL,

  # Core parameters
  # https://lightgbm.readthedocs.io/en/latest/Parameters.html#core-parameters
  input_model = NULL, # continue training a model that is stored to file
  task = "train",
  device_type = 'CPU',
  NThreads = parallel::detectCores() / 2,
  objective = 'binary',
  metric = 'binary_logloss',
  boosting = 'gbdt',
  LinearTree = FALSE,
  Trees = 50L,
  eta = NULL,
  num_leaves = 31,
  deterministic = TRUE,

  # Learning Parameters
 # https://lightgbm.readthedocs.io/en/latest/Parameters.html#learning-control-parameters
  force_col_wise = FALSE,
  force_row_wise = FALSE,
  max_depth = NULL,
  min_data_in_leaf = 20,
  min_sum_hessian_in_leaf = 0.001,
  bagging_freq = 0,
  bagging_fraction = 1.0,
  feature_fraction = 1.0,
  feature_fraction_bynode = 1.0,
  extra_trees = FALSE,
  early_stopping_round = 10,
  first_metric_only = TRUE,
  max_delta_step = 0.0,
  lambda_l1 = 0.0,
  lambda_l2 = 0.0,
  linear_lambda = 0.0,
  min_gain_to_split = 0,
  drop_rate_dart = 0.10,
  max_drop_dart = 50,
  skip_drop_dart = 0.50,
  uniform_drop_dart = FALSE,
  top_rate_goss = FALSE,
  other_rate_goss = FALSE,
  monotone_constraints = NULL,
  monotone_constraints_method = "advanced",
  monotone_penalty = 0.0,
```

```
  forcedsplits_filename = NULL, # use for AutoStack option; .json file
  refit_decay_rate = 0.90,
  path_smooth = 0.0,

  # IO Dataset Parameters
  # https://lightgbm.readthedocs.io/en/latest/Parameters.html#io-parameters
  max_bin = 255,
  min_data_in_bin = 3,
  data_random_seed = 1,
  is_enable_sparse = TRUE,
  enable_bundle = TRUE,
  use_missing = TRUE,
  zero_as_missing = FALSE,
  two_round = FALSE,

  # Convert Parameters
  convert_model = NULL,
  convert_model_language = "cpp",

  # Objective Parameters
  # https://lightgbm.readthedocs.io/en/latest/Parameters.html#objective-parameters
  boost_from_average = TRUE,
  is_unbalance = FALSE,
  scale_pos_weight = 1.0,

  # Metric Parameters (metric is in Core)
  # https://lightgbm.readthedocs.io/en/latest/Parameters.html#metric-parameters
  is_provide_training_metric = TRUE,
  eval_at = c(1,2,3,4,5),

  # Network Parameters
  # https://lightgbm.readthedocs.io/en/latest/Parameters.html#network-parameters
  num_machines = 1,

  # GPU Parameters
  # https://lightgbm.readthedocs.io/en/latest/Parameters.html#gpu-parameters
  gpu_platform_id = -1,
  gpu_device_id = -1,
  gpu_use_dp = TRUE,
  num_gpu = 1)

## End(Not run)
```

`AutoLightGBMFunnelCARMA`

AutoLightGBMFunnelCARMA

Description

AutoLightGBMFunnelCARMA is a forecasting model for cohort funnel forecasting for grouped data or non-grouped data

Usage

```
AutoLightGBMFunnelCARMA(
  data,
  GroupVariables = NULL,
  BaseFunnelMeasure = NULL,
  ConversionMeasure = NULL,
  ConversionRateMeasure = NULL,
  CohortPeriodsVariable = NULL,
  CalendarDate = NULL,
  CohortDate = NULL,
  EncodingMethod = "credibility",
  OutputSelection = c("Importances", "EvalPlots", "EvalMetrics", "Score_TrainData"),
  WeightsColumnName = NULL,
  TruncateDate = NULL,
  PartitionRatios = c(0.7, 0.2, 0.1),
  TimeUnit = c("day"),
  CalendarTimeGroups = c("day", "week", "month"),
  CohortTimeGroups = c("day", "week", "month"),
  TransformTargetVariable = TRUE,
  TransformMethods = c("Identity", "YeoJohnson"),
  AnomalyDetection = list(tstat_high = 3, tstat_low = -2),
  Jobs = c("Evaluate", "Train"),
  SaveModelObjects = TRUE,
  ModelID = "Segment_ID",
  ModelPath = NULL,
  MetaDataPath = NULL,
  DebugMode = FALSE,
  CalendarVariables = c("wday", "mday", "yday", "week", "isoweek", "month", "quarter",
    "year"),
  HolidayGroups = c("USPublicHolidays", "EasterGroup", "ChristmasGroup",
    "OtherEcclesticalFeasts"),
  HolidayLookback = NULL,
  CohortHolidayLags = c(1L, 2L, 7L),
  CohortHolidayMovingAverages = c(3L, 7L),
  CalendarHolidayLags = c(1L, 2L, 7L),
  CalendarHolidayMovingAverages = c(3L, 7L),
  ImputeRollStats = -0.001,
  CalendarLags = list(day = c(1L, 7L, 21L), week = c(1L, 4L, 52L), month = c(1L, 6L,
    12L)),
  CalendarMovingAverages = list(day = c(1L, 7L, 21L), week = c(1L, 4L, 52L), month =
    c(1L, 6L, 12L)),
  CalendarStandardDeviations = NULL,
  CalendarSkews = NULL,
  CalendarKurts = NULL,
  CalendarQuantiles = NULL,
  CalendarQuantilesSelected = "q50",
  CohortLags = list(day = c(1L, 7L, 21L), week = c(1L, 4L, 52L), month = c(1L, 6L, 12L)),
  CohortMovingAverages = list(day = c(1L, 7L, 21L), week = c(1L, 4L, 52L), month = c(1L,
    6L, 12L)),
  CohortStandardDeviations = NULL,
  CohortSkews = NULL,
  CohortKurts = NULL,
```

```
  CohortQuantiles = NULL,
  CohortQuantilesSelected = "q50",
  PassInGrid = NULL,
  GridTune = FALSE,
  BaselineComparison = "default",
  MaxModelsInGrid = 25L,
  MaxRunMinutes = 180L,
  MaxRunsWithoutNewWinner = 10L,
  LossFunction = "regression",
  EvalMetric = "mae",
  GridEvalMetric = "mae",
  NumOfParDepPlots = 1L,
  Device_Type = "CPU",
  Input_Model = NULL,
  Task = "train",
  Boosting = "gbdt",
  LinearTree = FALSE,
  Trees = 1000,
  ETA = 0.1,
  Num_Leaves = 31,
  Deterministic = TRUE,
  NThreads = parallel::detectCores()/2,
  SaveInfoToPDF = FALSE,
  Force_Col_Wise = FALSE,
  Force_Row_Wise = FALSE,
  Max_Depth = 6,
  Min_Data_In_Leaf = 20,
  Min_Sum_Hessian_In_Leaf = 0.001,
  Bagging_Freq = 1,
  Bagging_Fraction = 1,
  Feature_Fraction = 1,
  Feature_Fraction_Bynode = 1,
  Lambda_L1 = 0,
  Lambda_L2 = 0,
  Extra_Trees = FALSE,
  Early_Stopping_Round = 10,
  First_Metric_Only = TRUE,
  Max_Delta_Step = 0,
  Linear_Lambda = 0,
  Min_Gain_To_Split = 0,
  Drop_Rate_Dart = 0.1,
  Max_Drop_Dart = 50,
  Skip_Drop_Dart = 0.5,
  Uniform_Drop_Dart = FALSE,
  Top_Rate_Goss = FALSE,
  Other_Rate_Goss = FALSE,
  Monotone_Constraints = NULL,
  Monotone_Constraints_method = "advanced",
  Monotone_Penalty = 0,
  Forcedsplits_Filename = NULL,
  Refit_Decay_Rate = 0.9,
  Path_Smooth = 0,
```

```
  Max_Bin = 255,
  Min_Data_In_Bin = 3,
  Data_Random_Seed = 1,
  Is_Enable_Sparse = TRUE,
  Enable_Bundle = TRUE,
  Use_Missing = TRUE,
  Zero_As_Missing = FALSE,
  Two_Round = FALSE,
  Convert_Model = NULL,
  Convert_Model_Language = "cpp",
  Boost_From_Average = TRUE,
  Alpha = 0.9,
  Fair_C = 1,
  Poisson_Max_Delta_Step = 0.7,
  Tweedie_Variance_Power = 1.5,
  Lambdarank_Truncation_Level = 30,
  Is_Provide_Training_Metric = TRUE,
  Eval_At = c(1, 2, 3, 4, 5),
  Num_Machines = 1,
  Gpu_Platform_Id = -1,
  Gpu_Device_Id = -1,
  Gpu_Use_Dp = TRUE,
  Num_Gpu = 1
)
```

Arguments

data	data object
BaseFunnelMeasure	E.g. "Leads". This value should be a forward looking variable. Say you want to forecast ConversionMeasure 2 months into the future. You should have two months into the future of values of BaseFunnelMeasure
ConversionMeasure	E.g. "Conversions". Rate is derived as conversions over leads by cohort periods out
ConversionRateMeasure	Conversions over Leads for every cohort
CohortPeriodsVariable	Numeric. Numerical value of the the number of periods since cohort base date.
CalendarDate	The name of your date column that represents the calendar date
CohortDate	The name of your date column that represents the cohort date
OutputSelection	= c('Importances', 'EvalPlots', 'EvalMetrics', 'Score_TrainData')
WeightsColumnName	= NULL
TruncateDate	NULL. Supply a date to represent the earliest point in time you want in your data. Filtering takes place before partitioning data so feature engineering can include as many non null values as possible.
PartitionRatios	Requires three values for train, validation, and test data sets
TimeUnit	Base time unit of data. "days", "weeks", "months", "quarters", "years"

`CalendarTimeGroups`
: TimeUnit value must be included. If you want to generate lags and moving averages in several time based aggregations, choose from "days", "weeks", "months", "quarters", "years".

`CohortTimeGroups`
: TimeUnit value must be included. If you want to generate lags and moving averages in several time based aggregations, choose from "days", "weeks", "months", "quarters", "years".

`TransformTargetVariable`
: TRUE or FALSe

`TransformMethods`
: Choose from "Identity", "BoxCox", "Asinh", "Asin", "Log", "LogPlus1", "Logit", "YeoJohnson"

`AnomalyDetection`
: Provide a named list. See examples

`Jobs` Default is "eval" and "train"

`SaveModelObjects`
: Set to TRUE to return all modeling objects to your environment

`ModelID` A character string to name your model and output

`ModelPath` Path to where you want your models saved

`MetaDataPath` Path to where you want your metadata saved. If NULL, function will try ModelPath if it is not NULL.

`DebugMode` Internal use

`CalendarVariables`
: "wday", "mday", "yday", "week", "isoweek", "month", "quarter", "year"

`HolidayGroups` c("USPublicHolidays","EasterGroup","ChristmasGroup","OtherEcclesticalFeasts")

`HolidayLookback`
: Number of days in range to compute number of holidays from a given date in the data. If NULL, the number of days are computed for you.

`CohortHolidayLags`
: c(1L, 2L, 7L),

`CohortHolidayMovingAverages`
: c(3L, 7L),

`CalendarHolidayLags`
: c(1L, 2L, 7L),

`CalendarHolidayMovingAverages`
: = c(3L, 7L),

`ImputeRollStats`
: Constant value to fill NA after running AutoLagRollStats()

`CalendarLags` List of the form list("day" = c(1L, 7L, 21L), "week" = c(1L, 4L, 52L), "month" = c(1L, 6L, 12L))

`CalendarMovingAverages`
: List of the form list("day" = c(1L, 7L, 21L), "week" = c(1L, 4L, 52L), "month" = c(1L, 6L, 12L))

`CalendarStandardDeviations`
: List of the form list("day" = c(1L, 7L, 21L), "week" = c(1L, 4L, 52L), "month" = c(1L, 6L, 12L))

`CalendarSkews` List of the form list("day" = c(1L, 7L, 21L), "week" = c(1L, 4L, 52L), "month" = c(1L, 6L, 12L))

`CalendarKurts` List of the form list("day" = c(1L, 7L, 21L), "week" = c(1L, 4L, 52L), "month" = c(1L, 6L, 12L))

`CalendarQuantiles`
List of the form list("day" = c(1L, 7L, 21L), "week" = c(1L, 4L, 52L), "month" = c(1L, 6L, 12L))

`CalendarQuantilesSelected`
Supply a vector of "q5", "q10", "q15", "q20", "q25", "q30", "q35", "q40", "q45", "q50", "q55", "q60", "q65", "q70", "q75", "q80", "q85", "q90", "q95"

`CohortLags` List of the form list("day" = c(1L, 7L, 21L), "week" = c(1L, 4L, 52L), "month" = c(1L, 6L, 12L))

`CohortMovingAverages`
List of the form list("day" = c(1L, 7L, 21L), "week" = c(1L, 4L, 52L), "month" = c(1L, 6L, 12L))

`CohortStandardDeviations`
List of the form list("day" = c(1L, 7L, 21L), "week" = c(1L, 4L, 52L), "month" = c(1L, 6L, 12L))

`CohortSkews` List of the form list("day" = c(1L, 7L, 21L), "week" = c(1L, 4L, 52L), "month" = c(1L, 6L, 12L))

`CohortKurts` List of the form list("day" = c(1L, 7L, 21L), "week" = c(1L, 4L, 52L), "month" = c(1L, 6L, 12L))

`CohortQuantiles`
List of the form list("day" = c(1L, 7L, 21L), "week" = c(1L, 4L, 52L), "month" = c(1L, 6L, 12L))

`CohortQuantilesSelected`
Supply a vector of "q5", "q10", "q15", "q20", "q25", "q30", "q35", "q40", "q45", "q50", "q55", "q60", "q65", "q70", "q75", "q80", "q85", "q90", "q95"

Grid tuning

`PassInGrid` Defaults to NULL. Pass in a single row of grid from a previous output as a data.table (they are collected as data.tables)

`GridTune` Set to TRUE to run a grid tuning procedure. Set a number in MaxModelsInGrid to tell the procedure how many models you want to test.

`BaselineComparison`
Set to either "default" or "best". Default is to compare each successive model build to the baseline model using max trees (from function args). Best makes the comparison to the current best model.

`MaxModelsInGrid`
Number of models to test from grid options

`MaxRunMinutes` Maximum number of minutes to let this run

`MaxRunsWithoutNewWinner`
Number of models built before calling it quits

ML Args begin

`LossFunction` = 'regression'

`EvalMetric` = 'mae'

`NumOfParDepPlots`
Tell the function the number of partial dependence calibration plots you want to create. Calibration boxplots will only be created for numerical features (not dummy variables)

`Device_Type` = 'CPU'

Input_Model = NULL

Task = 'train'

Boosting = 'gbdt'

LinearTree = FALSE

Trees = 1000

ETA = 0.10

Num_Leaves = 31

Deterministic = TRUE

Learning Parameters # https://lightgbm.readthedocs.io/en/latest/Parameters.html#learning-control-parameters

NThreads = parallel::detectCores() / 2

Force_Col_Wise = FALSE

Force_Row_Wise = FALSE

Max_Depth = 6

Min_Data_In_Leaf = 20

Min_Sum_Hessian_In_Leaf = 0.001

Bagging_Freq = 1.0

Bagging_Fraction = 1.0

Feature_Fraction = 1.0

Feature_Fraction_Bynode = 1.0

Lambda_L1 = 0.0

Lambda_L2 = 0.0

Extra_Trees = FALSE

Early_Stopping_Round = 10

First_Metric_Only = TRUE

Max_Delta_Step = 0.0

Linear_Lambda = 0.0

Min_Gain_To_Split = 0

Drop_Rate_Dart = 0.10

Max_Drop_Dart = 50

Skip_Drop_Dart = 0.50

Uniform_Drop_Dart = FALSE

Top_Rate_Goss = FALSE

Other_Rate_Goss = FALSE

```
Monotone_Constraints
                = NULL
Monotone_Constraints_method
                = 'advanced'
Monotone_Penalty
                = 0.0
Forcedsplits_Filename
                = NULL
Refit_Decay_Rate
                = 0.90
Path_Smooth     = 0.0
                # IO Dataset Parameters # https://lightgbm.readthedocs.io/en/latest/Parameters.html#io-
                parameters
Max_Bin         = 255
Min_Data_In_Bin
                = 3
Data_Random_Seed
                = 1
Is_Enable_Sparse
                = TRUE
Enable_Bundle   = TRUE
Use_Missing     = TRUE
Zero_As_Missing
                = FALSE
Two_Round       = FALSE
                # Convert Parameters
Convert_Model   = NULL
Convert_Model_Language
                = 'cpp'
                # Objective Parameters # https://lightgbm.readthedocs.io/en/latest/Parameters.html#objective-
                parameters
Boost_From_Average
                = TRUE
Alpha           = 0.90
Fair_C          = 1.0
Poisson_Max_Delta_Step
                = 0.70
Tweedie_Variance_Power
                = 1.5
Lambdarank_Truncation_Level
                = 30
                # Metric Parameters (metric is in Core) # https://lightgbm.readthedocs.io/en/latest/Parameters.html#m
                parameters
Is_Provide_Training_Metric
                = TRUE,
Eval_At         = c(1,2,3,4,5)
                # Network Parameters # https://lightgbm.readthedocs.io/en/latest/Parameters.html#network-
                parameters
```

Num_Machines = 1
# GPU Parameters
Gpu_Platform_Id = -1
Gpu_Device_Id = -1
Gpu_Use_Dp = TRUE
Num_Gpu = 1
# https://lightgbm.readthedocs.io/en/latest/Parameters.html#gpu-parameters

Author(s)

Adrian Antico

See Also

Other Automated Funnel Data Forecasting: AutoLightGBMFunnelCARMAScoring(), AutoXGBoostFunnelCARMAScorin
AutoXGBoostFunnelCARMA()

Examples

```
## Not run:
# Create Fake Data
data <- AutoQuant::FakeDataGenerator(ChainLadderData = TRUE)

# Subset data for training
ModelDataBase <- data[CalendarDateColumn < '2020-01-01' & CohortDateColumn < '2020-01-01']
ModelData <- data.table::copy(ModelDataBase)

# Train Funne Model
TestModel <- AutoQuant::AutoLightGBMFunnelCARMA(

  # Data Arguments
  data = ModelData,
  GroupVariables = NULL,
 BaseFunnelMeasure = "Leads", # if you have XREGS, supply vector such as c("Leads", "XREGS1", "XREGS2")
  ConversionMeasure = "Appointments",
  ConversionRateMeasure = NULL,
  CohortPeriodsVariable = "CohortDays",
  WeightsColumnName = NULL,
  CalendarDate = "CalendarDateColumn",
  CohortDate = "CohortDateColumn",
  PartitionRatios = c(0.70,0.20,0.10),
  TruncateDate = NULL,
  TimeUnit = "days",
  TransformTargetVariable = TRUE,
  TransformMethods = c("Asinh","Asin","Log","LogPlus1","Sqrt","Logit"),
  AnomalyDetection = list(tstat_high = 3, tstat_low = -2),

  # MetaData Arguments
  Jobs = c("eval","train"),
  SaveModelObjects = FALSE,
  ModelID = "ModelTest",
  ModelPath = getwd(),
  MetaDataPath = NULL,
  DebugMode = TRUE,
```

```
  NumOfParDepPlots = 1L,
  EncodingMethod = "credibility",
  NThreads = parallel::detectCores(),

  # Feature Engineering Arguments
  CalendarTimeGroups = c("days","weeks","months"),
  CohortTimeGroups = c("days", "weeks"),
  CalendarVariables = c("wday","mday","yday","week","month","quarter","year"),
 HolidayGroups = c("USPublicHolidays","EasterGroup","ChristmasGroup","OtherEcclesticalFeasts"),
  HolidayLookback = NULL,
  CohortHolidayLags = c(1L,2L,7L),
  CohortHolidayMovingAverages = c(3L,7L),
  CalendarHolidayLags = c(1L,2L,7L),
  CalendarHolidayMovingAverages = c(3L,7L),

  # Time Series Features
  ImputeRollStats = -0.001,
  CalendarLags = list("day" = c(1L,2L,7L,35L,42L), "week" = c(5L,6L,10L,12L,25L,26L)),
 CalendarMovingAverages = list("day" = c(7L,14L,35L,42L), "week" = c(5L,6L,10L,12L,20L,24L), "month" = c(6L,12
  CalendarStandardDeviations = NULL,
  CalendarSkews = NULL,
  CalendarKurts = NULL,
  CalendarQuantiles = NULL,
  CalendarQuantilesSelected = "q50",
  CohortLags = list("day" = c(1L,2L,7L,35L,42L), "week" = c(5L,6L)),
 CohortMovingAverages = list("day" = c(7L,14L,35L,42L), "week" = c(5L,6L), "month" = c(1L,2L)),
  CohortStandardDeviations = NULL,
  CohortSkews = NULL,
  CohortKurts = NULL,
  CohortQuantiles = NULL,
  CohortQuantilesSelected = "q50",

  # ML Grid Tuning
  PassInGrid = NULL,
  GridTune = FALSE,
  BaselineComparison = "default",
  MaxModelsInGrid = 25L,
  MaxRunMinutes = 180L,
  MaxRunsWithoutNewWinner = 10L,

  # ML Setup Parameters
  LossFunction = 'regression',
  EvalMetric = 'mae',
  GridEvalMetric = 'mae',

  # LightGBM Args
  Device_Type = 'CPU',
  Input_Model = NULL,
  Task = 'train',
  Boosting = 'gbdt',
  LinearTree = FALSE,
  Trees = 50,
  ETA = 0.10,
  Num_Leaves = 31,
  Deterministic = TRUE,

  # Learning Parameters
```

```
# https://lightgbm.readthedocs.io/en/latest/Parameters.html#learning-control-parameters
 Force_Col_Wise = FALSE,
 Force_Row_Wise = FALSE,
 Max_Depth = 6,
 Min_Data_In_Leaf = 20,
 Min_Sum_Hessian_In_Leaf = 0.001,
 Bagging_Freq = 1.0,
 Bagging_Fraction = 1.0,
 Feature_Fraction = 1.0,
 Feature_Fraction_Bynode = 1.0,
 Lambda_L1 = 0.0,
 Lambda_L2 = 0.0,
 Extra_Trees = FALSE,
 Early_Stopping_Round = 10,
 First_Metric_Only = TRUE,
 Max_Delta_Step = 0.0,
 Linear_Lambda = 0.0,
 Min_Gain_To_Split = 0,
 Drop_Rate_Dart = 0.10,
 Max_Drop_Dart = 50,
 Skip_Drop_Dart = 0.50,
 Uniform_Drop_Dart = FALSE,
 Top_Rate_Goss = FALSE,
 Other_Rate_Goss = FALSE,
 Monotone_Constraints = NULL,
 Monotone_Constraints_method = 'advanced',
 Monotone_Penalty = 0.0,
 Forcedsplits_Filename = NULL, # use for AutoStack option; .json file
 Refit_Decay_Rate = 0.90,
 Path_Smooth = 0.0,

 # IO Dataset Parameters
 # https://lightgbm.readthedocs.io/en/latest/Parameters.html#io-parameters
 Max_Bin = 255,
 Min_Data_In_Bin = 3,
 Data_Random_Seed = 1,
 Is_Enable_Sparse = TRUE,
 Enable_Bundle = TRUE,
 Use_Missing = TRUE,
 Zero_As_Missing = FALSE,
 Two_Round = FALSE,

 # Convert Parameters
 Convert_Model = NULL,
 Convert_Model_Language = 'cpp',

 # Objective Parameters
 # https://lightgbm.readthedocs.io/en/latest/Parameters.html#objective-parameters
 Boost_From_Average = TRUE,
 Alpha = 0.90,
 Fair_C = 1.0,
 Poisson_Max_Delta_Step = 0.70,
 Tweedie_Variance_Power = 1.5,
 Lambdarank_Truncation_Level = 30,

 # Metric Parameters (metric is in Core)
 # https://lightgbm.readthedocs.io/en/latest/Parameters.html#metric-parameters
```

```
  Is_Provide_Training_Metric = TRUE,
  Eval_At = c(1,2,3,4,5),

  # Network Parameters
  # https://lightgbm.readthedocs.io/en/latest/Parameters.html#network-parameters
  Num_Machines = 1,

  # GPU Parameters
  # https://lightgbm.readthedocs.io/en/latest/Parameters.html#gpu-parameters
  Gpu_Platform_Id = -1,
  Gpu_Device_Id = -1,
  Gpu_Use_Dp = TRUE,
  Num_Gpu = 1)

# Separate out the Base Funnel Measures Data
LeadsData <- data[, lapply(.SD, data.table::first), .SDcols = c("Leads"), by = c("CalendarDateColumn")]
ModelData <- ModelDataBase[, Leads := NULL]

# Forecast Funnel Model
Test <- AutoQuant::AutoLightGBMFunnelCARMAScoring(
  TrainData = ModelData,
  ForwardLookingData = LeadsData,
  TrainEndDate = ModelData[, max(CalendarDateColumn)],
  ForecastEndDate = LeadsData[, max(CalendarDateColumn)],
  TrainOutput = TestModel$ModelOutput,
  ArgsList = TestModel$ArgsList,
  ModelPath = NULL,
  MaxCohortPeriod = 15,
  DebugMode = TRUE)

## End(Not run)
```

AutoLightGBMFunnelCARMAScoring
AutoLightGBMFunnelCARMAScoring

Description

AutoLightGBMFunnelCARMAScoring for generating forecasts

Usage

```
AutoLightGBMFunnelCARMAScoring(
  TrainData,
  ForwardLookingData = NULL,
  TrainEndDate = NULL,
  ForecastEndDate = NULL,
  ArgsList = NULL,
  TrainOutput = NULL,
  ModelPath = NULL,
  MaxCohortPeriod = NULL,
  DebugMode = FALSE
)
```

Arguments

TrainData	Data utilized in training. Do not put the BaseFunnelMeasure in this data set. Put it in the ForwardLookingData object
ForwardLookingData	Base funnel measure data. Needs to cover the span of the forecast horizon
TrainEndDate	Max date from the training data
ForecastEndDate	Max date to forecast out to
ArgsList	Output list from AutoCatBoostFunnelCARMA
TrainOutput	Pass in the model object to speed up forecasting
ModelPath	Path to model location
MaxCohortPeriod	Max cohort periods to utilize when forecasting
DebugMode	For debugging issues

Author(s)

Adrian Antico

See Also

Other Automated Funnel Data Forecasting: AutoLightGBMFunnelCARMA(), AutoXGBoostFunnelCARMAScoring(), AutoXGBoostFunnelCARMA()

Examples

```
## Not run:
# Create Fake Data
data <- AutoQuant::FakeDataGenerator(ChainLadderData = TRUE)

# Subset data for training
ModelDataBase <- data[CalendarDateColumn < '2020-01-01' & CohortDateColumn < '2020-01-01']
ModelData <- data.table::copy(ModelDataBase)

# Train Funne Model
TestModel <- AutoQuant::AutoLightGBMFunnelCARMA(

  # Data Arguments
  data = ModelData,
  GroupVariables = NULL,
 BaseFunnelMeasure = "Leads", # if you have XREGS, supply vector such as c("Leads", "XREGS1", "XREGS2")
  ConversionMeasure = "Appointments",
  ConversionRateMeasure = NULL,
  CohortPeriodsVariable = "CohortDays",
  WeightsColumnName = NULL,
  CalendarDate = "CalendarDateColumn",
  CohortDate = "CohortDateColumn",
  PartitionRatios = c(0.70,0.20,0.10),
  TruncateDate = NULL,
  TimeUnit = "days",
  TransformTargetVariable = TRUE,
  TransformMethods = c("Asinh","Asin","Log","LogPlus1","Sqrt","Logit"),
  AnomalyDetection = list(tstat_high = 3, tstat_low = -2),
```

```
 # MetaData Arguments
 Jobs = c("eval","train"),
 SaveModelObjects = FALSE,
 ModelID = "ModelTest",
 ModelPath = getwd(),
 MetaDataPath = NULL,
 DebugMode = TRUE,
 NumOfParDepPlots = 1L,
 EncodingMethod = "credibility",
 NThreads = parallel::detectCores(),

 # Feature Engineering Arguments
 CalendarTimeGroups = c("days","weeks","months"),
 CohortTimeGroups = c("days", "weeks"),
 CalendarVariables = c("wday","mday","yday","week","month","quarter","year"),
HolidayGroups = c("USPublicHolidays","EasterGroup","ChristmasGroup","OtherEcclesticalFeasts"),
 HolidayLookback = NULL,
 CohortHolidayLags = c(1L,2L,7L),
 CohortHolidayMovingAverages = c(3L,7L),
 CalendarHolidayLags = c(1L,2L,7L),
 CalendarHolidayMovingAverages = c(3L,7L),

 # Time Series Features
 ImputeRollStats = -0.001,
 CalendarLags = list("day" = c(1L,2L,7L,35L,42L), "week" = c(5L,6L,10L,12L,25L,26L)),
CalendarMovingAverages = list("day" = c(7L,14L,35L,42L), "week" = c(5L,6L,10L,12L,20L,24L), "month" = c(6L,12
 CalendarStandardDeviations = NULL,
 CalendarSkews = NULL,
 CalendarKurts = NULL,
 CalendarQuantiles = NULL,
 CalendarQuantilesSelected = "q50",
 CohortLags = list("day" = c(1L,2L,7L,35L,42L), "week" = c(5L,6L)),
CohortMovingAverages = list("day" = c(7L,14L,35L,42L), "week" = c(5L,6L), "month" = c(1L,2L)),
 CohortStandardDeviations = NULL,
 CohortSkews = NULL,
 CohortKurts = NULL,
 CohortQuantiles = NULL,
 CohortQuantilesSelected = "q50",

 # ML Grid Tuning
 PassInGrid = NULL,
 GridTune = FALSE,
 BaselineComparison = "default",
 MaxModelsInGrid = 25L,
 MaxRunMinutes = 180L,
 MaxRunsWithoutNewWinner = 10L,

 # ML Setup Parameters
 LossFunction = 'regression',
 EvalMetric = 'mae',
 GridEvalMetric = 'mae',

 # LightGBM Args
 Device_Type = 'CPU',
 Input_Model = NULL,
 Task = 'train',
```

```
  Boosting = 'gbdt',
  LinearTree = FALSE,
  Trees = 50,
  ETA = 0.10,
  Num_Leaves = 31,
  Deterministic = TRUE,

  # Learning Parameters
  # https://lightgbm.readthedocs.io/en/latest/Parameters.html#learning-control-parameters
  Force_Col_Wise = FALSE,
  Force_Row_Wise = FALSE,
  Max_Depth = 6,
  Min_Data_In_Leaf = 20,
  Min_Sum_Hessian_In_Leaf = 0.001,
  Bagging_Freq = 1.0,
  Bagging_Fraction = 1.0,
  Feature_Fraction = 1.0,
  Feature_Fraction_Bynode = 1.0,
  Lambda_L1 = 0.0,
  Lambda_L2 = 0.0,
  Extra_Trees = FALSE,
  Early_Stopping_Round = 10,
  First_Metric_Only = TRUE,
  Max_Delta_Step = 0.0,
  Linear_Lambda = 0.0,
  Min_Gain_To_Split = 0,
  Drop_Rate_Dart = 0.10,
  Max_Drop_Dart = 50,
  Skip_Drop_Dart = 0.50,
  Uniform_Drop_Dart = FALSE,
  Top_Rate_Goss = FALSE,
  Other_Rate_Goss = FALSE,
  Monotone_Constraints = NULL,
  Monotone_Constraints_method = 'advanced',
  Monotone_Penalty = 0.0,
  Forcedsplits_Filename = NULL, # use for AutoStack option; .json file
  Refit_Decay_Rate = 0.90,
  Path_Smooth = 0.0,

  # IO Dataset Parameters
  # https://lightgbm.readthedocs.io/en/latest/Parameters.html#io-parameters
  Max_Bin = 255,
  Min_Data_In_Bin = 3,
  Data_Random_Seed = 1,
  Is_Enable_Sparse = TRUE,
  Enable_Bundle = TRUE,
  Use_Missing = TRUE,
  Zero_As_Missing = FALSE,
  Two_Round = FALSE,

  # Convert Parameters
  Convert_Model = NULL,
  Convert_Model_Language = 'cpp',

  # Objective Parameters
  # https://lightgbm.readthedocs.io/en/latest/Parameters.html#objective-parameters
  Boost_From_Average = TRUE,
```

```
  Alpha = 0.90,
  Fair_C = 1.0,
  Poisson_Max_Delta_Step = 0.70,
  Tweedie_Variance_Power = 1.5,
  Lambdarank_Truncation_Level = 30,

  # Metric Parameters (metric is in Core)
  # https://lightgbm.readthedocs.io/en/latest/Parameters.html#metric-parameters
  Is_Provide_Training_Metric = TRUE,
  Eval_At = c(1,2,3,4,5),

  # Network Parameters
  # https://lightgbm.readthedocs.io/en/latest/Parameters.html#network-parameters
  Num_Machines = 1,

  # GPU Parameters
  # https://lightgbm.readthedocs.io/en/latest/Parameters.html#gpu-parameters
  Gpu_Platform_Id = -1,
  Gpu_Device_Id = -1,
  Gpu_Use_Dp = TRUE,
  Num_Gpu = 1)

# Separate out the Base Funnel Measures Data
LeadsData <- data[, lapply(.SD, data.table::first), .SDcols = c("Leads"), by = c("CalendarDateColumn")]
ModelData <- ModelDataBase[, Leads := NULL]

# Forecast Funnel Model
Test <- AutoQuant::AutoLightGBMFunnelCARMAScoring(
  TrainData = ModelData,
  ForwardLookingData = LeadsData,
  TrainEndDate = ModelData[, max(CalendarDateColumn)],
  ForecastEndDate = LeadsData[, max(CalendarDateColumn)],
  TrainOutput = TestModel$ModelOutput,
  ArgsList = TestModel$ArgsList,
  ModelPath = NULL,
  MaxCohortPeriod = 15,
  DebugMode = TRUE)

## End(Not run)
```

`AutoLightGBMMultiClass` *AutoLightGBMMultiClass*

Description

AutoLightGBMMultiClass is an automated lightgbm modeling framework with grid-tuning and model evaluation that runs a variety of steps. First, the function will run a random grid tune over N number of models and find which model is the best (a default model is always included in that set). Once the model is identified and built, several other outputs are generated: validation data with predictions, evaluation plot, evaluation boxplot, evaluation metrics, variable importance, partial dependence calibration plots, partial dependence calibration box plots, and column names used in model fitting.

Usage

```
AutoLightGBMMultiClass(
  data = NULL,
  TrainOnFull = FALSE,
  ValidationData = NULL,
  TestData = NULL,
  TargetColumnName = NULL,
  FeatureColNames = NULL,
  PrimaryDateColumn = NULL,
  IDcols = NULL,
  WeightsColumnName = NULL,
  CostMatrixWeights = c(1, 0, 0, 1),
  EncodingMethod = "credibility",
 OutputSelection = c("Importances", "EvalPlots", "EvalMetrics", "Score_TrainData"),
  model_path = NULL,
  metadata_path = NULL,
  DebugMode = FALSE,
  SaveInfoToPDF = FALSE,
  ModelID = "TestModel",
  ReturnFactorLevels = TRUE,
  ReturnModelObjects = TRUE,
  SaveModelObjects = FALSE,
  NumOfParDepPlots = 3L,
  Verbose = 0L,
  GridTune = FALSE,
  grid_eval_metric = "microauc",
  BaselineComparison = "default",
  MaxModelsInGrid = 10L,
  MaxRunsWithoutNewWinner = 20L,
  MaxRunMinutes = 24L * 60L,
  PassInGrid = NULL,
  input_model = NULL,
  task = "train",
  device_type = "CPU",
  NThreads = parallel::detectCores()/2,
  objective = "multiclass",
  multi_error_top_k = 1,
  metric = "multi_logloss",
  boosting = "gbdt",
  LinearTree = FALSE,
  Trees = 50L,
  eta = NULL,
  num_leaves = 31,
  deterministic = TRUE,
  force_col_wise = FALSE,
  force_row_wise = FALSE,
  max_depth = NULL,
  min_data_in_leaf = 20,
  min_sum_hessian_in_leaf = 0.001,
  bagging_freq = 0,
  bagging_fraction = 1,
  feature_fraction = 1,
```

```
  feature_fraction_bynode = 1,
  extra_trees = FALSE,
  early_stopping_round = 10,
  first_metric_only = TRUE,
  max_delta_step = 0,
  lambda_l1 = 0,
  lambda_l2 = 0,
  linear_lambda = 0,
  min_gain_to_split = 0,
  drop_rate_dart = 0.1,
  max_drop_dart = 50,
  skip_drop_dart = 0.5,
  uniform_drop_dart = FALSE,
  top_rate_goss = FALSE,
  other_rate_goss = FALSE,
  monotone_constraints = NULL,
  monotone_constraints_method = "advanced",
  monotone_penalty = 0,
  forcedsplits_filename = NULL,
  refit_decay_rate = 0.9,
  path_smooth = 0,
  max_bin = 255,
  min_data_in_bin = 3,
  data_random_seed = 1,
  is_enable_sparse = TRUE,
  enable_bundle = TRUE,
  use_missing = TRUE,
  zero_as_missing = FALSE,
  two_round = FALSE,
  convert_model = NULL,
  convert_model_language = "cpp",
  boost_from_average = TRUE,
  is_unbalance = FALSE,
  scale_pos_weight = 1,
  is_provide_training_metric = TRUE,
  eval_at = c(1, 2, 3, 4, 5),
  num_machines = 1,
  gpu_platform_id = -1,
  gpu_device_id = -1,
  gpu_use_dp = TRUE,
  num_gpu = 1
)
```

Arguments

data	This is your data set for training and testing your model
TrainOnFull	Set to TRUE to train on full data
ValidationData	This is your holdout data set used in modeling either refine your hyperparameters.
TestData	This is your holdout data set.
TargetColumnName	Either supply the target column name OR the column number where the target

is located (but not mixed types).

`FeatureColNames`
: Either supply the feature column names OR the column number where the target is located (but not mixed types)

`PrimaryDateColumn`
: Supply a date or datetime column for catboost to utilize time as its basis for handling categorical features, instead of random shuffling

`IDcols`
: A vector of column names or column numbers to keep in your data but not include in the modeling.

`WeightsColumnName`
: Supply a column name for your weights column. Leave NULL otherwise

`EncodingMethod`
: Choose from 'binary', 'm_estimator', 'credibility', 'woe', 'target_encoding', 'poly_encode', 'backward_difference', 'helmert'

`OutputSelection`
: You can select what type of output you want returned. Choose from c("Importances", "EvalPlots", "EvalMetrics", "Score_TrainData")

`model_path`
: A character string of your path file to where you want your output saved

`metadata_path`
: A character string of your path file to where you want your model evaluation output saved. If left NULL, all output will be saved to model_path.

`DebugMode`
: Set to TRUE to get a print out of the steps taken throughout the function

`SaveInfoToPDF`
: Set to TRUE to save model insights to pdf

`ModelID`
: A character string to name your model and output

`ReturnFactorLevels`
: Set to TRUE to have the factor levels returned with the other model objects

`ReturnModelObjects`
: Set to TRUE to output all modeling objects (E.g. plots and evaluation metrics)

`SaveModelObjects`
: Set to TRUE to return all modeling objects to your environment

`NumOfParDepPlots`
: Tell the function the number of partial dependence calibration plots you want to create.

`Verbose`
: Set to 0 if you want to suppress model evaluation updates in training

`GridTune`
: Set to TRUE to run a grid tuning procedure. Set a number in MaxModelsInGrid to tell the procedure how many models you want to test.

`grid_eval_metric`
: "mae", "mape", "rmse", "r2". Case sensitive

`BaselineComparison`
: Set to either "default" or "best". Default is to compare each successive model build to the baseline model using max trees (from function args). Best makes the comparison to the current best model.

  # Core parameters https://lightgbm.readthedocs.io/en/latest/Parameters.html#core-parameter

`MaxModelsInGrid`
: Number of models to test from grid options (243 total possible options)

`MaxRunsWithoutNewWinner`
: Runs without new winner to end procedure

`MaxRunMinutes`
: In minutes

PassInGrid Default is NULL. Provide a data.table of grid options from a previous run.

input_model = NULL, # continue training a model that is stored to fil

task 'train' or 'refit'

device_type 'cpu' or 'gpu'

NThreads only list up to number of cores, not threads. parallel::detectCores() / 2

objective 'multiclass', 'multiclassova'

multi_error_top_k
Default 1. Counts a prediction as correct if the chosen label is in the top K labels.
K = 1 == multi_error

metric 'multi_logloss', 'multi_error', 'kullback_leibler', 'cross_entropy', 'cross_entropy_lambda'

boosting 'gbdt', 'rf', 'dart', 'goss'

LinearTree FALSE

Trees 50L

eta NULL

num_leaves 31

deterministic TRUE
Learning Parameters https://lightgbm.readthedocs.io/en/latest/Parameters.html#learning-control-parameter

force_col_wise FALSE

force_row_wise FALSE

max_depth NULL

min_data_in_leaf
20

min_sum_hessian_in_leaf
0.001

bagging_freq 0

bagging_fraction
1.0

feature_fraction
1.0

feature_fraction_bynode
1.0

extra_trees FALSE

early_stopping_round
10

first_metric_only
TRUE

max_delta_step 0.0

lambda_l1 0.0

lambda_l2 0.0

linear_lambda 0.0

min_gain_to_split
0

drop_rate_dart 0.10

max_drop_dart 50

skip_drop_dart 0.50

uniform_drop_dart
FALSE

top_rate_goss FALSE

other_rate_goss
FALSE

monotone_constraints
"gbdt_prediction.cpp"

monotone_constraints_method
'advanced'

monotone_penalty
0.0

forcedsplits_filename
NULL # use for AutoStack option; .json fil

refit_decay_rate
0.90

path_smooth 0.0
IO Dataset Parameters https://lightgbm.readthedocs.io/en/latest/Parameters.html#io-parameters

max_bin 255

min_data_in_bin
3

data_random_seed
1

is_enable_sparse
TRUE

enable_bundle TRUE

use_missing TRUE

zero_as_missing
FALSE

two_round FALSE
Convert Parameters # https://lightgbm.readthedocs.io/en/latest/Parameters.html#convert-parameters

convert_model 'gbdt_prediction.cpp'

convert_model_language
'cpp'
Objective Parameters https://lightgbm.readthedocs.io/en/latest/Parameters.html#objective-parameters

boost_from_average
TRUE

is_unbalance FALSE

scale_pos_weight
1.0
Metric Parameters (metric is in Core)

is_provide_training_metric
TRUE

eval_at	c(1,2,3,4,5)
	# Network Parameter
num_machines	1
	# GPU Parameter
gpu_platform_id	
	-1
gpu_device_id	-1
gpu_use_dp	TRUE
num_gpu	1

Value

Saves to file and returned in list: VariableImportance.csv, Model, ValidationData.csv, EvalutionPlot.png, EvalutionBoxPlot.png, EvaluationMetrics.csv, ParDepPlots.R a named list of features with partial dependence calibration plots, ParDepBoxPlots.R, GridCollect, and GridList

Author(s)

Adrian Antico

Examples

```
## Not run:
# Create some dummy correlated data
data <- AutoQuant::FakeDataGenerator(
  Correlation = 0.85,
  N = 1000,
  ID = 2,
  ZIP = 0,
  AddDate = FALSE,
  Classification = FALSE,
  MultiClass = FALSE)

# Run function
TestModel <- AutoQuant::AutoLightGBMMultiClass(

  # Metadata args
  OutputSelection = c("Importances","EvalPlots","EvalMetrics","Score_TrainData"),
  model_path = normalizePath("./"),
  metadata_path = NULL,
  ModelID = "Test_Model_1",
  NumOfParDepPlots = 3L,
  EncodingMethod = "credibility",
  ReturnFactorLevels = TRUE,
  ReturnModelObjects = TRUE,
  SaveModelObjects = FALSE,
  SaveInfoToPDF = FALSE,
  DebugMode = FALSE,

  # Data args
  data = data,
  TrainOnFull = FALSE,
  ValidationData = NULL,
  TestData = NULL,
```

```
  TargetColumnName = "Adrian",
  FeatureColNames = names(data)[!names(data) %in% c("IDcol_1", "IDcol_2","Adrian")],
  PrimaryDateColumn = NULL,
  WeightsColumnName = NULL,
  IDcols = c("IDcol_1","IDcol_2"),

  # Grid parameters
  GridTune = FALSE,
  grid_eval_metric = 'microauc',
  BaselineComparison = 'default',
  MaxModelsInGrid = 10L,
  MaxRunsWithoutNewWinner = 20L,
  MaxRunMinutes = 24L*60L,
  PassInGrid = NULL,

  # Core parameters
  # https://lightgbm.readthedocs.io/en/latest/Parameters.html#core-parameters
  input_model = NULL, # continue training a model that is stored to file
  task = "train",
  device_type = 'CPU',
  NThreads = parallel::detectCores() / 2,
  objective = 'multiclass',
  multi_error_top_k = 1,
  metric = 'multi_logloss',
  boosting = 'gbdt',
  LinearTree = FALSE,
  Trees = 50L,
  eta = NULL,
  num_leaves = 31,
  deterministic = TRUE,

  # Learning Parameters
 # https://lightgbm.readthedocs.io/en/latest/Parameters.html#learning-control-parameters
  force_col_wise = FALSE,
  force_row_wise = FALSE,
  max_depth = NULL,
  min_data_in_leaf = 20,
  min_sum_hessian_in_leaf = 0.001,
  bagging_freq = 0,
  bagging_fraction = 1.0,
  feature_fraction = 1.0,
  feature_fraction_bynode = 1.0,
  extra_trees = FALSE,
  early_stopping_round = 10,
  first_metric_only = TRUE,
  max_delta_step = 0.0,
  lambda_l1 = 0.0,
  lambda_l2 = 0.0,
  linear_lambda = 0.0,
  min_gain_to_split = 0,
  drop_rate_dart = 0.10,
  max_drop_dart = 50,
  skip_drop_dart = 0.50,
  uniform_drop_dart = FALSE,
  top_rate_goss = FALSE,
  other_rate_goss = FALSE,
  monotone_constraints = NULL,
```

```
  monotone_constraints_method = "advanced",
  monotone_penalty = 0.0,
  forcedsplits_filename = NULL, # use for AutoStack option; .json file
  refit_decay_rate = 0.90,
  path_smooth = 0.0,

  # IO Dataset Parameters
  # https://lightgbm.readthedocs.io/en/latest/Parameters.html#io-parameters
  max_bin = 255,
  min_data_in_bin = 3,
  data_random_seed = 1,
  is_enable_sparse = TRUE,
  enable_bundle = TRUE,
  use_missing = TRUE,
  zero_as_missing = FALSE,
  two_round = FALSE,

  # Convert Parameters
  convert_model = NULL,
  convert_model_language = "cpp",

  # Objective Parameters
  # https://lightgbm.readthedocs.io/en/latest/Parameters.html#objective-parameters
  boost_from_average = TRUE,
  is_unbalance = FALSE,
  scale_pos_weight = 1.0,

  # Metric Parameters (metric is in Core)
  # https://lightgbm.readthedocs.io/en/latest/Parameters.html#metric-parameters
  is_provide_training_metric = TRUE,
  eval_at = c(1,2,3,4,5),

  # Network Parameters
  # https://lightgbm.readthedocs.io/en/latest/Parameters.html#network-parameters
  num_machines = 1,

  # GPU Parameters
  # https://lightgbm.readthedocs.io/en/latest/Parameters.html#gpu-parameters
  gpu_platform_id = -1,
  gpu_device_id = -1,
  gpu_use_dp = TRUE,
  num_gpu = 1)

## End(Not run)
```

`AutoLightGBMRegression`

AutoLightGBMRegression

Description

AutoLightGBMRegression is an automated lightgbm modeling framework with grid-tuning and model evaluation that runs a variety of steps. First, the function will run a random grid tune over N number of models and find which model is the best (a default model is always included in that set).

Once the model is identified and built, several other outputs are generated: validation data with predictions, evaluation plot, evaluation boxplot, evaluation metrics, variable importance, partial dependence calibration plots, partial dependence calibration box plots, and column names used in model fitting.

Usage

```
AutoLightGBMRegression(
  data = NULL,
  TrainOnFull = FALSE,
  ValidationData = NULL,
  TestData = NULL,
  TargetColumnName = NULL,
  FeatureColNames = NULL,
  PrimaryDateColumn = NULL,
  WeightsColumnName = NULL,
  IDcols = NULL,
 OutputSelection = c("Importances", "EvalPlots", "EvalMetrics", "Score_TrainData"),
  model_path = NULL,
  metadata_path = NULL,
  DebugMode = FALSE,
  SaveInfoToPDF = FALSE,
  ModelID = "TestModel",
  ReturnFactorLevels = TRUE,
  ReturnModelObjects = TRUE,
  SaveModelObjects = FALSE,
  EncodingMethod = "credibility",
  TransformNumericColumns = NULL,
  Methods = c("Asinh", "Log", "LogPlus1", "Sqrt", "Asin", "Logit"),
  Verbose = 0L,
  NumOfParDepPlots = 3L,
  GridTune = FALSE,
  grid_eval_metric = "r2",
  BaselineComparison = "default",
  MaxModelsInGrid = 10L,
  MaxRunsWithoutNewWinner = 20L,
  MaxRunMinutes = 24L * 60L,
  PassInGrid = NULL,
  input_model = NULL,
  task = "train",
  device_type = "CPU",
  NThreads = parallel::detectCores()/2,
  objective = "regression",
  metric = "rmse",
  boosting = "gbdt",
  LinearTree = FALSE,
  Trees = 50L,
  eta = NULL,
  num_leaves = 31,
  deterministic = TRUE,
  force_col_wise = FALSE,
  force_row_wise = FALSE,
  max_depth = NULL,
```

```
  min_data_in_leaf = 20,
  min_sum_hessian_in_leaf = 0.001,
  bagging_freq = 0,
  bagging_fraction = 1,
  feature_fraction = 1,
  feature_fraction_bynode = 1,
  extra_trees = FALSE,
  early_stopping_round = 10,
  first_metric_only = TRUE,
  max_delta_step = 0,
  lambda_l1 = 0,
  lambda_l2 = 0,
  linear_lambda = 0,
  min_gain_to_split = 0,
  drop_rate_dart = 0.1,
  max_drop_dart = 50,
  skip_drop_dart = 0.5,
  uniform_drop_dart = FALSE,
  top_rate_goss = FALSE,
  other_rate_goss = FALSE,
  monotone_constraints = NULL,
  monotone_constraints_method = "advanced",
  monotone_penalty = 0,
  forcedsplits_filename = NULL,
  refit_decay_rate = 0.9,
  path_smooth = 0,
  max_bin = 255,
  min_data_in_bin = 3,
  data_random_seed = 1,
  is_enable_sparse = TRUE,
  enable_bundle = TRUE,
  use_missing = TRUE,
  zero_as_missing = FALSE,
  two_round = FALSE,
  convert_model = NULL,
  convert_model_language = "cpp",
  boost_from_average = TRUE,
  alpha = 0.9,
  fair_c = 1,
  poisson_max_delta_step = 0.7,
  tweedie_variance_power = 1.5,
  lambdarank_truncation_level = 30,
  is_provide_training_metric = TRUE,
  eval_at = c(1, 2, 3, 4, 5),
  num_machines = 1,
  gpu_platform_id = -1,
  gpu_device_id = -1,
  gpu_use_dp = TRUE,
  num_gpu = 1
)
```

Arguments

data	This is your data set for training and testing your model
TrainOnFull	Set to TRUE to train on full data
ValidationData	This is your holdout data set used in modeling either refine your hyperparameters.
TestData	This is your holdout data set.
TargetColumnName	Either supply the target column name OR the column number where the target is located (but not mixed types).
FeatureColNames	Either supply the feature column names OR the column number where the target is located (but not mixed types)
PrimaryDateColumn	Supply a date or datetime column for catboost to utilize time as its basis for handling categorical features, instead of random shuffling
WeightsColumnName	Supply a column name for your weights column. Leave NULL otherwise
IDcols	A vector of column names or column numbers to keep in your data but not include in the modeling.
OutputSelection	You can select what type of output you want returned. Choose from c('Importances', 'EvalPlots', 'EvalMetrics', 'Score_TrainData')
model_path	A character string of your path file to where you want your output saved
metadata_path	A character string of your path file to where you want your model evaluation output saved. If left NULL, all output will be saved to model_path.
DebugMode	Set to TRUE to get a print out of the steps taken throughout the function
SaveInfoToPDF	Set to TRUE to save model insights to pdf
ModelID	A character string to name your model and output
ReturnFactorLevels	Set to TRUE to have the factor levels returned with the other model objects
ReturnModelObjects	Set to TRUE to output all modeling objects (E.g. plots and evaluation metrics)
SaveModelObjects	Set to TRUE to return all modeling objects to your environment
EncodingMethod	Choose from 'binary', 'm_estimator', 'credibility', 'woe', 'target_encoding', 'poly_encode', 'backward_difference', 'helmert'
TransformNumericColumns	Set to NULL to do nothing; otherwise supply the column names of numeric variables you want transformed
Methods	Choose from 'BoxCox', 'Asinh', 'Asin', 'Log', 'LogPlus1', 'Sqrt', 'Logit', 'YeoJohnson'. Function will determine if one cannot be used because of the underlying data.
Verbose	Set to 0 if you want to suppress model evaluation updates in training
NumOfParDepPlots	Tell the function the number of partial dependence calibration plots you want to create.

GridTune — Set to TRUE to run a grid tuning procedure. Set a number in MaxModelsInGrid to tell the procedure how many models you want to test.

grid_eval_metric — 'mae', 'mape', 'rmse', 'r2'. Case sensitive

BaselineComparison — Set to either 'default' or 'best'. Default is to compare each successive model build to the baseline model using max trees (from function args). Best makes the comparison to the current best model.

MaxModelsInGrid — Number of models to test from grid options (243 total possible options)

MaxRunsWithoutNewWinner — Runs without new winner to end procedure

MaxRunMinutes — In minutes

PassInGrid — Default is NULL. Provide a data.table of grid options from a previous run.

input_model — = NULL, # continue training a model that is stored to fil

Core parameters https://lightgbm.readthedocs.io/en/latest/Parameters.html#core-parameter

task — 'train' or 'refit'

device_type — 'cpu' or 'gpu'

NThreads — only list up to number of cores, not threads. parallel::detectCores() / 2

objective — 'regression' (or 'mean_squared_error'), 'regression_l1' (or 'mean_absolute_error'), 'mae' (or 'mean_absolute_percentage_error'), 'huber', 'fair', 'poisson', 'quantile', 'gamma', 'tweedie'

metric — 'rmse', 'l1', 'l2', 'quantile', 'mape', 'huber', 'fair', 'poisson', 'gamma', 'gamma_deviance', 'tweedie', 'ndcg'

boosting — 'gbdt', 'rf', 'dart', 'goss'

LinearTree — FALSE

Trees — 50L

eta — NULL

num_leaves — 31

deterministic — TRUE

Learning Parameters https://lightgbm.readthedocs.io/en/latest/Parameters.html#learning-control-parameter

force_col_wise — FALSE

force_row_wise — FALSE

max_depth — NULL

min_data_in_leaf — 20

min_sum_hessian_in_leaf — 0.001

bagging_freq — 0

bagging_fraction — 1.0

feature_fraction — 1.0

feature_fraction_bynode
: 1.0

extra_trees
: FALSE

early_stopping_round
: 10

first_metric_only
: TRUE

max_delta_step
: 0.0

lambda_l1
: 0.0

lambda_l2
: 0.0

linear_lambda
: 0.0

min_gain_to_split
: 0

drop_rate_dart
: 0.10

max_drop_dart
: 50

skip_drop_dart
: 0.50

uniform_drop_dart
: FALSE

top_rate_goss
: FALSE

other_rate_goss
: FALSE

monotone_constraints
: NULL, 'gbdt_prediction.cpp'

monotone_constraints_method
: 'advanced'

monotone_penalty
: 0.0

forcedsplits_filename
: NULL # use for AutoStack option; .json fil

refit_decay_rate
: 0.90

path_smooth
: 0.0 # IO Dataset Parameters https://lightgbm.readthedocs.io/en/latest/Parameters.html#io-parameters

max_bin
: 255

min_data_in_bin
: 3

data_random_seed
: 1

is_enable_sparse
: TRUE

enable_bundle
: TRUE

use_missing
: TRUE

zero_as_missing
: FALSE

two_round
: FALSE # Convert Parameters # https://lightgbm.readthedocs.io/en/latest/Parameters.html#convert-parameters

convert_model 'gbdt_prediction.cpp'

convert_model_language
'cpp'

Objective Parameters https://lightgbm.readthedocs.io/en/latest/Parameters.html#objective-parameters

boost_from_average
TRUE

alpha 0.90

fair_c 1.0

poisson_max_delta_step
0.70

tweedie_variance_power
1.5

lambdarank_truncation_level
30

Metric Parameters (metric is in Core)

is_provide_training_metric
TRUE

eval_at c(1,2,3,4,5)

Network Parameter

num_machines 1

GPU Parameter

gpu_platform_id
-1

gpu_device_id -1

gpu_use_dp TRUE

num_gpu 1

Value

Saves to file and returned in list: VariableImportance.csv, Model, ValidationData.csv, EvalutionPlot.png, EvalutionBoxPlot.png, EvaluationMetrics.csv, ParDepPlots.R a named list of features with partial dependence calibration plots, ParDepBoxPlots.R, GridCollect, and GridList

Author(s)

Adrian Antico

See Also

Other Automated Supervised Learning - Regression: AutoCatBoostRegression(), AutoH2oDRFRegression(), AutoH2oGAMRegression(), AutoH2oGBMRegression(), AutoH2oGLMRegression(), AutoH2oMLRegression(), AutoXGBoostRegression()

Examples

```
## Not run:
# Create some dummy correlated data
data <- AutoQuant::FakeDataGenerator(
  Correlation = 0.85,
  N = 1000,
  ID = 2,
  ZIP = 0,
  AddDate = FALSE,
  Classification = FALSE,
  MultiClass = FALSE)

# Run function
TestModel <- AutoQuant::AutoLightGBMRegression(

  # Metadata args
  OutputSelection = c('Importances','EvalPlots','EvalMetrics','Score_TrainData'),
  model_path = normalizePath('./'),
  metadata_path = NULL,
  ModelID = 'Test_Model_1',
  NumOfParDepPlots = 3L,
  EncodingMethod = 'credibility',
  ReturnFactorLevels = TRUE,
  ReturnModelObjects = TRUE,
  SaveModelObjects = FALSE,
  SaveInfoToPDF = FALSE,
  DebugMode = FALSE,

  # Data args
  data = data,
  TrainOnFull = FALSE,
  ValidationData = NULL,
  TestData = NULL,
  TargetColumnName = 'Adrian',
  FeatureColNames = names(data)[!names(data) %in% c('IDcol_1', 'IDcol_2','Adrian')],
  PrimaryDateColumn = NULL,
  WeightsColumnName = NULL,
  IDcols = c('IDcol_1','IDcol_2'),
  TransformNumericColumns = NULL,
  Methods = c('Asinh','Asin','Log','LogPlus1','Sqrt','Logit'),

  # Grid parameters
  GridTune = FALSE,
  grid_eval_metric = 'r2',
  BaselineComparison = 'default',
  MaxModelsInGrid = 10L,
  MaxRunsWithoutNewWinner = 20L,
  MaxRunMinutes = 24L*60L,
  PassInGrid = NULL,

  # Core parameters
  # https://lightgbm.readthedocs.io/en/latest/Parameters.html#core-parameters
  input_model = NULL, # continue training a model that is stored to file
  task = 'train',
  device_type = 'CPU',
  NThreads = parallel::detectCores() / 2,
```

```
  objective = 'regression',
  metric = 'rmse',
  boosting = 'gbdt',
  LinearTree = FALSE,
  Trees = 50L,
  eta = NULL,
  num_leaves = 31,
  deterministic = TRUE,

  # Learning Parameters
  # https://lightgbm.readthedocs.io/en/latest/Parameters.html#learning-control-parameters
  force_col_wise = FALSE,
  force_row_wise = FALSE,
  max_depth = NULL,
  min_data_in_leaf = 20,
  min_sum_hessian_in_leaf = 0.001,
  bagging_freq = 0,
  bagging_fraction = 1.0,
  feature_fraction = 1.0,
  feature_fraction_bynode = 1.0,
  extra_trees = FALSE,
  early_stopping_round = 10,
  first_metric_only = TRUE,
  max_delta_step = 0.0,
  lambda_l1 = 0.0,
  lambda_l2 = 0.0,
  linear_lambda = 0.0,
  min_gain_to_split = 0,
  drop_rate_dart = 0.10,
  max_drop_dart = 50,
  skip_drop_dart = 0.50,
  uniform_drop_dart = FALSE,
  top_rate_goss = FALSE,
  other_rate_goss = FALSE,
  monotone_constraints = NULL,
  monotone_constraints_method = 'advanced',
  monotone_penalty = 0.0,
  forcedsplits_filename = NULL, # use for AutoStack option; .json file
  refit_decay_rate = 0.90,
  path_smooth = 0.0,

  # IO Dataset Parameters
  # https://lightgbm.readthedocs.io/en/latest/Parameters.html#io-parameters
  max_bin = 255,
  min_data_in_bin = 3,
  data_random_seed = 1,
  is_enable_sparse = TRUE,
  enable_bundle = TRUE,
  use_missing = TRUE,
  zero_as_missing = FALSE,
  two_round = FALSE,

  # Convert Parameters
  convert_model = NULL,
  convert_model_language = 'cpp',

  # Objective Parameters
```

```
  # https://lightgbm.readthedocs.io/en/latest/Parameters.html#objective-parameters
  boost_from_average = TRUE,
  alpha = 0.90,
  fair_c = 1.0,
  poisson_max_delta_step = 0.70,
  tweedie_variance_power = 1.5,
  lambdarank_truncation_level = 30,

  # Metric Parameters (metric is in Core)
  # https://lightgbm.readthedocs.io/en/latest/Parameters.html#metric-parameters
  is_provide_training_metric = TRUE,
  eval_at = c(1,2,3,4,5),

  # Network Parameters
  # https://lightgbm.readthedocs.io/en/latest/Parameters.html#network-parameters
  num_machines = 1,

  # GPU Parameters
  # https://lightgbm.readthedocs.io/en/latest/Parameters.html#gpu-parameters
  gpu_platform_id = -1,
  gpu_device_id = -1,
  gpu_use_dp = TRUE,
  num_gpu = 1)

## End(Not run)
```

`AutoLightGBMScoring` *AutoLightGBMScoring*

Description

AutoLightGBMScoring is an automated scoring function that compliments the AutoLightGBM model training functions. This function requires you to supply features for scoring. It will run ModelDataPrep() and the DummifyDT() function to prepare your features for xgboost data conversion and scoring.

Usage

```
AutoLightGBMScoring(
  TargetType = NULL,
  ScoringData = NULL,
  ReturnShapValues = FALSE,
  FeatureColumnNames = NULL,
  IDcols = NULL,
  EncodingMethod = "credibility",
  FactorLevelsList = NULL,
  TargetLevels = NULL,
  OneHot = FALSE,
  ModelObject = NULL,
  ModelPath = NULL,
  ModelID = NULL,
  ReturnFeatures = TRUE,
  TransformNumeric = FALSE,
```

```
  BackTransNumeric = FALSE,
  TargetColumnName = NULL,
  TransformationObject = NULL,
  TransID = NULL,
  TransPath = NULL,
  MDP_Impute = TRUE,
  MDP_CharToFactor = TRUE,
  MDP_RemoveDates = TRUE,
  MDP_MissFactor = "0",
  MDP_MissNum = -1
)
```

Arguments

TargetType	Set this value to 'regression', 'classification', or 'multiclass' to score models built using AutoLightGBMRegression(), AutoLightGBMClassifier() or AutoLightGBMMultiClass()
ScoringData	This is your data.table of features for scoring. Can be a single row or batch.
ReturnShapValues	Not functional yet. The shap values are returned in a way that is slow and incompatible with the existing tools. Working on a better solution.
FeatureColumnNames	Supply either column names or column numbers used in the AutoLightGBM__() function
IDcols	Supply ID column numbers for any metadata you want returned with your predicted values
EncodingMethod	Choose from 'binary', 'm_estimator', 'credibility', 'woe', 'target_encoding', 'poly_encode', 'backward_difference', 'helmert'
FactorLevelsList	Supply the factor variables' list from DummifyDT()
TargetLevels	Supply the target levels output from AutoLightGBMMultiClass() or the scoring function will go looking for it in the file path you supply.
ModelObject	Supply a model for scoring, otherwise it will have to search for it in the file path you specify
ModelPath	Supply your path file used in the AutoLightGBM__() function
ModelID	Supply the model ID used in the AutoLightGBM__() function
ReturnFeatures	Set to TRUE to return your features with the predicted values.
TransformNumeric	Set to TRUE if you have features that were transformed automatically from an Auto__Regression() model AND you haven't already transformed them.
BackTransNumeric	Set to TRUE to generate back-transformed predicted values. Also, if you return features, those will also be back-transformed.
TargetColumnName	Input your target column name used in training if you are utilizing the transformation service
TransformationObject	Set to NULL if you didn't use transformations or if you want the function to pull from the file output from the Auto__Regression() function. You can also supply the transformation data.table object with the transformation details versus having it pulled from file.

TransID	Set to the ID used for saving the transformation data.table object or set it to the ModelID if you are pulling from file from a build with Auto__Regression().
TransPath	Set the path file to the folder where your transformation data.table detail object is stored. If you used the Auto__Regression() to build, set it to the same path as ModelPath.
MDP_Impute	Set to TRUE if you did so for modeling and didn't do so before supplying ScoringData in this function
MDP_CharToFactor	Set to TRUE to turn your character columns to factors if you didn't do so to your ScoringData that you are supplying to this function
MDP_RemoveDates	Set to TRUE if you have date of timestamp columns in your ScoringData
MDP_MissFactor	If you set MDP_Impute to TRUE, supply the character values to replace missing values with
MDP_MissNum	If you set MDP_Impute to TRUE, supply a numeric value to replace missing values with

Value

A data.table of predicted values with the option to return model features as well.

Author(s)

Adrian Antico

See Also

Other Automated Model Scoring: AutoCatBoostScoring(), AutoH2OMLScoring(), AutoXGBoostScoring()

Examples

```
## Not run:
Preds <- AutoQuant::AutoLightGBMScoring(
  TargetType = 'regression',
  ScoringData = data,
  ReturnShapValues = FALSE,
  FeatureColumnNames = 2:12,
  IDcols = NULL,
  EncodingMethod = 'credibility',
  FactorLevelsList = NULL,
  TargetLevels = NULL,
  ModelObject = NULL,
  ModelPath = 'home',
  ModelID = 'ModelTest',
  ReturnFeatures = TRUE,
  TransformNumeric = FALSE,
  BackTransNumeric = FALSE,
  TargetColumnName = NULL,
  TransformationObject = NULL,
  TransID = NULL,
  TransPath = NULL,
  MDP_Impute = TRUE,
  MDP_CharToFactor = TRUE,
  MDP_RemoveDates = TRUE,
```

```
  MDP_MissFactor = '0',
  MDP_MissNum = -1)

## End(Not run)
```

AutoShapeShap *AutoShapeShap*

Description

AutoShapeShap will convert your scored shap values from CatBoost

Usage

```
AutoShapeShap(
  ScoringData = NULL,
  Threads = max(1L, parallel::detectCores() - 2L),
  DateColumnName = "Date",
  ByVariableName = "GroupVariable"
)
```

Arguments

ScoringData	Scoring data from AutoCatBoostScoring with classification or regression
Threads	Number of threads to use for the parellel routine
DateColumnName	Name of the date column in scoring data
ByVariableName	Name of your base entity column name

Author(s)

Adrian Antico

See Also

Other Model Evaluation and Interpretation: CumGainsChart(), EvalPlot(), ParDepCalPlots(), ROCPlot(), RedYellowGreen(), ResidualPlots(), SingleRowShapeShap(), threshOptim()

AutoTBATS *AutoTBATS*

Description

AutoTBATS is a multi-armed bandit model testing framework for AR and SAR NNets. Randomized probability matching is the underlying bandit algorithm. Model evaluation is done by blending the training error and the validation error from testing the model on out of sample data. The bandit algorithm compares the performance of the current build against the previous builds which starts with the classic nnetar model from the forecast package. Depending on how many lags, seasonal lags, and fourier pairs you test the number of combinations of features to test begins to approach 10,000 different combinations of settings. The function tests out transformations, differencing, and variations of the lags, seasonal lags, and fourier pairs. The paramter space is broken up into various buckets that are increasing in sophistication. The bandit algorithm samples from those buckets and based on many rounds of testing it determines which buckets to generate samples from more frequently based on the models performance coming from that bucket. All of the models have performance data collected on them and a final rebuild is initiated when a winner is found. The rebuild process begins by retraining the model with the settings that produced the best performance. If the model fails to build, for whatever reason, the next best buildable model is rebuilt.

Usage

```
AutoTBATS(
  data,
  FilePath = NULL,
  TargetVariableName,
  DateColumnName,
  TimeAggLevel = "week",
  EvaluationMetric = "MAE",
  NumHoldOutPeriods = 5L,
  NumFCPeriods = 5L,
  MaxLags = 5L,
  MaxMovingAverages = 5L,
  MaxSeasonalPeriods = 1L,
  TrainWeighting = 0.5,
  MaxConsecutiveFails = 12L,
  MaxNumberModels = 100L,
  MaxRunTimeMinutes = 10L,
  NumberCores = max(1L, min(4L, parallel::detectCores() - 2L))
)
```

Arguments

`data`	Source data.table
`FilePath`	NULL to return nothing. Provide a file path to save the model and xregs if available
`TargetVariableName`	Name of your time series target variable
`DateColumnName`	Name of your date column
`TimeAggLevel`	Choose from "year", "quarter", "month", "week", "day", "hour"
`EvaluationMetric`	Choose from MAE, MSE, and MAPE
`NumHoldOutPeriods`	Number of time periods to use in the out of sample testing
`NumFCPeriods`	Number of periods to forecast

MaxLags A single value of the max number of lags to use in the internal auto.arima of tbats

MaxMovingAverages
A single value of the max number of moving averages to use in the internal auto.arima of tbats

MaxSeasonalPeriods
A single value for the max allowable seasonal periods to be tested in the tbats framework

TrainWeighting Model ranking is based on a weighted average of training metrics and out of sample metrics. Supply the weight of the training metrics, such as 0.50 for 50 percent.

MaxConsecutiveFails
When a new best model is found MaxConsecutiveFails resets to zero. Indicated the number of model attemps without a new winner before terminating the procedure.

MaxNumberModels
Indicate the maximum number of models to test.

MaxRunTimeMinutes
Indicate the maximum number of minutes to wait for a result.

NumberCores Default max(1L, min(4L, parallel::detectCores()-2L))

Author(s)

Adrian Antico

See Also

Other Automated Time Series: AutoArfima(), AutoBanditNNet(), AutoBanditSarima(), AutoETS()

Examples

```
## Not run:
# Create fake data
data <- AutoQuant::FakeDataGenerator(TimeSeries = TRUE, TimeSeriesTimeAgg = "days")

# Build model
Output <- AutoQuant::AutoTBATS(
  data,
  FilePath = NULL,
  TargetVariableName = "Weekly_Sales",
  DateColumnName = "Date",
  TimeAggLevel = "weeks",
  EvaluationMetric = "MAE",
  NumHoldOutPeriods = 5L,
  NumFCPeriods = 5L,
  MaxLags = 5L,
  MaxMovingAverages = 5L,
  MaxSeasonalPeriods = 1L,
  TrainWeighting = 0.50,
  MaxConsecutiveFails = 12L,
  MaxNumberModels = 100L,
  MaxRunTimeMinutes = 10L,
  NumberCores = max(1L, min(4L, parallel::detectCores()-2L)))
```

```
# Output
Output$ForecastPlot
Output$Forecast
Output$PerformanceGrid

## End(Not run)
```

AutoTransformationCreate

AutoTransformationCreate

Description

AutoTransformationCreate is a function for automatically identifying the optimal transformations for numeric features and transforming them once identified. This function will loop through your selected transformation options (YeoJohnson, BoxCox, Asinh, Asin, and Logit) and find the one that produces data that is the closest to normally distributed data. It then makes the transformation and collects the metadata information for use in the AutoTransformationScore() function, either by returning the objects (always) or saving them to file (optional).

Usage

```
AutoTransformationCreate(
  data,
  ColumnNames = NULL,
  Methods = c("BoxCox", "YeoJohnson", "Asinh", "Log", "LogPlus1", "Sqrt", "Asin",
    "Logit", "Identity"),
  Path = NULL,
  TransID = "ModelID",
  SaveOutput = FALSE
)
```

Arguments

data	This is your source data
ColumnNames	List your columns names in a vector, for example, c("Target", "IV1")
Methods	Choose from "YeoJohnson", "BoxCox", "Asinh", "Log", "LogPlus1", "Asin", "Logit", and "Identity". Note, LogPlus1 runs
Path	Set to the directly where you want to save all of your modeling files
TransID	Set to a character value that corresponds with your modeling project
SaveOutput	Set to TRUE to save necessary file to run AutoTransformationScore()

Value

data with transformed columns and the transformation object for back-transforming later

Author(s)

Adrian Antico

See Also

Other Feature Engineering: AutoDataPartition(), AutoDiffLagN(), AutoHierarchicalFourier(), AutoInteraction(), AutoLagRollMode(), AutoLagRollStatsScoring(), AutoLagRollStats(), AutoTransformationScore(), AutoWord2VecModeler(), AutoWord2VecScoring(), CategoricalEncoding(), CreateCalendarVariables(), CreateHolidayVariables(), DummifyDT(), H2OAutoencoderScoring(), H2OAutoencoder(), ModelDataPrep(), PercRankScoring(), PercRank(), StandardizeScoring(), Standardize(), TimeSeriesFillRoll(), TimeSeriesFill()

Examples

```
## Not run:
# Create Fake Data
data <- AutoQuant::FakeDataGenerator(
  Correlation = 0.85,
  N = 25000,
  ID = 2L,
  ZIP = 0,
  FactorCount = 2L,
  AddDate = FALSE,
  Classification = FALSE,
  MultiClass = FALSE)

# Columns to transform
Cols <- names(data)[1L:11L]
print(Cols)

# Run function
data <- AutoQuant::AutoTransformationCreate(
  data,
  ColumnNames = Cols,
 Methods = c("YeoJohnson", "BoxCox", "Asinh", "Log", "LogPlus1", "Sqrt", "Asin", "Logit", "Identity"),
  Path = getwd(),
  TransID = "Trans",
  SaveOutput = TRUE)

## End(Not run)
```

AutoTransformationScore

AutoTransformationScore() is a the complimentary function to AutoTransformationCreate()

Description

AutoTransformationScore() is a the compliment function to AutoTransformationCreate(). Automatically apply or inverse the transformations you identified in AutoTransformationCreate() to other data sets. This is useful for applying transformations to your validation and test data sets for modeling. It's also useful for back-transforming your target and prediction columns after you have build and score your models so you can obtain statistics on the original features.

Usage

```
AutoTransformationScore(
  ScoringData,
  FinalResults,
  Type = "Inverse",
  TransID = "TestModel",
  Path = NULL
)
```

Arguments

ScoringData	This is your source data
FinalResults	This is the FinalResults output object from AutoTransformationCreate().
Type	Set to "Inverse" to back-transfrom or "Apply" for applying the transformation.
TransID	Set to a character value that corresponds with your modeling project
Path	Set to the directly where you want to save all of your modeling files

Value

data with transformed columns

Author(s)

Adrian Antico

See Also

Other Feature Engineering: AutoDataPartition(), AutoDiffLagN(), AutoHierarchicalFourier(), AutoInteraction(), AutoLagRollMode(), AutoLagRollStatsScoring(), AutoLagRollStats(), AutoTransformationCreate(), AutoWord2VecModeler(), AutoWord2VecScoring(), CategoricalEncoding(), CreateCalendarVariables(), CreateHolidayVariables(), DummifyDT(), H2OAutoencoderScoring(), H2OAutoencoder(), ModelDataPrep(), PercRankScoring(), PercRank(), StandardizeScoring(), Standardize(), TimeSeriesFillRoll(), TimeSeriesFill()

Examples

```
## Not run:
# Create Fake Data
data <- AutoQuant::FakeDataGenerator(
  Correlation = 0.85,
  N = 25000,
  ID = 2L,
  ZIP = 0,
  FactorCount = 2L,
  AddDate = FALSE,
  Classification = FALSE,
  MultiClass = FALSE)

# Columns to transform
Cols <- names(data)[1L:11L]
print(Cols)

data <- data[1]
```

```
# Run function
Output <- AutoQuant::AutoTransformationCreate(
  data,
  ColumnNames = Cols,
 Methods = c("YeoJohnson", "BoxCox", "Asinh", "Log", "LogPlus1", "Sqrt", "Asin", "Logit", "Identity"),
  Path = getwd(),
  TransID = "Model_1",
  SaveOutput = TRUE)

# Output
data <- Output$Data
TransInfo <- Output$FinalResults

# Back Transform
data <- AutoQuant::AutoTransformationScore(
  data,
  FinalResults = TransInfo,
  Path = NULL,
  TransID = "Model_1")

## End(Not run)
```

AutoWord2VecModeler *AutoWord2VecModeler*

Description

This function allows you to automatically build a word2vec model and merge the data onto your supplied dataset

Usage

```
AutoWord2VecModeler(
  data,
  BuildType = "Combined",
  stringCol = c("Text_Col1", "Text_Col2"),
  KeepStringCol = FALSE,
  model_path = NULL,
  vects = 100,
  MinWords = 1,
  WindowSize = 12,
  Epochs = 25,
  SaveModel = "standard",
  Threads = max(1L, parallel::detectCores() - 2L),
  MaxMemory = "28G",
  ModelID = "Model_1"
)
```

Arguments

data	Source data table to merge vects onto

BuildType	Choose from "individual" or "combined". Individual will build a model for every text column. Combined will build a single model for all columns.
stringCol	A string name for the column to convert via word2vec
KeepStringCol	Set to TRUE if you want to keep the original string column that you convert via word2vec
model_path	A string path to the location where you want the model and metadata stored
vects	The number of vectors to retain from the word2vec model
MinWords	For H2O word2vec model
WindowSize	For H2O word2vec model
Epochs	For H2O word2vec model
SaveModel	Set to "standard" to save normally; set to "mojo" to save as mojo. NOTE: while you can save a mojo, I haven't figured out how to score it in the AutoH20Scoring function.
Threads	Number of available threads you want to dedicate to model building
MaxMemory	Amount of memory you want to dedicate to model building
ModelID	Name for saving to file

Author(s)

Adrian Antico

See Also

Other Feature Engineering: AutoDataPartition(), AutoDiffLagN(), AutoHierarchicalFourier(), AutoInteraction(), AutoLagRollMode(), AutoLagRollStatsScoring(), AutoLagRollStats(), AutoTransformationCreate(), AutoTransformationScore(), AutoWord2VecScoring(), CategoricalEncoding() CreateCalendarVariables(), CreateHolidayVariables(), DummifyDT(), H2OAutoencoderScoring(), H2OAutoencoder(), ModelDataPrep(), PercRankScoring(), PercRank(), StandardizeScoring(), Standardize(), TimeSeriesFillRoll(), TimeSeriesFill()

Examples

```
## Not run:

# Create fake data
data <- AutoQuant::FakeDataGenerator(
  Correlation = 0.70,
  N = 1000L,
  ID = 2L,
  FactorCount = 2L,
  AddDate = TRUE,
  AddComment = TRUE,
  ZIP = 2L,
  TimeSeries = FALSE,
  ChainLadderData = FALSE,
  Classification = FALSE,
  MultiClass = FALSE)

# Create Model and Vectors
data <- AutoQuant::AutoWord2VecModeler(
  data,
```

```
  BuildType = "individual",
  stringCol = c("Comment"),
  KeepStringCol = FALSE,
  ModelID = "Model_1",
  model_path = getwd(),
  vects = 10,
  MinWords = 1,
  WindowSize = 1,
  Epochs = 25,
  SaveModel = "standard",
  Threads = max(1,parallel::detectCores()-2),
  MaxMemory = "28G")

# Remove data
rm(data)

# Create fake data for mock scoring
data <- AutoQuant::FakeDataGenerator(
  Correlation = 0.70,
  N = 1000L,
  ID = 2L,
  FactorCount = 2L,
  AddDate = TRUE,
  AddComment = TRUE,
  ZIP = 2L,
  TimeSeries = FALSE,
  ChainLadderData = FALSE,
  Classification = FALSE,
  MultiClass = FALSE)

# Give h2o a few seconds
Sys.sleep(5L)

# Create vectors for scoring
data <- AutoQuant::AutoWord2VecScoring(
  data,
  BuildType = 'individual',
  ModelObject = NULL,
  ModelID = "Model_1",
  model_path = getwd(),
  stringCol = "Comment",
  KeepStringCol = FALSE,
  H2OStartUp = TRUE,
  H2OShutdown = TRUE,
  Threads = max(1L, parallel::detectCores() - 2L),
  MaxMemory = "28G")

## End(Not run)
```

AutoWord2VecScoring *AutoWord2VecScoring*

Description

AutoWord2VecScoring is for scoring models generated by AutoWord2VecModeler()

Usage

```
AutoWord2VecScoring(
  data,
  BuildType = "individual",
  ModelObject = NULL,
  ModelID = "Model_1",
  model_path = NULL,
  stringCol = NULL,
  KeepStringCol = FALSE,
  H2OStartUp = TRUE,
  H2OShutdown = TRUE,
  Threads = max(1L, parallel::detectCores() - 2L),
  MaxMemory = "28G"
)
```

Arguments

data	data.table
BuildType	"individual" or "combined". Used to locate model in file
ModelObject	NULL if you want it loaded in the function
ModelID	Same as in training
model_path	Location of model
stringCol	Columns to transform
KeepStringCol	FALSE to remove string col after creating vectors
H2OStartUp	= TRUE,
Threads	max(1L, parallel::detectCores() - 2L)
MaxMemory	"28G"

Author(s)

Adrian Antico

See Also

Other Feature Engineering: AutoDataPartition(), AutoDiffLagN(), AutoHierarchicalFourier(), AutoInteraction(), AutoLagRollMode(), AutoLagRollStatsScoring(), AutoLagRollStats(), AutoTransformationCreate(), AutoTransformationScore(), AutoWord2VecModeler(), CategoricalEncoding() CreateCalendarVariables(), CreateHolidayVariables(), DummifyDT(), H2OAutoencoderScoring(), H2OAutoencoder(), ModelDataPrep(), PercRankScoring(), PercRank(), StandardizeScoring(), Standardize(), TimeSeriesFillRoll(), TimeSeriesFill()

Examples

```
## Not run:
# Create fake data
data <- AutoQuant::FakeDataGenerator(
  Correlation = 0.70,
  N = 1000L,
  ID = 2L,
  FactorCount = 2L,
  AddDate = TRUE,
```

```
  AddComment = TRUE,
  ZIP = 2L,
  TimeSeries = FALSE,
  ChainLadderData = FALSE,
  Classification = FALSE,
  MultiClass = FALSE)

# Create Model and Vectors
data <- AutoQuant::AutoWord2VecModeler(
  data,
  BuildType = "individual",
  stringCol = c("Comment"),
  KeepStringCol = FALSE,
  ModelID = "Model_1",
  model_path = getwd(),
  vects = 10,
  MinWords = 1,
  WindowSize = 1,
  Epochs = 25,
  SaveModel = "standard",
  Threads = max(1,parallel::detectCores()-2),
  MaxMemory = "28G")

# Remove data
rm(data)

# Create fake data for mock scoring
data <- AutoQuant::FakeDataGenerator(
  Correlation = 0.70,
  N = 1000L,
  ID = 2L,
  FactorCount = 2L,
  AddDate = TRUE,
  AddComment = TRUE,
  ZIP = 2L,
  TimeSeries = FALSE,
  ChainLadderData = FALSE,
  Classification = FALSE,
  MultiClass = FALSE)

# Create vectors for scoring
data <- AutoQuant::AutoWord2VecScoring(
  data,
  BuildType = "individual",
  ModelObject = NULL,
  ModelID = "Model_1",
  model_path = getwd(),
  stringCol = "Comment",
  KeepStringCol = FALSE,
  H2OStartUp = TRUE,
  H2OShutdown = TRUE,
  Threads = max(1L, parallel::detectCores() - 2L),
  MaxMemory = "28G")

## End(Not run)
```

AutoWordFreq *Automated Word Frequency and Word Cloud Creation*

Description

This function builds a word frequency table and a word cloud. It prepares data, cleans text, and generates output.

Usage

```
AutoWordFreq(
  data,
  TextColName = "DESCR",
  GroupColName = "ClusterAllNoTarget",
  GroupLevel = 0,
  RemoveEnglishStopwords = TRUE,
  Stemming = TRUE,
  StopWords = c("bla", "bla2")
)
```

Arguments

data	Source data table
TextColName	A string name for the column
GroupColName	Set to NULL to ignore, otherwise set to Cluster column name (or factor column name)
GroupLevel	Must be set if GroupColName is defined. Set to cluster ID (or factor level)
RemoveEnglishStopwords	Set to TRUE to remove English stop words, FALSE to ignore
Stemming	Set to TRUE to run stemming on your text data
StopWords	Add your own stopwords, in vector format

Author(s)

Adrian Antico

See Also

Other EDA: EDA_Histograms(), Mode(), PlotGUI(), ScatterCopula(), UserBaseEvolution()

Examples

```
## Not run:
data <- data.table::data.table(
DESCR = c(
  "Gru", "Gru", "Gru", "Gru", "Gru", "Gru", "Gru",
  "Gru", "Gru", "Gru", "Gru", "Gru", "Gru", "Urkle",
  "Urkle", "Urkle", "Urkle", "Urkle", "Urkle", "Urkle",
  "Gru", "Gru", "Gru", "bears", "bears", "bears",
  "bears", "bears", "bears", "smug", "smug", "smug", "smug",
```

```
  "smug", "smug", "smug", "smug", "smug", "smug",
  "smug", "smug", "smug", "smug", "smug", "eats", "eats",
  "eats", "eats", "eats", "eats", "beats", "beats", "beats", "beats",
  "beats", "beats", "beats", "beats", "beats", "beats",
  "beats", "science", "science", "Dwigt", "Dwigt", "Dwigt", "Dwigt",
  "Dwigt", "Dwigt", "Dwigt", "Dwigt", "Dwigt", "Dwigt",
  "Schrute", "Schrute", "Schrute", "Schrute", "Schrute",
  "Schrute", "Schrute", "James", "James", "James", "James",
  "James", "James", "James", "James", "James", "James",
  "Halpert", "Halpert", "Halpert", "Halpert",
  "Halpert", "Halpert", "Halpert", "Halpert"))
data <- AutoWordFreq(
  data,
  TextColName = "DESCR",
  GroupColName = NULL,
  GroupLevel = NULL,
  RemoveEnglishStopwords = FALSE,
  Stemming = FALSE,
  StopWords = c("Bla"))

## End(Not run)
```

AutoXGBoostCARMA *AutoXGBoostCARMA*

Description

AutoXGBoostCARMA Mutlivariate Forecasting with calendar variables, Holiday counts, holiday lags, holiday moving averages, differencing, transformations, interaction-based categorical encoding using target variable and features to generate various time-based aggregated lags, moving averages, moving standard deviations, moving skewness, moving kurtosis, moving quantiles, parallelized interaction-based fourier pairs by grouping variables, and Trend Variables.

Usage

```
AutoXGBoostCARMA(
  data = NULL,
  XREGS = NULL,
  TimeWeights = NULL,
  NonNegativePred = FALSE,
  RoundPreds = FALSE,
  TrainOnFull = FALSE,
  TargetColumnName = NULL,
  DateColumnName = NULL,
  HierarchGroups = NULL,
  GroupVariables = NULL,
  FC_Periods = 1,
  SaveDataPath = NULL,
  TimeUnit = NULL,
  TimeGroups = NULL,
  TargetTransformation = FALSE,
  Methods = c("Asinh", "Log", "LogPlus1", "Sqrt"),
  EncodingMethod = "target_encoding",
```

```
  AnomalyDetection = NULL,
  Lags = NULL,
  MA_Periods = NULL,
  SD_Periods = NULL,
  Skew_Periods = NULL,
  Kurt_Periods = NULL,
  Quantile_Periods = NULL,
  Quantiles_Selected = c("q5", "q95"),
  Difference = FALSE,
  FourierTerms = 0,
  CalendarVariables = NULL,
  HolidayVariable = NULL,
  HolidayLookback = NULL,
  HolidayLags = NULL,
  HolidayMovingAverages = NULL,
  TimeTrendVariable = FALSE,
  DataTruncate = FALSE,
  ZeroPadSeries = NULL,
  SplitRatios = c(0.95, 0.05),
  PartitionType = "random",
  TreeMethod = "hist",
  NThreads = max(1, parallel::detectCores() - 2L),
  Timer = TRUE,
  DebugMode = FALSE,
  EvalMetric = "MAE",
  LossFunction = "reg:squarederror",
  GridTune = FALSE,
  GridEvalMetric = "mae",
  ModelCount = 30L,
  MaxRunsWithoutNewWinner = 20L,
  MaxRunMinutes = 24L * 60L,
  EarlyStoppingRounds = 100L,
  NTrees = 500L,
  num_parallel_tree = 1,
  LearningRate = 0.5,
  MaxDepth = 6L,
  MinChildWeight = 1,
  SubSample = 0.7,
  ColSampleByTree = 1,
  alpha = 0.1,
  lambda = 0.9,
  SaveModel = FALSE,
  ArgsList = NULL,
  ModelID = "FC001",
  TVT = NULL
)
```

Arguments

data	Supply your full series data set here
XREGS	Additional data to use for model development and forecasting. Data needs to be a complete series which means both the historical and forward looking values

over the specified forecast window needs to be supplied.

`TimeWeights` = NULL

`NonNegativePred`
TRUE or FALSE

`RoundPreds` Rounding predictions to an integer value. TRUE or FALSE. Defaults to FALSE

`TrainOnFull` Set to TRUE to train on full data

`TargetColumnName`
List the column name of your target variables column. E.g. 'Target'

`DateColumnName` List the column name of your date column. E.g. 'DateTime'

`HierarchGroups` = NULL Character vector or NULL with names of the columns that form the interaction hierarchy

`GroupVariables` Defaults to NULL. Use NULL when you have a single series. Add in GroupVariables when you have a series for every level of a group or multiple groups.

`FC_Periods` Set the number of periods you want to have forecasts for. E.g. 52 for weekly data to forecast a year ahead

`SaveDataPath` Path to save modeling data

`TimeUnit` List the time unit your data is aggregated by. E.g. '1min', '5min', '10min', '15min', '30min', 'hour', 'day', 'week', 'month', 'quarter', 'year'

`TimeGroups` Select time aggregations for adding various time aggregated GDL features.

`TargetTransformation`
Run AutoTransformationCreate() to find best transformation for the target variable. Tests YeoJohnson, BoxCox, and Asigh (also Asin and Logit for proportion target variables).

`Methods` Choose from 'YeoJohnson', 'BoxCox', 'Asinh', 'Log', 'LogPlus1', 'Sqrt', 'Asin', or 'Logit'. If more than one is selected, the one with the best normalization pearson statistic will be used. Identity is automatically selected and compared.

`EncodingMethod` Choose from 'binary', 'm_estimator', 'credibility', 'woe', 'target_encoding', 'poly_encode', 'backward_difference', 'helmert'

`AnomalyDetection`
NULL for not using the service. Other, provide a list, e.g. AnomalyDetection = list('tstat_high' = 4, tstat_low = -4)

`Lags` Select the periods for all lag variables you want to create. E.g. c(1:5,52) or list('day' = c(1:10), 'weeks' = c(1:4))

`MA_Periods` Select the periods for all moving average variables you want to create. E.g. c(1:5,52) or list('day' = c(2:10), 'weeks' = c(2:4))

`SD_Periods` Select the periods for all moving standard deviation variables you want to create. E.g. c(1:5,52) or list('day' = c(2:10), 'weeks' = c(2:4))

`Skew_Periods` Select the periods for all moving skewness variables you want to create. E.g. c(1:5,52) or list('day' = c(2:10), 'weeks' = c(2:4))

`Kurt_Periods` Select the periods for all moving kurtosis variables you want to create. E.g. c(1:5,52) or list('day' = c(2:10), 'weeks' = c(2:4))

`Quantile_Periods`
Select the periods for all moving quantiles variables you want to create. E.g. c(1:5,52) or list('day' = c(2:10), 'weeks' = c(2:4))

`Quantiles_Selected`
Select from the following c('q5','q10','q15','q20','q25','q30','q35','q40','q45','q50','q55','q60','q6

`Difference` Set to TRUE to put the I in ARIMA

`FourierTerms` Set to the max number of pairs

`CalendarVariables`
NULL, or select from 'second', 'minute', 'hour', 'wday', 'mday', 'yday', 'week', 'wom', 'isoweek', 'month', 'quarter', 'year'

`HolidayVariable`
NULL, or select from 'USPublicHolidays', 'EasterGroup', 'ChristmasGroup', 'OtherEcclesticalFeasts'

`HolidayLookback`
Number of days in range to compute number of holidays from a given date in the data. If NULL, the number of days are computed for you.

`HolidayLags` Number of lags for the holiday counts

`HolidayMovingAverages`
Number of moving averages for holiday counts

`TimeTrendVariable`
Set to TRUE to have a time trend variable added to the model. Time trend is numeric variable indicating the numeric value of each record in the time series (by group). Time trend starts at 1 for the earliest point in time and increments by one for each success time point.

`DataTruncate` Set to TRUE to remove records with missing values from the lags and moving average features created

`ZeroPadSeries` NULL to do nothing. Otherwise, set to 'maxmax', 'minmax', 'maxmin', 'minmin'. See `TimeSeriesFill` for explanations of each type

`SplitRatios` E.g c(0.7,0.2,0.1) for train, validation, and test sets

`PartitionType` Select 'random' for random data partitioning 'time' for partitioning by time frames

`TreeMethod` Choose from 'hist', 'gpu_hist'

`NThreads` Set the maximum number of threads you'd like to dedicate to the model run. E.g. 8

`Timer` Setting to TRUE prints out the forecast number while it is building

`DebugMode` Setting to TRUE generates printout of all header code comments during run time of function

`EvalMetric` Select from 'r2', 'RMSE', 'MSE', 'MAE'

`LossFunction` Default is 'reg:squarederror'. Other options include 'reg:squaredlogerror', 'reg:pseudohubererror', 'count:poisson', 'survival:cox', 'survival:aft', 'aft_loss_distribution', 'reg:gamma', 'reg:tweedie'

`GridTune` Set to TRUE to run a grid tune

`GridEvalMetric` This is the metric used to find the threshold 'poisson', 'mae', 'mape', 'mse', 'msle', 'kl', 'cs', 'r2'

`ModelCount` Set the number of models to try in the grid tune

`MaxRunsWithoutNewWinner`
Number of consecutive runs without a new winner in order to terminate procedure

`MaxRunMinutes` Default 24L*60L

`NTrees` Select the number of trees you want to have built to train the model

`LearningRate` Learning Rate

MaxDepth	Depth
MinChildWeight	Records in leaf
SubSample	Random forecast setting
ColSampleByTree	Self explanatory
alpha	0. L1 Reg.
lambda	1. L2 Reg.
SaveModel	Logical. If TRUE, output ArgsList will have a named element 'Model' with the CatBoost model object
ArgsList	ArgsList is for scoring. Must contain named element 'Model' with a catboost model object
ModelID	Something to name your model if you want it saved
TVT	Passthrough

Value

See examples

Author(s)

Adrian Antico

See Also

Other Automated Panel Data Forecasting: AutoCatBoostCARMA(), AutoH2OCARMA(), AutoLightGBMCARMA()

Examples

```
## Not run:

# Load data
data <- data.table::fread('https://www.dropbox.com/s/2str3ek4f4cheqi/walmart_train.csv?dl=1')

# Ensure series have no missing dates (also remove series with more than 25% missing values)
data <- AutoQuant::TimeSeriesFill(
  data,
  DateColumnName = 'Date',
  GroupVariables = c('Store','Dept'),
  TimeUnit = 'weeks',
  FillType = 'maxmax',
  MaxMissingPercent = 0.25,
  SimpleImpute = TRUE)

# Set negative numbers to 0
data <- data[, Weekly_Sales := data.table::fifelse(Weekly_Sales < 0, 0, Weekly_Sales)]

# Remove IsHoliday column
data[, IsHoliday := NULL]

# Create xregs (this is the include the categorical variables instead of utilizing only the interaction of them)
xregs <- data[, .SD, .SDcols = c('Date', 'Store', 'Dept')]

# Change data types
```

```
data[, ':=' (Store = as.character(Store), Dept = as.character(Dept))]
xregs[, ':=' (Store = as.character(Store), Dept = as.character(Dept))]

 # Build forecast
XGBoostResults <- AutoXGBoostCARMA(

  # Data Artifacts
  data = data,
  NonNegativePred = FALSE,
  RoundPreds = FALSE,
  TargetColumnName = 'Weekly_Sales',
  DateColumnName = 'Date',
  HierarchGroups = NULL,
  GroupVariables = c('Store','Dept'),
  TimeUnit = 'weeks',
  TimeGroups = c('weeks','months'),

  # Data Wrangling Features
  EncodingMethod = 'binary',
  ZeroPadSeries = NULL,
  DataTruncate = FALSE,
  SplitRatios = c(1 - 10 / 138, 10 / 138),
  PartitionType = 'timeseries',
  AnomalyDetection = NULL,

  # Productionize
  FC_Periods = 0,
  TrainOnFull = FALSE,
  NThreads = 8,
  Timer = TRUE,
  DebugMode = FALSE,
  SaveDataPath = NULL,

  # Target Transformations
  TargetTransformation = TRUE,
  Methods = c('BoxCox', 'Asinh', 'Asin', 'Log',
              'LogPlus1', 'Sqrt', 'Logit','YeoJohnson'),
  Difference = FALSE,

  # Features
  Lags = list('weeks' = seq(1L, 10L, 1L),
              'months' = seq(1L, 5L, 1L)),
  MA_Periods = list('weeks' = seq(5L, 20L, 5L),
                    'months' = seq(2L, 10L, 2L)),
  SD_Periods = NULL,
  Skew_Periods = NULL,
  Kurt_Periods = NULL,
  Quantile_Periods = NULL,
  Quantiles_Selected = c('q5','q95'),
  XREGS = xregs,
  FourierTerms = 4,
  CalendarVariables = c('week', 'wom', 'month', 'quarter'),
  HolidayVariable = c('USPublicHolidays','EasterGroup',
    'ChristmasGroup','OtherEcclesticalFeasts'),
  HolidayLookback = NULL,
  HolidayLags = 1,
  HolidayMovingAverages = 1:2,
```

```
  TimeTrendVariable = TRUE,

  # ML eval args
  TreeMethod = 'hist',
  EvalMetric = 'RMSE',
  LossFunction = 'reg:squarederror',

  # ML grid tuning
  GridTune = FALSE,
  ModelCount = 5,
  MaxRunsWithoutNewWinner = 20L,
  MaxRunMinutes = 24L*60L,

  # ML args
  NTrees = 300,
  LearningRate = 0.3,
  MaxDepth = 9L,
  MinChildWeight = 1.0,
  SubSample = 1.0,
  ColSampleByTree = 1.0)

UpdateMetrics <- print(
  XGBoostResults$ModelInformation$EvaluationMetrics[
    Metric == 'MSE', MetricValue := sqrt(MetricValue)])
print(UpdateMetrics)
XGBoostResults$ModelInformation$EvaluationMetricsByGroup[order(-R2_Metric)]
XGBoostResults$ModelInformation$EvaluationMetricsByGroup[order(MAE_Metric)]
XGBoostResults$ModelInformation$EvaluationMetricsByGroup[order(MSE_Metric)]
XGBoostResults$ModelInformation$EvaluationMetricsByGroup[order(MAPE_Metric)]

## End(Not run)
```

`AutoXGBoostClassifier` *AutoXGBoostClassifier*

Description

AutoXGBoostClassifier is an automated XGBoost modeling framework with grid-tuning and model evaluation that runs a variety of steps. First, a stratified sampling (by the target variable) is done to create train and validation sets. Then, the function will run a random grid tune over N number of models and find which model is the best (a default model is always included in that set). Once the model is identified and built, several other outputs are generated: validation data with predictions, evaluation plot, evaluation boxplot, evaluation metrics, variable importance, partial dependence calibration plots, partial dependence calibration box plots, and column names used in model fitting.

Usage

```
AutoXGBoostClassifier(
 OutputSelection = c("Importances", "EvalPlots", "EvalMetrics", "Score_TrainData"),
  data = NULL,
  TrainOnFull = FALSE,
  ValidationData = NULL,
  TestData = NULL,
```

```
  TargetColumnName = NULL,
  FeatureColNames = NULL,
  WeightsColumnName = NULL,
  IDcols = NULL,
  model_path = NULL,
  metadata_path = NULL,
  SaveInfoToPDF = FALSE,
  ModelID = "FirstModel",
  EncodingMethod = "credibility",
  ReturnFactorLevels = TRUE,
  ReturnModelObjects = TRUE,
  SaveModelObjects = FALSE,
  Verbose = 0L,
  NumOfParDepPlots = 3L,
  NThreads = max(1L, parallel::detectCores() - 2L),
  LossFunction = "reg:logistic",
  CostMatrixWeights = c(0, 1, 1, 0),
  grid_eval_metric = "MCC",
  eval_metric = "auc",
  TreeMethod = "hist",
  GridTune = FALSE,
  BaselineComparison = "default",
  MaxModelsInGrid = 10L,
  MaxRunsWithoutNewWinner = 20L,
  MaxRunMinutes = 24L * 60L,
  PassInGrid = NULL,
  early_stopping_rounds = 100L,
  Trees = 1000L,
  num_parallel_tree = 1,
  eta = 0.3,
  max_depth = 9,
  min_child_weight = 1,
  subsample = 1,
  colsample_bytree = 1,
  DebugMode = FALSE,
  alpha = 0,
  lambda = 1
)
```

Arguments

OutputSelection	You can select what type of output you want returned. Choose from c("Importances", "EvalPlots", "EvalMetrics", "Score_TrainData")
data	This is your data set for training and testing your model
TrainOnFull	Set to TRUE to train on full data
ValidationData	This is your holdout data set used in modeling either refine your hyperparameters.
TestData	This is your holdout data set. Catboost using both training and validation data in the training process so you should evaluate out of sample performance with this data set.

`TargetColumnName`
: Either supply the target column name OR the column number where the target is located (but not mixed types). Note that the target column needs to be a 0 | 1 numeric variable.

`FeatureColNames`
: Either supply the feature column names OR the column number where the target is located (but not mixed types)

`WeightsColumnName`
: Supply a column name for your weights column. Leave NULL otherwise

`IDcols`
: A vector of column names or column numbers to keep in your data but not include in the modeling.

`model_path`
: A character string of your path file to where you want your output saved

`metadata_path`
: A character string of your path file to where you want your model evaluation output saved. If left NULL, all output will be saved to model_path.

`SaveInfoToPDF`
: Set to TRUE to save modeling information to PDF. If model_path or metadata_path aren't defined then output will be saved to the working directory

`ModelID`
: A character string to name your model and output

`EncodingMethod`
: Choose from 'binary', 'm_estimator', 'credibility', 'woe', 'target_encoding', 'poly_encode', 'backward_difference', 'helmert'

`ReturnFactorLevels`
: TRUE or FALSE. Set to FALSE to not return factor levels.

`ReturnModelObjects`
: Set to TRUE to output all modeling objects (E.g. plots and evaluation metrics)

`SaveModelObjects`
: Set to TRUE to return all modeling objects to your environment

`Verbose`
: Set to 0 if you want to suppress model evaluation updates in training

`NumOfParDepPlots`
: Tell the function the number of partial dependence calibration plots you want to create.

`NThreads`
: Set the maximum number of threads you'd like to dedicate to the model run. E.g. 8

`LossFunction`
: Select from 'reg:logistic', "binary:logistic"

`CostMatrixWeights`
: A vector with 4 elements c(True Positive Cost, False Negative Cost, False Positive Cost, True Negative Cost). Default c(1,0,0,1),

`grid_eval_metric`
: Case sensitive. I typically choose 'Utility' or 'MCC'. Choose from 'Utility', 'MCC', 'Acc', 'F1_Score', 'F2_Score', 'F0.5_Score', 'TPR', 'TNR', 'FNR', 'FPR', 'FDR', 'FOR', 'NPV', 'PPV', 'ThreatScore'

`eval_metric`
: This is the metric used to identify best grid tuned model. Choose from "logloss","error","aucpr","auc"

`TreeMethod`
: Choose from "hist", "gpu_hist"

`GridTune`
: Set to TRUE to run a grid tuning procedure

`BaselineComparison`
: Set to either "default" or "best". Default is to compare each successive model build to the baseline model using max trees (from function args). Best makes the comparison to the current best model.

`MaxModelsInGrid`
: Number of models to test from grid options.

`MaxRunsWithoutNewWinner`
: A number

`MaxRunMinutes`
: In minutes

`PassInGrid`
: Default is NULL. Provide a data.table of grid options from a previous run.

`early_stopping_rounds`
: = 100L

`Trees`
: Bandit grid partitioned. Supply a single value for non-grid tuning cases. Otherwise, supply a vector for the trees numbers you want to test. For running grid tuning, a NULL value supplied will mean these values are tested seq(1000L, 10000L, 1000L)

`num_parallel_tree`
: = 1. If setting greater than 1, set colsample_bytree < 1, subsample < 1 and round = 1

`eta`
: Bandit grid partitioned. Supply a single value for non-grid tuning cases. Otherwise, supply a vector for the LearningRate values to test. For running grid tuning, a NULL value supplied will mean these values are tested c(0.01,0.02,0.03,0.04)

`max_depth`
: Bandit grid partitioned. Number, or vector for depth to test. For running grid tuning, a NULL value supplied will mean these values are tested seq(4L, 16L, 2L)

`min_child_weight`
: Number, or vector for min_child_weight to test. For running grid tuning, a NULL value supplied will mean these values are tested seq(1.0, 10.0, 1.0)

`subsample`
: Number, or vector for subsample to test. For running grid tuning, a NULL value supplied will mean these values are tested seq(0.55, 1.0, 0.05)

`colsample_bytree`
: Number, or vector for colsample_bytree to test. For running grid tuning, a NULL value supplied will mean these values are tested seq(0.55, 1.0, 0.05)

`DebugMode`
: TRUE to print to console the steps taken

`alpha`
: 0. L1 Reg.

`lambda`
: 1. L2 Reg.

Value

Saves to file and returned in list: VariableImportance.csv, Model, ValidationData.csv, EvalutionPlot.png, EvaluationMetrics.csv, ParDepPlots.R a named list of features with partial dependence calibration plots, GridCollect, and GridList

Author(s)

Adrian Antico

See Also

Other Automated Supervised Learning - Binary Classification: `AutoCatBoostClassifier()`, `AutoH2oDRFClassifier()`, `AutoH2oGAMClassifier()`, `AutoH2oGBMClassifier()`, `AutoH2oGLMClassifier()`, `AutoH2oMLClassifier()`, `AutoLightGBMClassifier()`

Examples

```
## Not run:
# Create some dummy correlated data
data <- AutoQuant::FakeDataGenerator(
  Correlation = 0.85,
  N = 1000L,
  ID = 2L,
  ZIP = 0L,
  AddDate = FALSE,
  Classification = TRUE,
  MultiClass = FALSE)

# Run function
TestModel <- AutoQuant::AutoXGBoostClassifier(

  # GPU or CPU
  TreeMethod = "hist",
  NThreads = parallel::detectCores(),

  # Metadata args
  OutputSelection = c('Importances', 'EvalPlots', 'EvalMetrics', 'Score_TrainData'),
  model_path = normalizePath("./"),
  metadata_path = NULL,
  ModelID = "Test_Model_1",
  EncodingMethod = "binary",
  ReturnFactorLevels = TRUE,
  ReturnModelObjects = TRUE,
  SaveModelObjects = FALSE,
  SaveInfoToPDF = FALSE,

  # Data args
  data = data,
  TrainOnFull = FALSE,
  ValidationData = NULL,
  TestData = NULL,
  TargetColumnName = "Adrian",
  FeatureColNames = names(data)[!names(data) %in%
    c("IDcol_1", "IDcol_2","Adrian")],
  WeightsColumnName = NULL,
  IDcols = c("IDcol_1","IDcol_2"),

  # Model evaluation
  LossFunction = 'reg:logistic',
  CostMatrixWeights = c(0,1,1,0),
  eval_metric = "auc",
  grid_eval_metric = "MCC",
  NumOfParDepPlots = 3L,

  # Grid tuning args
  PassInGrid = NULL,
  GridTune = FALSE,
  BaselineComparison = "default",
  MaxModelsInGrid = 10L,
  MaxRunsWithoutNewWinner = 20L,
  MaxRunMinutes = 24L*60L,
  Verbose = 1L,
```

```
  # ML args
  Trees = 500L,
  eta = 0.30,
  max_depth = 9L,
  min_child_weight = 1.0,
  subsample = 1,
  colsample_bytree = 1,
  DebugMode = FALSE)

## End(Not run)
```

AutoXGBoostFunnelCARMA

AutoXGBoostFunnelCARMA

Description

AutoXGBoostFunnelCARMA is a forecasting model for cohort funnel forecasting for grouped data or non-grouped data

Usage

```
AutoXGBoostFunnelCARMA(
  data,
  GroupVariables = NULL,
  BaseFunnelMeasure = NULL,
  ConversionMeasure = NULL,
  ConversionRateMeasure = NULL,
  CohortPeriodsVariable = NULL,
  CalendarDate = NULL,
  CohortDate = NULL,
  EncodingMethod = "credibility",
 OutputSelection = c("Importances", "EvalPlots", "EvalMetrics", "Score_TrainData"),
  WeightsColumnName = NULL,
  TruncateDate = NULL,
  PartitionRatios = c(0.7, 0.2, 0.1),
  TimeUnit = c("day"),
  CalendarTimeGroups = c("day", "week", "month"),
  CohortTimeGroups = c("day", "week", "month"),
  TransformTargetVariable = TRUE,
  TransformMethods = c("Identity", "YeoJohnson"),
  AnomalyDetection = list(tstat_high = 3, tstat_low = -2),
  Jobs = c("Evaluate", "Train"),
  SaveModelObjects = TRUE,
  ModelID = "Segment_ID",
  ModelPath = NULL,
  MetaDataPath = NULL,
  DebugMode = FALSE,
 CalendarVariables = c("wday", "mday", "yday", "week", "isoweek", "month", "quarter",
    "year"),
  HolidayGroups = c("USPublicHolidays", "EasterGroup", "ChristmasGroup",
```

```
    "OtherEcclesticalFeasts"),
  HolidayLookback = NULL,
  CohortHolidayLags = c(1L, 2L, 7L),
  CohortHolidayMovingAverages = c(3L, 7L),
  CalendarHolidayLags = c(1L, 2L, 7L),
  CalendarHolidayMovingAverages = c(3L, 7L),
  ImputeRollStats = -0.001,
 CalendarLags = list(day = c(1L, 7L, 21L), week = c(1L, 4L, 52L), month = c(1L, 6L,
    12L)),
 CalendarMovingAverages = list(day = c(1L, 7L, 21L), week = c(1L, 4L, 52L), month =
    c(1L, 6L, 12L)),
  CalendarStandardDeviations = NULL,
  CalendarSkews = NULL,
  CalendarKurts = NULL,
  CalendarQuantiles = NULL,
  CalendarQuantilesSelected = "q50",
 CohortLags = list(day = c(1L, 7L, 21L), week = c(1L, 4L, 52L), month = c(1L, 6L, 12L)),
 CohortMovingAverages = list(day = c(1L, 7L, 21L), week = c(1L, 4L, 52L), month = c(1L,
    6L, 12L)),
  CohortStandardDeviations = NULL,
  CohortSkews = NULL,
  CohortKurts = NULL,
  CohortQuantiles = NULL,
  CohortQuantilesSelected = "q50",
  PassInGrid = NULL,
  GridTune = FALSE,
  BaselineComparison = "default",
  MaxModelsInGrid = 25L,
  MaxRunMinutes = 180L,
  MaxRunsWithoutNewWinner = 10L,
  GridEvalMetric = "mae",
  NumOfParDepPlots = 1L,
  NThreads = parallel::detectCores(),
  TreeMethod = "hist",
  EvalMetric = "MAE",
  LossFunction = "reg:squarederror",
  Trees = 1000L,
  LearningRate = 0.3,
  MaxDepth = 9L,
  MinChildWeight = 1,
  SubSample = 1,
  ColSampleByTree = 1
)
```

Arguments

data	data object
BaseFunnelMeasure	E.g. "Leads". This value should be a forward looking variable. Say you want to forecast ConversionMeasure 2 months into the future. You should have two months into the future of values of BaseFunnelMeasure
ConversionMeasure	E.g. "Conversions". Rate is derived as conversions over leads by cohort periods

out

`ConversionRateMeasure`
: Conversions over Leads for every cohort

`CohortPeriodsVariable`
: Numeric. Numerical value of the the number of periods since cohort base date.

`CalendarDate`
: The name of your date column that represents the calendar date

`CohortDate`
: The name of your date column that represents the cohort date

`OutputSelection`
: = c('Importances', 'EvalPlots', 'EvalMetrics', 'Score_TrainData')

`WeightsColumnName`
: = NULL

`TruncateDate`
: NULL. Supply a date to represent the earliest point in time you want in your data. Filtering takes place before partitioning data so feature engineering can include as many non null values as possible.

`PartitionRatios`
: Requires three values for train, validation, and test data sets

`TimeUnit`
: Base time unit of data. "days", "weeks", "months", "quarters", "years"

`CalendarTimeGroups`
: TimeUnit value must be included. If you want to generate lags and moving averages in several time based aggregations, choose from "days", "weeks", "months", "quarters", "years".

`CohortTimeGroups`
: TimeUnit value must be included. If you want to generate lags and moving averages in several time based aggregations, choose from "days", "weeks", "months", "quarters", "years".

`TransformTargetVariable`
: TRUE or FALSe

`TransformMethods`
: Choose from "Identity", "BoxCox", "Asinh", "Asin", "Log", "LogPlus1", "Logit", "YeoJohnson"

`AnomalyDetection`
: Provide a named list. See examples

`Jobs`
: Default is "eval" and "train"

`SaveModelObjects`
: Set to TRUE to return all modeling objects to your environment

`ModelID`
: A character string to name your model and output

`ModelPath`
: Path to where you want your models saved

`MetaDataPath`
: Path to where you want your metadata saved. If NULL, function will try ModelPath if it is not NULL.

`DebugMode`
: Internal use

`CalendarVariables`
: "wday", "mday", "yday", "week", "isoweek", "month", "quarter", "year"

`HolidayGroups`
: c("USPublicHolidays","EasterGroup","ChristmasGroup","OtherEcclesticalFeasts")

`HolidayLookback`
: Number of days in range to compute number of holidays from a given date in the data. If NULL, the number of days are computed for you.

`CohortHolidayLags`
: c(1L, 2L, 7L),

CohortHolidayMovingAverages
: c(3L, 7L),

CalendarHolidayLags
: c(1L, 2L, 7L),

CalendarHolidayMovingAverages
: = c(3L, 7L),

ImputeRollStats
: Constant value to fill NA after running AutoLagRollStats()

CalendarLags
: List of the form list("day" = c(1L, 7L, 21L), "week" = c(1L, 4L, 52L), "month" = c(1L, 6L, 12L))

CalendarMovingAverages
: List of the form list("day" = c(1L, 7L, 21L), "week" = c(1L, 4L, 52L), "month" = c(1L, 6L, 12L))

CalendarStandardDeviations
: List of the form list("day" = c(1L, 7L, 21L), "week" = c(1L, 4L, 52L), "month" = c(1L, 6L, 12L))

CalendarSkews
: List of the form list("day" = c(1L, 7L, 21L), "week" = c(1L, 4L, 52L), "month" = c(1L, 6L, 12L))

CalendarKurts
: List of the form list("day" = c(1L, 7L, 21L), "week" = c(1L, 4L, 52L), "month" = c(1L, 6L, 12L))

CalendarQuantiles
: List of the form list("day" = c(1L, 7L, 21L), "week" = c(1L, 4L, 52L), "month" = c(1L, 6L, 12L))

CalendarQuantilesSelected
: Supply a vector of "q5", "q10", "q15", "q20", "q25", "q30", "q35", "q40", "q45", "q50", "q55", "q60", "q65", "q70", "q75", "q80", "q85", "q90", "q95"

CohortLags
: List of the form list("day" = c(1L, 7L, 21L), "week" = c(1L, 4L, 52L), "month" = c(1L, 6L, 12L))

CohortMovingAverages
: List of the form list("day" = c(1L, 7L, 21L), "week" = c(1L, 4L, 52L), "month" = c(1L, 6L, 12L))

CohortStandardDeviations
: List of the form list("day" = c(1L, 7L, 21L), "week" = c(1L, 4L, 52L), "month" = c(1L, 6L, 12L))

CohortSkews
: List of the form list("day" = c(1L, 7L, 21L), "week" = c(1L, 4L, 52L), "month" = c(1L, 6L, 12L))

CohortKurts
: List of the form list("day" = c(1L, 7L, 21L), "week" = c(1L, 4L, 52L), "month" = c(1L, 6L, 12L))

CohortQuantiles
: List of the form list("day" = c(1L, 7L, 21L), "week" = c(1L, 4L, 52L), "month" = c(1L, 6L, 12L))

CohortQuantilesSelected
: Supply a vector of "q5", "q10", "q15", "q20", "q25", "q30", "q35", "q40", "q45", "q50", "q55", "q60", "q65", "q70", "q75", "q80", "q85", "q90", "q95"

  # Grid tuning

PassInGrid
: Defaults to NULL. Pass in a single row of grid from a previous output as a data.table (they are collected as data.tables)

GridTune
: Set to TRUE to run a grid tuning procedure. Set a number in MaxModelsInGrid to tell the procedure how many models you want to test.

`BaselineComparison`
: Set to either "default" or "best". Default is to compare each successive model build to the baseline model using max trees (from function args). Best makes the comparison to the current best model.

`MaxModelsInGrid`
: Number of models to test from grid options

`MaxRunMinutes`
: Maximum number of minutes to let this run

`MaxRunsWithoutNewWinner`
: Number of models built before calling it quits

ML Args begin

`NumOfParDepPlots`
: Tell the function the number of partial dependence calibration plots you want to create. Calibration boxplots will only be created for numerical features (not dummy variables)

`NThreads`
: = parallel::detectCores()

`TreeMethod`
: Choose from 'hist', 'gpu_hist'

`EvalMetric`
: Select from 'r2', 'RMSE', 'MSE', 'MAE'

`LossFunction`
: Default is 'reg:squarederror'. Other options include 'reg:squaredlogerror', 'reg:pseudohubererror', 'count:poisson', 'survival:cox', 'survival:aft', 'aft_loss_distribution', 'reg:gamma', 'reg:tweedie'

`Trees`
: Select the number of trees you want to have built to train the model

`LearningRate`
: Learning Rate

`MaxDepth`
: Depth

`MinChildWeight`
: Records in leaf

`SubSample`
: Random forecast setting

`ColSampleByTree`
: Self explanatory

Author(s)

Adrian Antico

See Also

Other Automated Funnel Data Forecasting: `AutoLightGBMFunnelCARMAScoring()`, `AutoLightGBMFunnelCARMA()`, `AutoXGBoostFunnelCARMAScoring()`

Examples

```
## Not run:
# Create fake data
data <- AutoQuant::FakeDataGenerator(ChainLadderData = TRUE)

# Subset data for training
ModelDataBase <- data[CalendarDateColumn < '2020-01-01' & CohortDateColumn < '2020-01-01']
ModelData <- data.table::copy(ModelDataBase)

# Train Funne Model
TestModel <- AutoQuant::AutoXGBoostFunnelCARMA(
```

```
 # Data Arguments
 data = ModelData,
 GroupVariables = NULL,
BaseFunnelMeasure = "Leads", # if you have XREGS, supply vector such as c("Leads", "XREGS1", "XREGS2")
 ConversionMeasure = "Appointments",
 ConversionRateMeasure = NULL,
 CohortPeriodsVariable = "CohortDays",
 WeightsColumnName = NULL,
 CalendarDate = "CalendarDateColumn",
 CohortDate = "CohortDateColumn",
 PartitionRatios = c(0.70,0.20,0.10),
 TruncateDate = NULL,
 TimeUnit = "days",
 TransformTargetVariable = TRUE,
 TransformMethods = c("Asinh","Asin","Log","LogPlus1","Sqrt","Logit"),
 AnomalyDetection = list(tstat_high = 3, tstat_low = -2),

 # MetaData Arguments
 Jobs = c("eval","train"),
 SaveModelObjects = FALSE,
 ModelID = "ModelTest",
 ModelPath = getwd(),
 MetaDataPath = NULL,
 DebugMode = TRUE,
 NumOfParDepPlots = 1L,
 EncodingMethod = "credibility",
 NThreads = parallel::detectCores(),

 # Feature Engineering Arguments
 CalendarTimeGroups = c("days","weeks","months"),
 CohortTimeGroups = c("days", "weeks"),
 CalendarVariables = c("wday","mday","yday","week","month","quarter","year"),
HolidayGroups = c("USPublicHolidays","EasterGroup","ChristmasGroup","OtherEcclesticalFeasts"),
 HolidayLookback = NULL,
 CohortHolidayLags = c(1L,2L,7L),
 CohortHolidayMovingAverages = c(3L,7L),
 CalendarHolidayLags = c(1L,2L,7L),
 CalendarHolidayMovingAverages = c(3L,7L),

 # Time Series Features
 ImputeRollStats = -0.001,
 CalendarLags = list("day" = c(1L,2L,7L,35L,42L), "week" = c(5L,6L,10L,12L,25L,26L)),
CalendarMovingAverages = list("day" = c(7L,14L,35L,42L), "week" = c(5L,6L,10L,12L,20L,24L), "month" = c(6L,12
 CalendarStandardDeviations = NULL,
 CalendarSkews = NULL,
 CalendarKurts = NULL,
 CalendarQuantiles = NULL,
 CalendarQuantilesSelected = "q50",
 CohortLags = list("day" = c(1L,2L,7L,35L,42L), "week" = c(5L,6L)),
CohortMovingAverages = list("day" = c(7L,14L,35L,42L), "week" = c(5L,6L), "month" = c(1L,2L)),
 CohortStandardDeviations = NULL,
 CohortSkews = NULL,
 CohortKurts = NULL,
 CohortQuantiles = NULL,
 CohortQuantilesSelected = "q50",

 # ML Grid Tuning
```

```
  PassInGrid = NULL,
  GridTune = FALSE,
  BaselineComparison = "default",
  MaxModelsInGrid = 25L,
  MaxRunMinutes = 180L,
  MaxRunsWithoutNewWinner = 10L,

  # ML Setup Parameters
  GridEvalMetric = 'mae',

  # XGBoost arguments
  TreeMethod = 'hist',
  EvalMetric = 'MAE',
  LossFunction = 'reg:squarederror',
  Trees = 50L,
  LearningRate = 0.3,
  MaxDepth = 9L,
  MinChildWeight = 1.0,
  SubSample = 1.0,
  ColSampleByTree = 1.0)

# Separate out the Base Funnel Measures Data
LeadsData <- data[, lapply(.SD, data.table::first), .SDcols = c("Leads"), by = c("CalendarDateColumn")]
ModelData <- ModelDataBase[, Leads := NULL]

# Forecast Funnel Model
Test <- AutoQuant::AutoXGBoostFunnelCARMAScoring(
  TrainData = ModelData,
  ForwardLookingData = LeadsData,
  TrainEndDate = ModelData[, max(CalendarDateColumn)],
  ForecastEndDate = LeadsData[, max(CalendarDateColumn)],
  TrainOutput = TestModel$ModelOutput,
  ArgsList = TestModel$ArgsList,
  ModelPath = NULL,
  MaxCohortPeriod = 15,
  DebugMode = TRUE)

## End(Not run)
```

AutoXGBoostFunnelCARMAScoring *AutoLightGBMFunnelCARMAScoring*

Description

AutoLightGBMFunnelCARMAScoring for generating forecasts

Usage

```
AutoXGBoostFunnelCARMAScoring(
  TrainData,
  ForwardLookingData = NULL,
  TrainEndDate = NULL,
  ForecastEndDate = NULL,
```

```
  ArgsList = NULL,
  TrainOutput = NULL,
  ModelPath = NULL,
  MaxCohortPeriod = NULL,
  DebugMode = FALSE
)
```

Arguments

TrainData	Data utilized in training. Do not put the BaseFunnelMeasure in this data set. Put it in the ForwardLookingData object
ForwardLookingData	Base funnel measure data. Needs to cover the span of the forecast horizon
TrainEndDate	Max date from the training data
ForecastEndDate	Max date to forecast out to
ArgsList	Output list from AutoCatBoostFunnelCARMA
TrainOutput	Pass in the model object to speed up forecasting
ModelPath	Path to model location
MaxCohortPeriod	Max cohort periods to utilize when forecasting
DebugMode	For debugging issues

Author(s)

Adrian Antico

See Also

Other Automated Funnel Data Forecasting: AutoLightGBMFunnelCARMAScoring(), AutoLightGBMFunnelCARMA(), AutoXGBoostFunnelCARMA()

Examples

```
## Not run:
# Create fake data
data <- AutoQuant::FakeDataGenerator(ChainLadderData = TRUE)

# Subset data for training
ModelDataBase <- data[CalendarDateColumn < '2020-01-01' & CohortDateColumn < '2020-01-01']
ModelData <- data.table::copy(ModelDataBase)

# Train Funne Model
TestModel <- AutoQuant::AutoXGBoostFunnelCARMA(

  # Data Arguments
  data = ModelData,
  GroupVariables = NULL,
 BaseFunnelMeasure = "Leads", # if you have XREGS, supply vector such as c("Leads", "XREGS1", "XREGS2")
  ConversionMeasure = "Appointments",
  ConversionRateMeasure = NULL,
  CohortPeriodsVariable = "CohortDays",
  WeightsColumnName = NULL,
```

```
 CalendarDate = "CalendarDateColumn",
 CohortDate = "CohortDateColumn",
 PartitionRatios = c(0.70,0.20,0.10),
 TruncateDate = NULL,
 TimeUnit = "days",
 TransformTargetVariable = TRUE,
 TransformMethods = c("Asinh","Asin","Log","LogPlus1","Sqrt","Logit"),
 AnomalyDetection = list(tstat_high = 3, tstat_low = -2),

 # MetaData Arguments
 Jobs = c("eval","train"),
 SaveModelObjects = FALSE,
 ModelID = "ModelTest",
 ModelPath = getwd(),
 MetaDataPath = NULL,
 DebugMode = TRUE,
 NumOfParDepPlots = 1L,
 EncodingMethod = "credibility",
 NThreads = parallel::detectCores(),

 # Feature Engineering Arguments
 CalendarTimeGroups = c("days","weeks","months"),
 CohortTimeGroups = c("days", "weeks"),
 CalendarVariables = c("wday","mday","yday","week","month","quarter","year"),
HolidayGroups = c("USPublicHolidays","EasterGroup","ChristmasGroup","OtherEcclesticalFeasts"),
 HolidayLookback = NULL,
 CohortHolidayLags = c(1L,2L,7L),
 CohortHolidayMovingAverages = c(3L,7L),
 CalendarHolidayLags = c(1L,2L,7L),
 CalendarHolidayMovingAverages = c(3L,7L),

 # Time Series Features
 ImputeRollStats = -0.001,
 CalendarLags = list("day" = c(1L,2L,7L,35L,42L), "week" = c(5L,6L,10L,12L,25L,26L)),
CalendarMovingAverages = list("day" = c(7L,14L,35L,42L), "week" = c(5L,6L,10L,12L,20L,24L), "month" = c(6L,12
 CalendarStandardDeviations = NULL,
 CalendarSkews = NULL,
 CalendarKurts = NULL,
 CalendarQuantiles = NULL,
 CalendarQuantilesSelected = "q50",
 CohortLags = list("day" = c(1L,2L,7L,35L,42L), "week" = c(5L,6L)),
CohortMovingAverages = list("day" = c(7L,14L,35L,42L), "week" = c(5L,6L), "month" = c(1L,2L)),
 CohortStandardDeviations = NULL,
 CohortSkews = NULL,
 CohortKurts = NULL,
 CohortQuantiles = NULL,
 CohortQuantilesSelected = "q50",

 # ML Grid Tuning
 PassInGrid = NULL,
 GridTune = FALSE,
 BaselineComparison = "default",
 MaxModelsInGrid = 25L,
 MaxRunMinutes = 180L,
 MaxRunsWithoutNewWinner = 10L,

 # ML Setup Parameters
```

```
  GridEvalMetric = 'mae',

  # XGBoost arguments
  TreeMethod = 'hist',
  EvalMetric = 'MAE',
  LossFunction = 'reg:squarederror',
  Trees = 50L,
  LearningRate = 0.3,
  MaxDepth = 9L,
  MinChildWeight = 1.0,
  SubSample = 1.0,
  ColSampleByTree = 1.0)

# Separate out the Base Funnel Measures Data
LeadsData <- data[, lapply(.SD, data.table::first), .SDcols = c("Leads"), by = c("CalendarDateColumn")]
ModelData <- ModelDataBase[, Leads := NULL]

# Forecast Funnel Model
Test <- AutoQuant::AutoXGBoostFunnelCARMAScoring(
  TrainData = ModelData,
  ForwardLookingData = LeadsData,
  TrainEndDate = ModelData[, max(CalendarDateColumn)],
  ForecastEndDate = LeadsData[, max(CalendarDateColumn)],
  TrainOutput = TestModel$ModelOutput,
  ArgsList = TestModel$ArgsList,
  ModelPath = NULL,
  MaxCohortPeriod = 15,
  DebugMode = TRUE)

## End(Not run)
```

`AutoXGBoostMultiClass` *AutoXGBoostMultiClass*

Description

AutoXGBoostMultiClass is an automated XGBoost modeling framework with grid-tuning and model evaluation that runs a variety of steps. First, a stratified sampling (by the target variable) is done to create train and validation sets. Then, the function will run a random grid tune over N number of models and find which model is the best (a default model is always included in that set). Once the model is identified and built, several other outputs are generated: validation data with predictions, evaluation metrics, variable importance, and column names used in model fitting.

Usage

```
AutoXGBoostMultiClass(
 OutputSelection = c("Importances", "EvalPlots", "EvalMetrics", "Score_TrainData"),
  data = NULL,
  TrainOnFull = FALSE,
  ValidationData = NULL,
  TestData = NULL,
  TargetColumnName = NULL,
  FeatureColNames = NULL,
```

```
  WeightsColumnName = NULL,
  IDcols = NULL,
  model_path = NULL,
  metadata_path = NULL,
  ModelID = "FirstModel",
  LossFunction = "multi:softprob",
  EncodingMethod = "credibility",
  ReturnFactorLevels = TRUE,
  ReturnModelObjects = TRUE,
  SaveModelObjects = FALSE,
  Verbose = 0L,
  DebugMode = FALSE,
  NumOfParDepPlots = 3L,
  NThreads = parallel::detectCores(),
  eval_metric = "merror",
  grid_eval_metric = "accuracy",
  TreeMethod = "hist",
  GridTune = FALSE,
  BaselineComparison = "default",
  MaxModelsInGrid = 10L,
  MaxRunsWithoutNewWinner = 20L,
  MaxRunMinutes = 24L * 60L,
  PassInGrid = NULL,
  early_stopping_rounds = 100L,
  Trees = 50L,
  num_parallel_tree = 1,
  eta = NULL,
  max_depth = NULL,
  min_child_weight = NULL,
  subsample = NULL,
  colsample_bytree = NULL,
  alpha = 0,
  lambda = 1
)
```

Arguments

OutputSelection	You can select what type of output you want returned. Choose from c("Importances", "EvalPlots", "EvalMetrics", "Score_TrainData")
data	This is your data set for training and testing your model
TrainOnFull	Set to TRUE to train on full data
ValidationData	This is your holdout data set used in modeling either refine your hyperparameters.
TestData	This is your holdout data set. Catboost using both training and validation data in the training process so you should evaluate out of sample performance with this data set.
TargetColumnName	Either supply the target column name OR the column number where the target is located (but not mixed types). Note that the target column needs to be a 0 | 1 numeric variable.

`FeatureColNames`
: Either supply the feature column names OR the column number where the target is located (but not mixed types)

`WeightsColumnName`
: Supply a column name for your weights column. Leave NULL otherwise

`IDcols`
: A vector of column names or column numbers to keep in your data but not include in the modeling.

`model_path`
: A character string of your path file to where you want your output saved

`metadata_path`
: A character string of your path file to where you want your model evaluation output saved. If left NULL, all output will be saved to model_path.

`ModelID`
: A character string to name your model and output

`LossFunction`
: Use 'multi:sofprob', I set it up to return the class label and the individual probabilities, just like catboost. Doesn't come like that off the shelf

`EncodingMethod`
: Choose from 'binary', 'm_estimator', 'credibility', 'woe', 'target_encoding', 'poly_encode', 'backward_difference', 'helmert'

`ReturnFactorLevels`
: TRUE or FALSE. Set to FALSE to not return factor levels.

`ReturnModelObjects`
: Set to TRUE to output all modeling objects (E.g. plots and evaluation metrics)

`SaveModelObjects`
: Set to TRUE to return all modeling objects to your environment

`Verbose`
: Set to 0 if you want to suppress model evaluation updates in training

`DebugMode`
: Set to TRUE to get a print out of the steps taken internally

`NumOfParDepPlots`
: Tell the function the number of partial dependence calibration plots you want to create.

`NThreads`
: Set the maximum number of threads you'd like to dedicate to the model run. E.g. 8

`eval_metric`
: This is the metric used to identify best grid tuned model. Choose from 'merror' or 'mlogloss'

`grid_eval_metric`
: "accuracy", "logloss", "microauc"

`TreeMethod`
: Choose from "hist", "gpu_hist"

`GridTune`
: Set to TRUE to run a grid tuning procedure

`BaselineComparison`
: Set to either "default" or "best". Default is to compare each successive model build to the baseline model using max trees (from function args). Best makes the comparison to the current best model.

`MaxModelsInGrid`
: Number of models to test from grid options.

`MaxRunsWithoutNewWinner`
: A number

`MaxRunMinutes`
: In minutes

`PassInGrid`
: Default is NULL. Provide a data.table of grid options from a previous run.

`early_stopping_rounds`
: = 10L

`Trees` Bandit grid partitioned. Supply a single value for non-grid tuning cases. Otherwise, supply a vector for the trees numbers you want to test. For running grid tuning, a NULL value supplied will mean these values are tested seq(1000L, 10000L, 1000L)

`num_parallel_tree` = 1. If setting greater than 1, set colsample_bytree < 1, subsample < 1 and round = 1

`eta` Bandit grid partitioned. Supply a single value for non-grid tuning cases. Otherwise, supply a vector for the LearningRate values to test. For running grid tuning, a NULL value supplied will mean these values are tested c(0.01,0.02,0.03,0.04)

`max_depth` Bandit grid partitioned. Number, or vector for depth to test. For running grid tuning, a NULL value supplied will mean these values are tested seq(4L, 16L, 2L)

`min_child_weight` Number, or vector for min_child_weight to test. For running grid tuning, a NULL value supplied will mean these values are tested seq(1.0, 10.0, 1.0)

`subsample` Number, or vector for subsample to test. For running grid tuning, a NULL value supplied will mean these values are tested seq(0.55, 1.0, 0.05)

`colsample_bytree` Number, or vector for colsample_bytree to test. For running grid tuning, a NULL value supplied will mean these values are tested seq(0.55, 1.0, 0.05)

`alpha` 0. L1 Reg.

`lambda` 1. L2 Reg.

Value

Saves to file and returned in list: VariableImportance.csv, Model, ValidationData.csv, EvaluationMetrics.csv, GridCollect, GridList, and TargetLevels

Author(s)

Adrian Antico

See Also

Other Automated Supervised Learning - Multiclass Classification: `AutoCatBoostMultiClass()`, `AutoH2oDRFMultiClass()`, `AutoH2oGAMMultiClass()`, `AutoH2oGBMMultiClass()`, `AutoH2oGLMMultiClass()`, `AutoH2oMLMultiClass()`

Examples

```
## Not run:
data <- AutoQuant::FakeDataGenerator(
  Correlation = 0.85,
  N = 1000L,
  ID = 2L,
  ZIP = 0L,
  AddDate = FALSE,
  Classification = FALSE,
  MultiClass = TRUE)

# Run function
```

```
TestModel <- AutoQuant::AutoXGBoostMultiClass(

  # GPU or CPU
  TreeMethod = "hist",
  NThreads = parallel::detectCores(),

  # Metadata args
 OutputSelection = c("Importances", "EvalPlots", "EvalMetrics", "PDFs", "Score_TrainData"),
  model_path = normalizePath("./"),
  metadata_path = normalizePath("./"),
  ModelID = "Test_Model_1",
  EncodingMethod = "binary",
  ReturnFactorLevels = TRUE,
  ReturnModelObjects = TRUE,
  SaveModelObjects = FALSE,

  # Data args
  data = data,
  TrainOnFull = FALSE,
  ValidationData = NULL,
  TestData = NULL,
  TargetColumnName = "Adrian",
  FeatureColNames = names(data)[!names(data) %in%
                                  c("IDcol_1", "IDcol_2","Adrian")],
  WeightsColumnName = NULL,
  IDcols = c("IDcol_1","IDcol_2"),

  # Model evaluation args
  eval_metric = "merror",
  LossFunction = 'multi:softprob',
  grid_eval_metric = "accuracy",
  NumOfParDepPlots = 3L,

  # Grid tuning args
  PassInGrid = NULL,
  GridTune = FALSE,
  BaselineComparison = "default",
  MaxModelsInGrid = 10L,
  MaxRunsWithoutNewWinner = 20L,
  MaxRunMinutes = 24L*60L,
  Verbose = 1L,
  DebugMode = FALSE,

  # ML args
  Trees = 50L,
  eta = 0.05,
  max_depth = 4L,
  min_child_weight = 1.0,
  subsample = 0.55,
  colsample_bytree = 0.55)

## End(Not run)
```

AutoXGBoostRegression *AutoXGBoostRegression*

Description

AutoXGBoostRegression is an automated XGBoost modeling framework with grid-tuning and model evaluation that runs a variety of steps. First, the function will run a random grid tune over N number of models and find which model is the best (a default model is always included in that set). Once the model is identified and built, several other outputs are generated: validation data with predictions, evaluation plot, evaluation boxplot, evaluation metrics, variable importance, partial dependence calibration plots, partial dependence calibration box plots, and column names used in model fitting.

Usage

```
AutoXGBoostRegression(
 OutputSelection = c("Importances", "EvalPlots", "EvalMetrics", "Score_TrainData"),
  data = NULL,
  TrainOnFull = FALSE,
  ValidationData = NULL,
  TestData = NULL,
  TargetColumnName = NULL,
  FeatureColNames = NULL,
  PrimaryDateColumn = NULL,
  WeightsColumnName = NULL,
  IDcols = NULL,
  model_path = NULL,
  metadata_path = NULL,
  DebugMode = FALSE,
  SaveInfoToPDF = FALSE,
  ModelID = "FirstModel",
  EncodingMethod = "credibility",
  ReturnFactorLevels = TRUE,
  ReturnModelObjects = TRUE,
  SaveModelObjects = FALSE,
  TransformNumericColumns = NULL,
  Methods = c("Asinh", "Log", "LogPlus1", "Sqrt", "Asin", "Logit"),
  Verbose = 0L,
  NumOfParDepPlots = 3L,
  NThreads = parallel::detectCores(),
  LossFunction = "reg:squarederror",
  eval_metric = "rmse",
  grid_eval_metric = "r2",
  TreeMethod = "hist",
  GridTune = FALSE,
  BaselineComparison = "default",
  MaxModelsInGrid = 10L,
  MaxRunsWithoutNewWinner = 20L,
  MaxRunMinutes = 24L * 60L,
  PassInGrid = NULL,
  early_stopping_rounds = 100L,
  Trees = 50L,
  num_parallel_tree = 1,
  eta = NULL,
  max_depth = NULL,
  min_child_weight = NULL,
```

```
  subsample = NULL,
  colsample_bytree = NULL,
  alpha = 0,
  lambda = 1
)
```

Arguments

`OutputSelection`
: You can select what type of output you want returned. Choose from c("Importances", "EvalPlots", "EvalMetrics", "Score_TrainData")

`data`
: This is your data set for training and testing your model

`TrainOnFull`
: Set to TRUE to train on full data

`ValidationData`
: This is your holdout data set used in modeling either refine your hyperparameters.

`TestData`
: This is your holdout data set. Catboost using both training and validation data in the training process so you should evaluate out of sample performance with this data set.

`TargetColumnName`
: Either supply the target column name OR the column number where the target is located (but not mixed types).

`FeatureColNames`
: Either supply the feature column names OR the column number where the target is located (but not mixed types)

`PrimaryDateColumn`
: Supply a date or datetime column for model evaluation plots

`WeightsColumnName`
: Supply a column name for your weights column. Leave NULL otherwise

`IDcols`
: A vector of column names or column numbers to keep in your data but not include in the modeling.

`model_path`
: A character string of your path file to where you want your output saved

`metadata_path`
: A character string of your path file to where you want your model evaluation output saved. If left NULL, all output will be saved to model_path.

`DebugMode`
: Set to TRUE to get a print out of the steps taken throughout the function

`SaveInfoToPDF`
: Set to TRUE to save model insights to pdf

`ModelID`
: A character string to name your model and output

`EncodingMethod`
: Choose from 'binary', 'm_estimator', 'credibility', 'woe', 'target_encoding', 'poly_encode', 'backward_difference', 'helmert'

`ReturnFactorLevels`
: Set to TRUE to have the factor levels returned with the other model objects

`ReturnModelObjects`
: Set to TRUE to output all modeling objects (E.g. plots and evaluation metrics)

`SaveModelObjects`
: Set to TRUE to return all modeling objects to your environment

`TransformNumericColumns`
: Set to NULL to do nothing; otherwise supply the column names of numeric variables you want transformed

`Methods` Choose from "BoxCox", "Asinh", "Asin", "Log", "LogPlus1", "Sqrt", "Logit", "YeoJohnson". Function will determine if one cannot be used because of the underlying data.

`Verbose` Set to 0 if you want to suppress model evaluation updates in training

`NumOfParDepPlots` Tell the function the number of partial dependence calibration plots you want to create.

`NThreads` Set the maximum number of threads you'd like to dedicate to the model run. E.g. 8

`LossFunction` Default is 'reg:squarederror'. Other options include 'reg:squaredlogerror', 'reg:pseudohubererror', 'count:poisson', 'survival:cox', 'survival:aft', 'aft_loss_distribution', 'reg:gamma', 'reg:tweedie'

`eval_metric` This is the metric used to identify best grid tuned model. Choose from "rmse", "mae", "mape"

`grid_eval_metric` "mae", "mape", "rmse", "r2". Case sensitive

`TreeMethod` Choose from "hist", "gpu_hist"

`GridTune` Set to TRUE to run a grid tuning procedure. Set a number in MaxModelsInGrid to tell the procedure how many models you want to test.

`BaselineComparison` Set to either "default" or "best". Default is to compare each successive model build to the baseline model using max trees (from function args). Best makes the comparison to the current best model.

`MaxModelsInGrid` Number of models to test from grid options (243 total possible options)

`MaxRunsWithoutNewWinner` Runs without new winner to end procedure

`MaxRunMinutes` In minutes

`PassInGrid` Default is NULL. Provide a data.table of grid options from a previous run.

`early_stopping_rounds` = 100L

`Trees` Bandit grid partitioned. Supply a single value for non-grid tuning cases. Otherwise, supply a vector for the trees numbers you want to test. For running grid tuning, a NULL value supplied will mean these values are tested seq(1000L, 10000L, 1000L)

`num_parallel_tree` = 1. If setting greater than 1, set colsample_bytree < 1, subsample < 1 and round = 1

`eta` Bandit grid partitioned. Supply a single value for non-grid tuning cases. Otherwise, supply a vector for the LearningRate values to test. For running grid tuning, a NULL value supplied will mean these values are tested c(0.01,0.02,0.03,0.04)

`max_depth` Bandit grid partitioned. Number, or vector for depth to test. For running grid tuning, a NULL value supplied will mean these values are tested seq(4L, 16L, 2L)

`min_child_weight` Number, or vector for min_child_weight to test. For running grid tuning, a NULL value supplied will mean these values are tested seq(1.0, 10.0, 1.0)

subsample — Number, or vector for subsample to test. For running grid tuning, a NULL value supplied will mean these values are tested seq(0.55, 1.0, 0.05)

colsample_bytree — Number, or vector for colsample_bytree to test. For running grid tuning, a NULL value supplied will mean these values are tested seq(0.55, 1.0, 0.05)

alpha — 0. L1 Reg.

lambda — 1. L2 Reg.

Value

Saves to file and returned in list: VariableImportance.csv, Model, ValidationData.csv, EvalutionPlot.png, EvalutionBoxPlot.png, EvaluationMetrics.csv, ParDepPlots.R a named list of features with partial dependence calibration plots, ParDepBoxPlots.R, GridCollect, and GridList

Author(s)

Adrian Antico

See Also

Other Automated Supervised Learning - Regression: AutoCatBoostRegression(), AutoH2oDRFRegression(), AutoH2oGAMRegression(), AutoH2oGBMRegression(), AutoH2oGLMRegression(), AutoH2oMLRegression(), AutoLightGBMRegression()

Examples

```
## Not run:
# Create some dummy correlated data
data <- AutoQuant::FakeDataGenerator(
  Correlation = 0.85,
  N = 1000,
  ID = 2,
  ZIP = 0,
  AddDate = FALSE,
  Classification = FALSE,
  MultiClass = FALSE)

# Run function
TestModel <- AutoQuant::AutoXGBoostRegression(

  # GPU or CPU
  TreeMethod = 'hist',
  NThreads = parallel::detectCores(),
  LossFunction = 'reg:squarederror',

  # Metadata args
  OutputSelection = c('Importances', 'EvalPlots', 'EvalMetrics', 'Score_TrainData'),
  model_path = normalizePath("./"),
  metadata_path = NULL,
  ModelID = "Test_Model_1",
  EncodingMethod = 'credibility',
  ReturnFactorLevels = TRUE,
  ReturnModelObjects = TRUE,
  SaveModelObjects = FALSE,
  SaveInfoToPDF = FALSE,
```

```
  DebugMode = FALSE,

  # Data args
  data = data,
  TrainOnFull = FALSE,
  ValidationData = NULL,
  TestData = NULL,
  TargetColumnName = 'Adrian',
  FeatureColNames = names(data)[!names(data) %in%
    c('IDcol_1', 'IDcol_2', 'Adrian')],
  PrimaryDateColumn = NULL,
  WeightsColumnName = NULL,
  IDcols = c('IDcol_1', 'IDcol_2'),
  TransformNumericColumns = NULL,
  Methods = c('Asinh', 'Asin', 'Log', 'LogPlus1', 'Sqrt', 'Logit'),

  # Model evaluation args
  eval_metric = 'rmse',
  NumOfParDepPlots = 3L,

  # Grid tuning args
  PassInGrid = NULL,
  GridTune = FALSE,
  grid_eval_metric = 'r2',
  BaselineComparison = 'default',
  MaxModelsInGrid = 10L,
  MaxRunsWithoutNewWinner = 20L,
  MaxRunMinutes = 24L*60L,
  Verbose = 1L,

  # ML args
  Trees = 50L,
  eta = 0.05,
  max_depth = 4L,
  min_child_weight = 1.0,
  subsample = 0.55,
  colsample_bytree = 0.55)

## End(Not run)
```

AutoXGBoostScoring *AutoXGBoostScoring*

Description

AutoXGBoostScoring is an automated scoring function that compliments the AutoXGBoost model training functions. This function requires you to supply features for scoring. It will run ModelDataPrep() and the DummifyDT() function to prepare your features for xgboost data conversion and scoring.

Usage

```
AutoXGBoostScoring(
  TargetType = NULL,
```

```
  ScoringData = NULL,
  ReturnShapValues = FALSE,
  FeatureColumnNames = NULL,
  IDcols = NULL,
  EncodingMethod = "binary",
  FactorLevelsList = NULL,
  TargetLevels = NULL,
  OneHot = FALSE,
  ModelObject = NULL,
  ModelPath = NULL,
  ModelID = NULL,
  ReturnFeatures = TRUE,
  TransformNumeric = FALSE,
  BackTransNumeric = FALSE,
  TargetColumnName = NULL,
  TransformationObject = NULL,
  TransID = NULL,
  TransPath = NULL,
  MDP_Impute = TRUE,
  MDP_CharToFactor = TRUE,
  MDP_RemoveDates = TRUE,
  MDP_MissFactor = "0",
  MDP_MissNum = -1
)
```

Arguments

TargetType	Set this value to "regression", "classification", or "multiclass" to score models built using AutoXGBoostRegression(), AutoXGBoostClassify() or AutoXGBoostMultiClass()
ScoringData	This is your data.table of features for scoring. Can be a single row or batch.
ReturnShapValues	Set to TRUE to return shap values for the predicted values
FeatureColumnNames	Supply either column names or column numbers used in the AutoXGBoost__() function
IDcols	Supply ID column numbers for any metadata you want returned with your predicted values
EncodingMethod	Choose from 'binary', 'm_estimator', 'credibility', 'woe', 'target_encoding', 'poly_encode', 'backward_difference', 'helmert'
FactorLevelsList	Supply the factor variables' list from DummifyDT()
TargetLevels	Supply the target levels output from AutoXGBoostMultiClass() or the scoring function will go looking for it in the file path you supply.
ModelObject	Supply a model for scoring, otherwise it will have to search for it in the file path you specify
ModelPath	Supply your path file used in the AutoXGBoost__() function
ModelID	Supply the model ID used in the AutoXGBoost__() function
ReturnFeatures	Set to TRUE to return your features with the predicted values.

`TransformNumeric`
: Set to TRUE if you have features that were transformed automatically from an Auto__Regression() model AND you haven't already transformed them.

`BackTransNumeric`
: Set to TRUE to generate back-transformed predicted values. Also, if you return features, those will also be back-transformed.

`TargetColumnName`
: Input your target column name used in training if you are utilizing the transformation service

`TransformationObject`
: Set to NULL if you didn't use transformations or if you want the function to pull from the file output from the Auto__Regression() function. You can also supply the transformation data.table object with the transformation details versus having it pulled from file.

`TransID`
: Set to the ID used for saving the transformation data.table object or set it to the ModelID if you are pulling from file from a build with Auto__Regression().

`TransPath`
: Set the path file to the folder where your transformation data.table detail object is stored. If you used the Auto__Regression() to build, set it to the same path as ModelPath.

`MDP_Impute`
: Set to TRUE if you did so for modeling and didn't do so before supplying ScoringData in this function

`MDP_CharToFactor`
: Set to TRUE to turn your character columns to factors if you didn't do so to your ScoringData that you are supplying to this function

`MDP_RemoveDates`
: Set to TRUE if you have date of timestamp columns in your ScoringData

`MDP_MissFactor`
: If you set MDP_Impute to TRUE, supply the character values to replace missing values with

`MDP_MissNum`
: If you set MDP_Impute to TRUE, supply a numeric value to replace missing values with

Value

A data.table of predicted values with the option to return model features as well.

Author(s)

Adrian Antico

See Also

Other Automated Model Scoring: `AutoCatBoostScoring()`, `AutoH2OMLScoring()`, `AutoLightGBMScoring()`

Examples

```
## Not run:
Preds <- AutoXGBoostScoring(
  TargetType = "regression",
  ScoringData = data,
  ReturnShapValues = FALSE,
  FeatureColumnNames = 2:12,
  IDcols = NULL,
```

```
  EncodingMethod = "binary",
  FactorLevelsList = NULL,
  TargetLevels = NULL,
  ModelObject = NULL,
  ModelPath = "home",
  ModelID = "ModelTest",
  ReturnFeatures = TRUE,
  TransformNumeric = FALSE,
  BackTransNumeric = FALSE,
  TargetColumnName = NULL,
  TransformationObject = NULL,
  TransID = NULL,
  TransPath = NULL,
  MDP_Impute = TRUE,
  MDP_CharToFactor = TRUE,
  MDP_RemoveDates = TRUE,
  MDP_MissFactor = "0",
  MDP_MissNum = -1)

## End(Not run)
```

BarPlot *BarPlot*

Description

Build a bar plot by simply passing arguments to a single function. It will sample your data using SampleSize number of rows. Sampled data is randomized.

Usage

```
BarPlot(
  data = NULL,
  XVar = NULL,
  YVar = NULL,
  AggMethod = "mean",
  ColorVar = NULL,
  FacetVar1 = NULL,
  FacetVar2 = NULL,
  SampleSize = 1000000L,
  FillColor = "gray",
  YTicks = "Default",
  XTicks = "Default",
  TextSize = 12,
  AngleX = 90,
  AngleY = 0,
  ChartColor = "lightsteelblue1",
  BorderColor = "darkblue",
  TextColor = "darkblue",
  GridColor = "white",
  BackGroundColor = "gray95",
  SubTitleColor = "blue",
  LegendPosition = "bottom",
```

```
  LegendBorderSize = 0.5,
  LegendLineType = "solid",
  Debug = FALSE
)
```

Arguments

data	Source data.table
XVar	Column name of X-Axis variable. If NULL then ignored
YVar	Column name of Y-Axis variable. If NULL then ignored
AggMethod	Choose from 'mean', 'sum', 'sd', and 'median'
ColorVar	Column name of Group Variable for distinct colored histograms by group levels
FacetVar1	Column name of facet variable 1. If NULL then ignored
FacetVar2	Column name of facet variable 2. If NULL then ignored
SampleSize	An integer for the number of rows to use. Sampled data is randomized. If NULL then ignored
FillColor	'gray'
YTicks	Choose from 'Default', 'Percentiles', 'Every 5th percentile', 'Deciles', 'Quantiles', 'Quartiles'
XTicks	Choose from 'Default', '1 year', '1 day', '3 day', '1 week', '2 week', '1 month', '3 month', '6 month', '2 year', '5 year', '10 year', '1 minute', '15 minutes', '30 minutes', '1 hour', '3 hour', '6 hour', '12 hour'
TextSize	14
AngleX	90
AngleY	0
ChartColor	'lightsteelblue'
BorderColor	'darkblue'
TextColor	'darkblue'
GridColor	'white'
BackGroundColor	'gray95'
SubTitleColor	'darkblue'
LegendPosition	'bottom'
LegendBorderSize	0.50
LegendLineType	'solid'
Debug	FALSE
OutlierSize	0.10
OutlierColor	'blue'

Author(s)

Adrian Antico

See Also

Other Graphics: AddFacet(), BoxPlot(), ChartTheme(), CorrMatrixPlot(), DensityPlot(), HeatMapPlot(), HistPlot(), PlotlyConversion(), StockData(), StockPlot(), ViolinPlot(), multiplot()

Examples

```
## Not run:
# Load packages
library(AutoQuant)
library(data.table)

# Load data
data <- data.table::fread(file = file.path('C:/Users/Bizon/Documents/GitHub/BenchmarkData1.csv'))

# Run function
AutoQuant:::BarPlot(
  data = data,
  XVar = 'Region',
  YVar = 'Weekly_Sales',
  AggMethod = 'mean',
  ColorVar = NULL,
  FacetVar1 = 'Store',
  FacetVar2 = 'Dept',
  SampleSize = 1000000L,
  FillColor = 'gray',
  YTicks = 'Default',
  XTicks = 'Default',
  TextSize = 12,
  AngleX = 90,
  AngleY = 0,
  ChartColor = 'lightsteelblue1',
  BorderColor = 'darkblue',
  TextColor = 'darkblue',
  GridColor = 'white',
  BackGroundColor = 'gray95',
  SubTitleColor = 'blue',
  LegendPosition = 'bottom',
  LegendBorderSize = 0.50,
  LegendLineType = 'solid',
  Debug = FALSE)

# Step through function
# XVar = 'Region'
# YVar = 'Weekly_Sales'
# AggMethod = 'mean'
# ColorVar = NULL
# FacetVar1 = NULL
# FacetVar2 = NULL
# SampleSize = 1000000L
# FillColor = 'gray'
# YTicks = 'Default'
# XTicks = 'Default'
# TextSize = 12
# AngleX = 90
# AngleY = 0
```

```
# ChartColor = 'lightsteelblue1'
# BorderColor = 'darkblue'
# TextColor = 'darkblue'
# GridColor = 'white'
# BackGroundColor = 'gray95'
# SubTitleColor = 'blue'
# LegendPosition = 'bottom'
# LegendBorderSize = 0.50
# LegendLineType = 'solid'
# Debug = FALSE

## End(Not run)
```

BenchmarkData *BenchmarkData*

Description

Modified version of h2o datatable benchmark data

Usage

```
BenchmarkData(
  NRows = 1e+07,
  Levels = 1e+06,
  NAs = -1L,
  FixedEffects = c(5, 10, 15),
  CharVars = TRUE,
  IntVars = TRUE,
  Sort = TRUE
)
```

Arguments

NAs	= -1L
FixedEffects	c(5,10,15), number of levels for each variable
CharVars	FALSE
IntVars	TRUE
Sort	= TRUE
N	= 10000000,
RandomLevels	= 1000000
RandomEffects	c(3)

BoxPlot *BoxPlot*

Description

Build a box plot by simply passing arguments to a single function. It will sample your data using SampleSize number of rows. Sampled data is randomized.

Usage

```
BoxPlot(
  data = NULL,
  XVar = NULL,
  YVar = NULL,
  FacetVar1 = NULL,
  FacetVar2 = NULL,
  SampleSize = 1000000L,
  FillColor = "gray",
  OutlierSize = 0.1,
  OutlierColor = "blue",
  YTicks = "Default",
  XTicks = "Default",
  TextSize = 12,
  AngleX = 90,
  AngleY = 0,
  ChartColor = "lightsteelblue1",
  BorderColor = "darkblue",
  TextColor = "darkblue",
  GridColor = "white",
  BackGroundColor = "gray95",
  SubTitleColor = "blue",
  LegendPosition = "bottom",
  LegendBorderSize = 0.5,
  LegendLineType = "solid",
  Debug = FALSE
)
```

Arguments

data	Source data.table
XVar	Column name of X-Axis variable. If NULL then ignored
YVar	Column name of Y-Axis variable. If NULL then ignored
FacetVar1	Column name of facet variable 1. If NULL then ignored
FacetVar2	Column name of facet variable 2. If NULL then ignored
SampleSize	An integer for the number of rows to use. Sampled data is randomized. If NULL then ignored
FillColor	'gray'
OutlierSize	0.10
OutlierColor	'blue'

YTicks	Choose from 'Default', 'Percentiles', 'Every 5th percentile', 'Deciles', 'Quantiles', 'Quartiles'
XTicks	Choose from 'Default', '1 year', '1 day', '3 day', '1 week', '2 week', '1 month', '3 month', '6 month', '2 year', '5 year', '10 year', '1 minute', '15 minutes', '30 minutes', '1 hour', '3 hour', '6 hour', '12 hour'
TextSize	14
AngleX	90
AngleY	0
ChartColor	'lightsteelblue'
BorderColor	'darkblue'
TextColor	'darkblue'
GridColor	'white'
BackGroundColor	'gray95'
SubTitleColor	'darkblue'
LegendPosition	'bottom'
LegendBorderSize	0.50
LegendLineType	'solid'
Debug	FALSE

Author(s)

Adrian Antico

See Also

Other Graphics: AddFacet(), BarPlot(), ChartTheme(), CorrMatrixPlot(), DensityPlot(), HeatMapPlot(), HistPlot(), PlotlyConversion(), StockData(), StockPlot(), ViolinPlot(), multiplot()

Examples

```
## Not run:
# Load packages
library(AutoQuant)
library(data.table)

# Load data
data <- data.table::fread(file = file.path('C:/Users/Bizon/Documents/GitHub/BenchmarkData1.csv'))

# Run function
AutoQuant:::BoxPlot(
  data = data,
  XVar = 'Region',
  YVar = 'Weekly_Sales',
  FacetVar1 = 'Store',
  FacetVar2 = NULL,
  SampleSize = 1000000L,
  FillColor = 'gray',
  OutlierSize = 0.10,
```

```
  OutlierColor = 'blue',
  YTicks = 'Default',
  XTicks = 'Default',
  TextSize = 12,
  AngleX = 90,
  AngleY = 0,
  ChartColor = 'lightsteelblue1',
  BorderColor = 'darkblue',
  TextColor = 'darkblue',
  GridColor = 'white',
  BackGroundColor = 'gray95',
  SubTitleColor = 'blue',
  LegendPosition = 'bottom',
  LegendBorderSize = 0.50,
  LegendLineType = 'solid',
  Debug = FALSE)

# Step through function
# XVar = 'Region'
# YVar = 'Weekly_Sales'
# FacetVar1 = 'Store'
# FacetVar2 = 'Dept'
# SampleSize = 1000000L
# FillColor = 'gray'
# OutlierSize = 0.10
# OutlierColor = 'blue'
# YTicks = 'Default'
# XTicks = 'Default'
# TextSize = 12
# AngleX = 90
# AngleY = 0
# ChartColor = 'lightsteelblue1'
# BorderColor = 'darkblue'
# TextColor = 'darkblue'
# GridColor = 'white'
# BackGroundColor = 'gray95'
# SubTitleColor = 'blue'
# LegendPosition = 'bottom'
# LegendBorderSize = 0.50
# LegendLineType = 'solid'
# Debug = FALSE

## End(Not run)
```

`CategoricalEncoding` *CategoricalEncoding*

Description

Categorical encoding for factor and character columns

Usage

```
CategoricalEncoding(
```

```
  data = NULL,
  ML_Type = "classification",
  GroupVariables = NULL,
  TargetVariable = NULL,
  Method = NULL,
  SavePath = NULL,
  Scoring = FALSE,
  ImputeValueScoring = NULL,
  ReturnFactorLevelList = TRUE,
  SupplyFactorLevelList = NULL,
  KeepOriginalFactors = TRUE,
  Debug = FALSE
)
```

Arguments

data	Source data.table
ML_Type	Only use with Method "credibility'. Select from 'classification' or 'regression'.
GroupVariables	Columns to encode
Method	Method to utilize. Choose from 'credibility', 'target_encoding', 'woe', 'm_estimator', 'poly_encode', 'backward_difference', 'helmert'. Default is 'credibility' which is more specifically, Bulhmann Credibility
SavePath	Path to save artifacts for recreating in scoring environments
Scoring	Set to TRUE for scoring mode.
ImputeValueScoring	If levels cannot be matched on scoring data you can supply a value to impute the NA's. Otherwise, leave NULL and manage them outside the function
ReturnFactorLevelList	TRUE by default. Returns a list of the factor variable and transformations needed for regenerating them in a scoring environment. Alternatively, if you save them to file, they can be called for use in a scoring environment.
SupplyFactorLevelList	The FactorCompenents list that gets returned. Supply this to recreate features in scoring environment
KeepOriginalFactors	Defaults to TRUE. Set to FALSE to remove the original factor columns
Debug	= FALSE
TargetVariabl	Target column name

Author(s)

Adrian Antico

See Also

Other Feature Engineering: AutoDataPartition(), AutoDiffLagN(), AutoHierarchicalFourier(), AutoInteraction(), AutoLagRollMode(), AutoLagRollStatsScoring(), AutoLagRollStats(), AutoTransformationCreate(), AutoTransformationScore(), AutoWord2VecModeler(), AutoWord2VecScoring() CreateCalendarVariables(), CreateHolidayVariables(), DummifyDT(), H2OAutoencoderScoring(), H2OAutoencoder(), ModelDataPrep(), PercRankScoring(), PercRank(), StandardizeScoring(), Standardize(), TimeSeriesFillRoll(), TimeSeriesFill()

Examples

```
## Not run:
# Create fake data with 10 categorical
data <- AutoQuant::FakeDataGenerator(
  Correlation = 0.85,
  N = 1000000,
  ID = 2L,
  ZIP = 0,
  FactorCount = 10L,
  AddDate = FALSE,
  Classification = TRUE,
  MultiClass = FALSE)

# Take your pick
Meth <- c('m_estimator',
          'credibility',
          'woe',
          'target_encoding',
          'poly_encode',
          'backward_difference',
          'helmert')

# Pass to function
MethNum <- 1

# Mock test data with same factor levels
test <- data.table::copy(data)

# Run in Train Mode
data <- AutoQuant::CategoricalEncoding(
  data = data,
  ML_Type = "classification",
  GroupVariables = paste0("Factor_", 1:10),
  TargetVariable = "Adrian",
  Method = Meth[MethNum],
  SavePath = getwd(),
  Scoring = FALSE,
  ReturnFactorLevelList = FALSE,
  SupplyFactorLevelList = NULL,
  KeepOriginalFactors = FALSE,
  Debug = FALSE)

# View results
print(data)

# Run in Score Mode by pulling in the csv's
test <- AutoQuant::CategoricalEncoding(
  data = data,
  ML_Type = "classification",
  GroupVariables = paste0("Factor_", 1:10),
  TargetVariable = "Adrian",
  Method = Meth[MethNum],
  SavePath = getwd(),
  Scoring = TRUE,
  ImputeValueScoring = 222,
  ReturnFactorLevelList = FALSE,
```

```
  SupplyFactorLevelList = NULL,
  KeepOriginalFactors = FALSE,
  Debug = FALSE)

## End(Not run)
```

CausalMediation *CausalMediation*

Description

CausalMediation utilizes models from regmedint package

Usage

```
CausalMediation(
  data,
  OutcomeTargetVariable = NULL,
  TreatmentVariable = NULL,
  MediatorVariable = NULL,
  Covariates = NULL,
  MM_TreatmentCovariates = NULL,
  OM_TreatmentCovariates = NULL,
  OM_MediatorCovariates = NULL,
  SurvivalEventVariable = NULL,
  UnTreated_ReferenceIndicator = NULL,
  Treated_ReferenceIndicator = NULL,
  Mediator_ControlDirectEffectLevel = NULL,
  Covariate_NaturalDirectIndirect = 0,
  MediatorTargetType = "linear",
  OutcomeTargetType = "linear",
  TreatmentMediatorInteraction = TRUE,
  CaseControlSourceData = FALSE,
  RemoveNA = FALSE
)
```

Arguments

data	Data frame containing the following relevant variables.
OutcomeTargetVariable	yvar in underlying model. A character vector of length 1. Outcome variable name. It should be the time variable for the survival outcome.
TreatmentVariable	avar in underlying model. A character vector of length 1. Treatment variable name.
MediatorVariable	mvar in underlying model. A character vector of length 1. Mediator variable name.
Covariates	For main model

`MM_TreatmentCovariates`
: emm_ac_mreg in underlying model. A character vector of length > 0. Effect modifiers names. The covariate vector in treatment-covariate product term in the mediator model.

`OM_TreatmentCovariates`
: emm_ac_yreg in underlying model. A character vector of length > 0. Effect modifiers names. The covariate vector in treatment-covariate product term in the outcome model.

`OM_MediatorCovariates`
: emm_mc_yreg in underlying model. A character vector of length > 0. Effect modifiers names. The covariate vector in mediator-covariate product term in outcome model.

`SurvivalEventVariable`
: eventvar in underlying model. An character vector of length 1. Only required for survival outcome regression models. Note that the coding is 1 for event and 0 for censoring, following the R survival package convention.

`UnTreated_ReferenceIndicator`
: a0 in underlying model. A numeric vector of length 1. The reference level of treatment variable that is considered "untreated" or "unexposed".

`Treated_ReferenceIndicator`
: a1 in underlying model. A numeric vector of length 1.

`Mediator_ControlDirectEffectLevel`
: m_cde in underlying model. A numeric vector of length 1. Mediator level at which controlled direct effect is evaluated at.

`Covariate_NaturalDirectIndirect`
: c_cond in underlying model. A numeric vector of the same length as `cvar`. Covariate levels at which natural direct and indirect effects are evaluated at.

`MediatorTargetType`
: mreg in underlying model. A character vector of length 1. Mediator regression type: `"linear"` or `"logistic"`.

`OutcomeTargetType`
: yreg in underlying model. A character vector of length 1. Outcome regression type: `"linear"`, `"logistic"`, `"loglinear"`, `"poisson"`, `"negbin"`, `"survCox"`, `"survAFT_exp"`, or `"survAFT_weibull"`.

`TreatmentMediatorInteraction`
: interaction in underlying model. A logical vector of length 1. The presence of treatment-mediator interaction in the outcome model. Default to TRUE.

`CaseControlSourceData`
: casecontrol in underlying model. A logical vector of length 1. Default to FALSE. Whether data comes from a case-control study.

`RemoveNA`
: na_omit in underlying model. A logical vector of length 1. Default to FALSE. Whether to remove NAs in the columns of interest before fitting the models.

`ConfoundingVariables`
: cvar in underlying model. A character vector of length > 0. Covariate names. Use `NULL` if there is no covariate. However, this is a highly suspicious situation. Even if `avar` is randomized, `mvar` is not. Thus, there are usually some confounder(s) to account for the common cause structure (confounding) between `mvar` and `yvar`.

Value

list with model output object, summary output, effects output, and an effects plot

Author(s)

Adrian Antico

Examples

```
## Not run:
library(regmedint) # to load vv2015
data(vv2015)
Output <- AutoQuant::CausalMediation(
  data = vv2015,
  OutcomeTargetVariable = 'y',            # yvar char length = 0
  TreatmentVariable = "x",                # avar char length = 0 (binary)
  MediatorVariable = "m",                 # mvar char length = 0 (binary)
  Covariates = "c",                       # cvar char length > 0
  MM_TreatmentCovariates = NULL,          # emm_ac_mreg = NULL char length > 0
  OM_TreatmentCovariates = NULL,          # emm_ac_yreg = NULL char length > 0
  OM_MediatorCovariates = NULL,           # emm_mc_yreg = NULL char length > 0
  SurvivalEventVariable = "event",        # eventvar char length = 0
  UnTreated_ReferenceIndicator = 0,       # ao num length = 1
  Treated_ReferenceIndicator = 1,         # a1 num length = 1
  Mediator_ControlDirectEffectLevel = 1,  # m_cde num length = 1
 Covariate_NaturalDirectIndirect = 3,   # c_cond; same length as Covariates num length = length(Covariates)
  MediatorTargetType = 'logistic',        # mreg "linear" or "logistic",
 OutcomeTargetType = 'survAFT_weibull',  # yreg "linear", "logistic", "loglinear", "poisson", "negbin", "survC
  TreatmentMediatorInteraction = TRUE,    # interaction = TRUE,
  CaseControlSourceData = FALSE,          # casecontrol = FALSE,
  RemoveNA = FALSE)

# data = vv2015
# OutcomeTargetVariable = 'y'
# TreatmentVariable = "x"
# MediatorVariable = "m"
# Covariates = "c"
# MM_TreatmentCovariates = NULL
# OM_TreatmentCovariates = NULL
# OM_MediatorCovariates = NULL
# SurvivalEventVariable = "event"
# UnTreated_ReferenceIndicator = 0
# Treated_ReferenceIndicator = 1
# Mediator_ControlDirectEffectLevel = 1
# Covariate_NaturalDirectIndirect = 3
# MediatorTargetType = 'logistic'
# OutcomeTargetType = 'survAFT_weibull'
# TreatmentMediatorInteraction = TRUE
# CaseControlSourceData = FALSE
# RemoveNA = FALSE

## End(Not run)
```

ChartTheme *ChartTheme*

Description

This function helps your ggplots look professional with the choice of the two main colors that will dominate the theme

Usage

```
ChartTheme(
  Size = 12,
  AngleX = 90,
  AngleY = 0,
  ChartColor = "lightsteelblue1",
  BorderColor = "darkblue",
  TextColor = "darkblue",
  SubTitleColor = "blue",
  GridColor = "white",
  BackGroundColor = "gray95",
  LegendPosition = "bottom",
  LegendBorderSize = 0.01,
  LegendLineType = "solid"
)
```

Arguments

Size	The size of the axis labels and title
AngleX	The angle of the x axis labels
AngleY	The angle of the Y axis labels
ChartColor	"lightsteelblue1",
BorderColor	"darkblue"
TextColor	"darkblue"
SubTitleColor	'blue'
GridColor	"white"
BackGroundColor	"gray95"
LegendPosition	Where to place legend
LegendBorderSize	0.50
LegendLineType	'solid'

Value

An object to pass along to ggplot objects following the "+" sign

Author(s)

Adrian Antico

See Also

Other Graphics: AddFacet(), BarPlot(), BoxPlot(), CorrMatrixPlot(), DensityPlot(), HeatMapPlot(), HistPlot(), PlotlyConversion(), StockData(), StockPlot(), ViolinPlot(), multiplot()

Examples

```
## Not run:
data <- data.table::data.table(DateTime = as.Date(Sys.time()),
  Target = stats::filter(rnorm(1000,
                               mean = 50,
                               sd = 20),
                         filter=rep(1,10),
                         circular=TRUE))
data[, temp := seq(1:1000)][, DateTime := DateTime - temp][
  , temp := NULL]
data <- data[order(DateTime)]
p <- ggplot2::ggplot(data, ggplot2::aes(x = DateTime, y = Target)) +
  ggplot2::geom_line()
p <- p + ChartTheme(Size = 12)

## End(Not run)
```

`CorrMatrixPlot` *CorrMatrixPlot*

Description

Build a violin plot by simply passing arguments to a single function. It will sample your data using SampleSize number of rows. Sampled data is randomized.

Usage

```
CorrMatrixPlot(data = NULL, CorrVars = NULL, Method = "spearman")
```

Arguments

`data`	Source data.table
`CorrVars`	Column names of variables you want included in the correlation matrix
`Method`	'spearman' default, 'pearson' otherwise

Author(s)

Adrian Antico

See Also

Other Graphics: `AddFacet()`, `BarPlot()`, `BoxPlot()`, `ChartTheme()`, `DensityPlot()`, `HeatMapPlot()`, `HistPlot()`, `PlotlyConversion()`, `StockData()`, `StockPlot()`, `ViolinPlot()`, `multiplot()`

Examples

```
## Not run:
data <- data.table::fread(file.choose())
CorrVars <- c('Weekly_Sales', 'XREG1', 'XREG2', 'XREG3')
p <- cor(data[, .SD, .SDcols = c(CorrVars)])
p1 <- heatmaply::heatmaply_cor(
  p,
  colors = c('red', 'white', 'blue'),
```

```
  xlab = "Features",
  ylab = "Features",
  k_col = 2,
  k_row = 2)

## End(Not run)
```

`CreateCalendarVariables`
CreateCalendarVariables

Description

CreateCalendarVariables Rapidly creates calendar variables based on the date column you provide

Usage

```
CreateCalendarVariables(
  data,
  DateCols = NULL,
  AsFactor = FALSE,
  TimeUnits = "wday",
  CachePath = NULL,
  Debug = FALSE
)
```

Arguments

`data`	This is your data
`DateCols`	Supply either column names or column numbers of your date columns you want to use for creating calendar variables
`AsFactor`	Set to TRUE if you want factor type columns returned; otherwise integer type columns will be returned
`TimeUnits`	Supply a character vector of time units for creating calendar variables. Options include: "second", "minute", "hour", "wday", "mday", "yday", "week", "isoweek", "wom" (week of month), "month", "quarter", "year"
`CachePath`	Path to data in a local directory. .csv only for now
`Debug`	= FALSE

Value

Returns your data.table with the added calendar variables at the end

Author(s)

Adrian Antico

See Also

Other Feature Engineering: AutoDataPartition(), AutoDiffLagN(), AutoHierarchicalFourier(), AutoInteraction(), AutoLagRollMode(), AutoLagRollStatsScoring(), AutoLagRollStats(), AutoTransformationCreate(), AutoTransformationScore(), AutoWord2VecModeler(), AutoWord2VecScoring(), CategoricalEncoding(), CreateHolidayVariables(), DummifyDT(), H2OAutoencoderScoring(), H2OAutoencoder(), ModelDataPrep(), PercRankScoring(), PercRank(), StandardizeScoring(), Standardize(), TimeSeriesFillRoll(), TimeSeriesFill()

Examples

```
## Not run:
# Create fake data with a Date column----
data <- AutoQuant::FakeDataGenerator(
  Correlation = 0.75,
  N = 25000L,
  ID = 2L,
  ZIP = 0L,
  FactorCount = 4L,
  AddDate = TRUE,
  Classification = FALSE,
  MultiClass = FALSE)
for(i in seq_len(20L)) {
  print(i)
  data <- data.table::rbindlist(
    list(data, AutoQuant::FakeDataGenerator(
    Correlation = 0.75,
    N = 25000L,
    ID = 2L,
    ZIP = 0L,
    FactorCount = 4L,
    AddDate = TRUE,
    Classification = FALSE,
    MultiClass = FALSE)))
}

# Create calendar variables - automatically excludes
#   the second, minute, and hour selections since
#   it is not timestamp data
runtime <- system.time(
  data <- AutoQuant::CreateCalendarVariables(
    data = data,
    DateCols = "DateTime",
    AsFactor = FALSE,
    TimeUnits = c("second",
                  "minute",
                  "hour",
                  "wday",
                  "mday",
                  "yday",
                  "week",
                  "isoweek",
                  "wom",
                  "month",
                  "quarter",
                  "year")))
head(data)
```

```
print(runtime)

## End(Not run)
```

`CreateHolidayVariables` *CreateHolidayVariables*

Description

CreateHolidayVariables Rapidly creates holiday count variables based on the date columns you provide

Usage

```
CreateHolidayVariables(
  data,
  DateCols = NULL,
  LookbackDays = NULL,
  HolidayGroups = c("USPublicHolidays", "EasterGroup", "ChristmasGroup",
    "OtherEcclesticalFeasts"),
  Holidays = NULL,
  Print = FALSE,
  CachePath = NULL,
  Debug = FALSE
)
```

Arguments

`data`	This is your data
`DateCols`	Supply either column names or column numbers of your date columns you want to use for creating calendar variables
`LookbackDays`	Default NULL which investigates Date - Lag1Date to compute Holiday's per period. Otherwise it will lookback LokkbackDays.
`HolidayGroups`	Pick groups
`Holidays`	Pick holidays
`Print`	Set to TRUE to print iteration number to console
`CachePath`	= NULL
`Debug`	= FALSE

Value

Returns your data.table with the added holiday indicator variable

Author(s)

Adrian Antico

See Also

Other Feature Engineering: AutoDataPartition(), AutoDiffLagN(), AutoHierarchicalFourier(), AutoInteraction(), AutoLagRollMode(), AutoLagRollStatsScoring(), AutoLagRollStats(), AutoTransformationCreate(), AutoTransformationScore(), AutoWord2VecModeler(), AutoWord2VecScoring(), CategoricalEncoding(), CreateCalendarVariables(), DummifyDT(), H2OAutoencoderScoring(), H2OAutoencoder(), ModelDataPrep(), PercRankScoring(), PercRank(), StandardizeScoring(), Standardize(), TimeSeriesFillRoll(), TimeSeriesFill()

Examples

```
## Not run:
# Create fake data with a Date----
data <- AutoQuant::FakeDataGenerator(
  Correlation = 0.75,
  N = 25000L,
  ID = 2L,
  ZIP = 0L,
  FactorCount = 4L,
  AddDate = TRUE,
  Classification = FALSE,
  MultiClass = FALSE)
for(i in seq_len(20L)) {
  print(i)
  data <- data.table::rbindlist(list(data,
  AutoQuant::FakeDataGenerator(
    Correlation = 0.75,
    N = 25000L,
    ID = 2L,
    ZIP = 0L,
    FactorCount = 4L,
    AddDate = TRUE,
    Classification = FALSE,
    MultiClass = FALSE)))
}
# Run function and time it
runtime <- system.time(
  data <- AutoQuant::CreateHolidayVariables(
    data,
    DateCols = "DateTime",
    LookbackDays = NULL,
    HolidayGroups = c("USPublicHolidays","EasterGroup",
      "ChristmasGroup","OtherEcclesticalFeasts"),
    Holidays = NULL,
    Print = FALSE))
head(data)
print(runtime)

## End(Not run)
```

`CumGainsChart` *CumGainsChart*

Description

Create a cumulative gains chart

Usage

```
CumGainsChart(
  data = NULL,
  PredictedColumnName = "p1",
  TargetColumnName = NULL,
  NumBins = 20,
  SavePlot = FALSE,
  Name = NULL,
  metapath = NULL,
  modelpath = NULL
)
```

Arguments

data	Test data with predictions. data.table
PredictedColumnName	Name of column that is the model score
TargetColumnName	Name of your target variable column
NumBins	Number of percentile bins to plot
SavePlot	FALSE by default
Name	File name for saving
metapath	Path to directory
modelpath	Path to directory

Author(s)

Adrian Antico

See Also

Other Model Evaluation and Interpretation: AutoShapeShap(), EvalPlot(), ParDepCalPlots(), ROCPlot(), RedYellowGreen(), ResidualPlots(), SingleRowShapeShap(), threshOptim()

DataTable *DataTable*

Description

Fully loaded DT::datatable() with args prefilled

Usage

```
DataTable(data, FixedCols = 2)
```

Arguments

data	source data.table
FixedCols	Number of columns from the left to Freeze, like freeze panes in Excel. Default is 2

Author(s)

Adrian Antico

See Also

Other Shiny: DataTable2()

Examples

```
## Not run:
# Rmarkdown example of DataTable inside a <details> </Details> section

```{r Get Dependencies For DT::datatable(), echo=FALSE,include = FALSE}
# You need this code to conduct the magic dependences attaching...
DT::datatable(matrix())
```

```{js Nest All DT::datatable() inside a details drop down, echo=FALSE}
setTimeout(function() {
  var codes = document.querySelectorAll('.dataTables_wrapper');
  var code, i, d, s, p;
  for (i = 0; i < codes.length; i++) {
    code = codes[i];
    p = code.parentNode;
    d = document.createElement('details');
    s = document.createElement('summary');
    s.innerText = 'Details';
    // <details><summary>Details</summary></details>
      d.appendChild(s);
    // move the code into <details>
      p.replaceChild(d, code);
    d.appendChild(code);
  }
});
```

```{r Example, echo = FALSE}
AutoQuant::DataTable(data)
````

Shiny Usage
output$Table <- shiny::renderUI({AutoQuant::DataTable(data)})

End(Not run)
```

DataTable2 *DataTable2*

Description

Fully loaded DT::datatable() with args prefilled

Usage

```
DataTable2(data, FixedCols = 2L)
```

Arguments

data	source data.table
FixedCols	= 2L

Author(s)

Adrian Antico

See Also

Other Shiny: DataTable()

Examples

```
## Not run:
# Rmarkdown example of DataTable2 inside a <details> </Details> section

```{r Get Dependencies For DT::datatable(), echo=FALSE,include = FALSE}
# You need this code to conduct the magic dependences attaching...
DT::datatable(matrix())
```

```{js Nest All DT::datatable() inside a details drop down, echo=FALSE}
setTimeout(function() {
  var codes = document.querySelectorAll('.dataTables_wrapper');
  var code, i, d, s, p;
  for (i = 0; i < codes.length; i++) {
    code = codes[i];
    p = code.parentNode;
    d = document.createElement('details');
    s = document.createElement('summary');
    s.innerText = 'Details';
    // <details><summary>Details</summary></details>
      d.appendChild(s);
    // move the code into <details>
      p.replaceChild(d, code);
    d.appendChild(code);
  }
});
```

```{r Example, echo = FALSE}
AutoQuant::DataTable2(data)
````

Shiny Usage
output$Table <- shiny::renderUI({AutoQuant::DataTable2(data)})

End(Not run)
```

DensityPlot *DensityPlot*

Description

Density plots, by groups, with transparent continuous plots

Usage

```
DensityPlot(data, GroupVariables, MeasureVars)
```

Arguments

data	data.table
GroupVariables	= NULL
MeasureVariables	= NULL

See Also

Other Graphics: AddFacet(), BarPlot(), BoxPlot(), ChartTheme(), CorrMatrixPlot(), HeatMapPlot(), HistPlot(), PlotlyConversion(), StockData(), StockPlot(), ViolinPlot(), multiplot()

DummifyDT *DummifyDT*

Description

DummifyDT creates dummy variables for the selected columns. Either one-hot encoding, N+1 columns for N levels, or N columns for N levels.

Usage

```
DummifyDT(
  data,
  cols,
  TopN = NULL,
  KeepFactorCols = FALSE,
  OneHot = FALSE,
  SaveFactorLevels = FALSE,
  SavePath = NULL,
  ImportFactorLevels = FALSE,
  FactorLevelsList = NULL,
  ClustScore = FALSE,
  ReturnFactorLevels = FALSE,
  GroupVar = FALSE
)
```

Arguments

data	The data set to run the micro auc on
cols	A vector with the names of the columns you wish to dichotomize
TopN	Default is NULL. Scalar to apply to all categorical columns or a vector to apply to each categorical variable. Only create dummy variables for the TopN number of levels. Will be either TopN or max(levels)
KeepFactorCols	Set to TRUE to keep the original columns used in the dichotomization process
OneHot	Set to TRUE to run one hot encoding, FALSE to generate N columns for N levels
SaveFactorLevels	Set to TRUE to save unique levels of each factor column to file as a csv
SavePath	Provide a file path to save your factor levels. Use this for models that you have to create dummy variables for.
ImportFactorLevels	Instead of using the data you provide, import the factor levels csv to ensure you build out all of the columns you trained with in modeling.
FactorLevelsList	Supply a list of factor variable levels
ClustScore	This is for scoring AutoKMeans. It converts the added dummy column names to conform with H2O dummy variable naming convention
ReturnFactorLevels	If you want a named list of all the factor levels returned, set this to TRUE. Doing so will cause the function to return a list with the source data.table and the list of factor variables' levels
GroupVar	Ignore this

Value

Either a data table with new dummy variables columns and optionally removes base columns (if ReturnFactorLevels is FALSE), otherwise a list with the data.table and a list of the factor levels.

Author(s)

Adrian Antico

See Also

Other Feature Engineering: AutoDataPartition(), AutoDiffLagN(), AutoHierarchicalFourier(), AutoInteraction(), AutoLagRollMode(), AutoLagRollStatsScoring(), AutoLagRollStats(), AutoTransformationCreate(), AutoTransformationScore(), AutoWord2VecModeler(), AutoWord2VecScoring() CategoricalEncoding(), CreateCalendarVariables(), CreateHolidayVariables(), H2OAutoencoderScoring() H2OAutoencoder(), ModelDataPrep(), PercRankScoring(), PercRank(), StandardizeScoring(), Standardize(), TimeSeriesFillRoll(), TimeSeriesFill()

Examples

```
## Not run:
data <- AutoQuant::FakeDataGenerator(
  Correlation = 0.85,
  N = 25000,
```

```
  ID = 2L,
  ZIP = 0,
  FactorCount = 10L,
  AddDate = FALSE,
  Classification = FALSE,
  MultiClass = FALSE)

# Create dummy variables
data <- AutoQuant::DummifyDT(
  data = data,
  cols = c("Factor_1",
           "Factor_2",
           "Factor_3",
           "Factor_4",
           "Factor_5",
           "Factor_6",
           "Factor_8",
           "Factor_9",
           "Factor_10"),
  TopN = c(rep(3,9)),
  KeepFactorCols = TRUE,
  OneHot = FALSE,
  SaveFactorLevels = TRUE,
  SavePath = getwd(),
  ImportFactorLevels = FALSE,
  FactorLevelsList = NULL,
  ClustScore = FALSE,
  ReturnFactorLevels = FALSE)

# Create Fake Data for Scoring Replication
data <- AutoQuant::FakeDataGenerator(
  Correlation = 0.85,
  N = 25000,
  ID = 2L,
  ZIP = 0,
  FactorCount = 10L,
  AddDate = FALSE,
  Classification = FALSE,
  MultiClass = FALSE)

# Scoring Version
data <- AutoQuant::DummifyDT(
  data = data,
  cols = c("Factor_1",
           "Factor_2",
           "Factor_3",
           "Factor_4",
           "Factor_5",
           "Factor_6",
           "Factor_8",
           "Factor_9",
           "Factor_10"),
  TopN = c(rep(3,9)),
  KeepFactorCols = TRUE,
  OneHot = FALSE,
  SaveFactorLevels = TRUE,
  SavePath = getwd(),
```

```
  ImportFactorLevels = TRUE,
  FactorLevelsList = NULL,
  ClustScore = FALSE,
  ReturnFactorLevels = FALSE)

## End(Not run)
```

EDA_Histograms *EDA_Histograms*

Description

Creates histograms

Usage

```
EDA_Histograms(
  data = NULL,
  PlotColumns = NULL,
  SampleCount = 1e+05,
  SavePath = NULL,
  FactorCountPerPlot = 10,
  AddDensityLine = FALSE,
  PrintOutput = FALSE,
  Size = 12,
  AngleX = 35,
  AngleY = 0,
  ChartColor = "lightsteelblue1",
  BorderColor = "darkblue",
  TextColor = "darkblue",
  GridColor = "white",
  BackGroundColor = "gray95",
  LegendPosition = "bottom"
)
```

Arguments

data	Input data.table
PlotColumns	Default NULL. If NULL, all columns will be plotted (except date cols). Otherwise, supply a character vector of columns names to plot
SampleCount	Number of random samples to use from data. data is first shuffled and then random samples taken
SavePath	Output file path to where you can optionally save pdf
FactorCountPerPlot	Default 10
AddDensityLine	Set to TRUE to add a density line to the plots
PrintOutput	Default FALSE. TRUE will print results upon running function
Size	Default 12
AngleX	Default 35

AngleY	Default 0
ChartColor	Default "lightsteelblue1"
BorderColor	Default "darkblue"
TextColor	Default "darkblue"
GridColor	Default "white"
BackGroundColor	Default "gray95"
LegendPosition	Default "bottom"

Author(s)

Adrian Antico

See Also

Other EDA: AutoWordFreq(), Mode(), PlotGUI(), ScatterCopula(), UserBaseEvolution()

EvalPlot *EvalPlot*

Description

This function automatically builds calibration plots and calibration boxplots for model evaluation using regression, quantile regression, and binary and multinomial classification

Usage

```
EvalPlot(
  data,
  PredictionColName = c("PredictedValues"),
  TargetColName = c("ActualValues"),
  GraphType = c("calibration"),
  PercentileBucket = 0.05,
  aggrfun = function(x) mean(x, na.rm = TRUE)
)
```

Arguments

data	Data containing predicted values and actual values for comparison
PredictionColName	String representation of column name with predicted values from model
TargetColName	String representation of column name with target values from model
GraphType	Calibration or boxplot - calibration aggregated data based on summary statistic; boxplot shows variation
PercentileBucket	Number of buckets to partition the space on (0,1) for evaluation
aggrfun	The statistics function used in aggregation, listed as a function

Value

Calibration plot or boxplot

Author(s)

Adrian Antico

See Also

Other Model Evaluation and Interpretation: AutoShapeShap(), CumGainsChart(), ParDepCalPlots(), ROCPlot(), RedYellowGreen(), ResidualPlots(), SingleRowShapeShap(), threshOptim()

Examples

```
## Not run:
# Create fake data
data <- AutoQuant::FakeDataGenerator(
  Correlation = 0.70, N = 10000000, Classification = TRUE)
data.table::setnames(data, "IDcol_1", "Predict")

# Run function
AutoQuant::EvalPlot(
  data,
  PredictionColName = "Predict",
  TargetColName = "Adrian",
  GraphType = "calibration",
  PercentileBucket = 0.05,
  aggrfun = function(x) mean(x, na.rm = TRUE))

## End(Not run)
```

FakeDataGenerator *FakeDataGenerator*

Description

Create fake data for examples

Usage

```
FakeDataGenerator(
  Correlation = 0.7,
  N = 1000L,
  ID = 5L,
  FactorCount = 2L,
  AddDate = TRUE,
  AddComment = FALSE,
  AddWeightsColumn = FALSE,
  ZIP = 5L,
  TimeSeries = FALSE,
  TimeSeriesTimeAgg = "day",
  ChainLadderData = FALSE,
```

```
  Classification = FALSE,
  MultiClass = FALSE
)
```

Arguments

Correlation	Set the correlation value for simulated data
N	Number of records
ID	Number of IDcols to include
FactorCount	Number of factor type columns to create
AddDate	Set to TRUE to include a date column
AddComment	Set to TRUE to add a comment column
ZIP	Zero Inflation Model target variable creation. Select from 0 to 5 to create that number of distinctly distributed data, stratifed from small to large
TimeSeries	For testing AutoBanditSarima
TimeSeriesTimeAgg	Choose from "1min", "5min", "10min", "15min", "30min", "hour", "day", "week", "month", "quarter", "year",
ChainLadderData	Set to TRUE to return Chain Ladder Data for using AutoMLChainLadderTrainer
Classification	Set to TRUE to build classification data
MultiClass	Set to TRUE to build MultiClass data

Author(s)

Adrian Antico

Examples

```
## Not run:
# Create dummy data to test regression, classification, and multiclass models.
#   I don't care too much about actual relationships but I can test out on the
#   regression problem since those variables will be correlated. The binary and
#   multiclass won't however since they were created separately.

# Regression
data <- AutoQuant::FakeDataGenerator(
  Correlation = 0.77,
  N = 1000000L,
  ID = 4L,
  FactorCount = 5L,
  AddDate = TRUE,
  AddComment = TRUE,
  AddWeightsColumn = TRUE,
  ZIP = 0L,
  TimeSeries = FALSE,
  TimeSeriesTimeAgg = "day",
  ChainLadderData = FALSE,
  Classification = FALSE,
  MultiClass = FALSE)

# Classification
```

```
data2 <- AutoQuant::FakeDataGenerator(
  Correlation = 0.77,
  N = 1000000L,
  ID = 4L,
  FactorCount = 5L,
  AddDate = TRUE,
  AddComment = TRUE,
  AddWeightsColumn = TRUE,
  ZIP = 0L,
  TimeSeries = FALSE,
  TimeSeriesTimeAgg = "day",
  ChainLadderData = FALSE,
  Classification = TRUE,
  MultiClass = FALSE)

# MultiClass
data3 <- AutoQuant::FakeDataGenerator(
  Correlation = 0.77,
  N = 1000000L,
  ID = 4L,
  FactorCount = 5L,
  AddDate = TRUE,
  AddComment = TRUE,
  AddWeightsColumn = TRUE,
  ZIP = 0L,
  TimeSeries = FALSE,
  TimeSeriesTimeAgg = "day",
  ChainLadderData = FALSE,
  Classification = FALSE,
  MultiClass = TRUE)

data.table::setnames(data, 'Adrian', 'RegressionTarget')
data.table::setnames(data2, 'Adrian', 'BinaryTarget')
data.table::setnames(data3, 'Adrian', 'MultiClassTarget')

data <- cbind(data, data2$BinaryTarget, data3$MultiClassTarget)
data.table::setnames(data, c('V2','V3'), c('BinaryTarget','MultiClassTarget'))
data.table::setcolorder(data, c(1, c(ncol(data)-1,ncol(data),2:(ncol(data)-2))))

# Load to warehouse
AutoQuant::PostGRE_RemoveCreateAppend(
  data = data,
  Append = TRUE,
  TableName = "App_QA_BigData",
  CloseConnection = TRUE,
  CreateSchema = NULL,
  Host = "localhost",
  DBName = "AutoQuant",
  User = "postgres",
  Port = 5432,
  Password = "",
  Temporary = FALSE,
  Connection = NULL)

## End(Not run)
```

GenTSAnomVars *GenTSAnomVars*

Description

GenTSAnomVars is an automated z-score anomaly detection via GLM-like procedure. Data is z-scaled and grouped by factors and time periods to determine which points are above and below the control limits in a cumulative time fashion. Then a cumulative rate is created as the final variable. Set KeepAllCols to FALSE to utilize the intermediate features to create rolling stats from them. The anomalies are separated into those that are extreme on the positive end versus those that are on the negative end.

Usage

```
GenTSAnomVars(
  data,
  ValueCol = "Value",
  GroupVars = NULL,
  DateVar = "DATE",
  HighThreshold = 1.96,
  LowThreshold = -1.96,
  KeepAllCols = TRUE,
  IsDataScaled = FALSE
)
```

Arguments

data	the source residuals data.table
ValueCol	the numeric column to run anomaly detection over
GroupVars	this is a group by variable
DateVar	this is a time variable for grouping
HighThreshold	this is the threshold on the high end
LowThreshold	this is the threshold on the low end
KeepAllCols	set to TRUE to remove the intermediate features
IsDataScaled	set to TRUE if you already scaled your data

Value

The original data.table with the added columns merged in. When KeepAllCols is set to FALSE, you will get back two columns: AnomHighRate and AnomLowRate - these are the cumulative anomaly rates over time for when you get anomalies from above the thresholds (e.g. 1.96) and below the thresholds.

Author(s)

Adrian Antico

See Also

Other Unsupervised Learning: AutoClusteringScoring(), AutoClustering(), H2OIsolationForestScoring(), H2OIsolationForest(), ResidualOutliers()

Examples

```
## Not run:
data <- data.table::data.table(
  DateTime = as.Date(Sys.time()),
  Target = stats::filter(
    rnorm(10000, mean = 50, sd = 20),
  filter=rep(1,10),
  circular=TRUE))
data[, temp := seq(1:10000)][, DateTime := DateTime - temp][
  , temp := NULL]
data <- data[order(DateTime)]
x <- data.table::as.data.table(sde::GBM(N=10000)*1000)
data[, predicted := x[-1,]]
data[, Fact1 := sample(letters, size = 10000, replace = TRUE)]
data[, Fact2 := sample(letters, size = 10000, replace = TRUE)]
data[, Fact3 := sample(letters, size = 10000, replace = TRUE)]
stuff <- GenTSAnomVars(
  data,
  ValueCol = "Target",
  GroupVars = c("Fact1","Fact2","Fact3"),
  DateVar = "DateTime",
  HighThreshold = 1.96,
  LowThreshold = -1.96,
  KeepAllCols = TRUE,
  IsDataScaled  = FALSE)

## End(Not run)
```

`H2OAutoencoder` *H2OAutoencoder*

Description

H2OAutoencoder for anomaly detection and or dimensionality reduction

Usage

```
H2OAutoencoder(
  AnomalyDetection = FALSE,
  DimensionReduction = TRUE,
  data,
  Features = NULL,
  RemoveFeatures = FALSE,
  NThreads = max(1L, parallel::detectCores() - 2L),
  MaxMem = "28G",
  H2OStart = TRUE,
  H2OShutdown = TRUE,
  ModelID = "TestModel",
  model_path = NULL,
  LayerStructure = NULL,
  NodeShrinkRate = (sqrt(5) - 1)/2,
  ReturnLayer = 4L,
  ReturnFactorCount = NULL,
```

```
  per_feature = TRUE,
  Activation = "Tanh",
  Epochs = 5L,
  L2 = 0.1,
  ElasticAveraging = TRUE,
  ElasticAveragingMovingRate = 0.9,
  ElasticAveragingRegularization = 0.001
)
```

Arguments

AnomalyDetection	Set to TRUE to run anomaly detection
DimensionReduction	Set to TRUE to run dimension reduction
data	The data.table with the columns you wish to have analyzed
Features	NULL Column numbers or column names
RemoveFeatures	Set to TRUE if you want the features you specify in the Features argument to be removed from the data returned
NThreads	max(1L, parallel::detectCores()-2L)
MaxMem	"28G"
H2OStart	TRUE to start H2O inside the function
H2OShutdown	Setting to TRUE will shutdown H2O when it done being used internally.
ModelID	"TestModel"
model_path	If NULL no model will be saved. If a valid path is supplied the model will be saved there
LayerStructure	If NULL, layers and sizes will be created for you, using NodeShrinkRate and 7 layers will be created.
NodeShrinkRate	= (sqrt(5) - 1) / 2,
ReturnLayer	Which layer of the NNet to return. Choose from 1-7 with 4 being the layer with the least amount of nodes
ReturnFactorCount	Default is NULL. If you supply a number, the final layer will be that number. Otherwise, it will be based on the NodeShrinkRate math.
per_feature	Set to TRUE to have per feature anomaly detection generated. Otherwise and overall value will be generated
Activation	Choose from "Tanh", "TanhWithDropout", "Rectifier", "RectifierWithDropout","Maxout", "MaxoutWithDropout"
Epochs	Quantile value to find the cutoff value for classifying outliers
L2	Specify the amount of memory to allocate to H2O. E.g. "28G"
ElasticAveraging	Specify the number of threads (E.g. cores * 2)
ElasticAveragingMovingRate	Specify the number of decision trees to build
ElasticAveragingRegularization	Specify the row sample rate per tree

Value

A data.table

Author(s)

Adrian Antico

See Also

Other Feature Engineering: AutoDataPartition(), AutoDiffLagN(), AutoHierarchicalFourier(), AutoInteraction(), AutoLagRollMode(), AutoLagRollStatsScoring(), AutoLagRollStats(), AutoTransformationCreate(), AutoTransformationScore(), AutoWord2VecModeler(), AutoWord2VecScoring() CategoricalEncoding(), CreateCalendarVariables(), CreateHolidayVariables(), DummifyDT(), H2OAutoencoderScoring(), ModelDataPrep(), PercRankScoring(), PercRank(), StandardizeScoring(), Standardize(), TimeSeriesFillRoll(), TimeSeriesFill()

Examples

```
## Not run:
############################
# Training
############################

# Create simulated data
data <- AutoQuant::FakeDataGenerator(
  Correlation = 0.70,
  N = 1000L,
  ID = 2L,
  FactorCount = 2L,
  AddDate = TRUE,
  AddComment = FALSE,
  ZIP = 2L,
  TimeSeries = FALSE,
  ChainLadderData = FALSE,
  Classification = FALSE,
  MultiClass = FALSE)

# Run algo
Output <- AutoQuant::H2OAutoencoder(

  # Select the service
  AnomalyDetection = TRUE,
  DimensionReduction = TRUE,

  # Data related args
  data = data,
  Features = names(data)[2L:(ncol(data)-1L)],
  per_feature = FALSE,
  RemoveFeatures = FALSE,
  ModelID = "TestModel",
  model_path = getwd(),

  # H2O Environment
  NThreads = max(1L, parallel::detectCores()-2L),
  MaxMem = "28G",
  H2OStart = TRUE,
```

```
  H2OShutdown = TRUE,

  # H2O ML Args
  LayerStructure = NULL,
  NodeShrinkRate = (sqrt(5) - 1) / 2,
  ReturnLayer = 4L,
  ReturnFactorCount = NULL,
  Activation = "Tanh",
  Epochs = 5L,
  L2 = 0.10,
  ElasticAveraging = TRUE,
  ElasticAveragingMovingRate = 0.90,
  ElasticAveragingRegularization = 0.001)

# Inspect output
data <- Output$Data
Model <- Output$Model

# If ValidationData is not null
ValidationData <- Output$ValidationData

############################
# Scoring
############################

# Create simulated data
data <- AutoQuant::FakeDataGenerator(
  Correlation = 0.70,
  N = 1000L,
  ID = 2L,
  FactorCount = 2L,
  AddDate = TRUE,
  AddComment = FALSE,
  ZIP = 2L,
  TimeSeries = FALSE,
  ChainLadderData = FALSE,
  Classification = FALSE,
  MultiClass = FALSE)

# Run algo
data <- AutoQuant::H2OAutoencoderScoring(

  # Select the service
  AnomalyDetection = TRUE,
  DimensionReduction = TRUE,

  # Data related args
  data = data,
  Features = names(data)[2L:ncol(data)],
  RemoveFeatures = TRUE,
  per_feature = FALSE,
  ModelObject = NULL,
  ModelID = "TestModel",
  model_path = getwd(),

  # H2O args
  NThreads = max(1L, parallel::detectCores()-2L),
```

```
  MaxMem = "28G",
  H2OStart = TRUE,
  H2OShutdown = TRUE,
  ReturnLayer = 4L)

## End(Not run)
```

H2OAutoencoderScoring *H2OAutoencoderScoring*

Description

H2OAutoencoderScoring for anomaly detection and or dimensionality reduction

Usage

```
H2OAutoencoderScoring(
  data,
  Features = NULL,
  RemoveFeatures = FALSE,
  ModelObject = NULL,
  AnomalyDetection = TRUE,
  DimensionReduction = TRUE,
  ReturnLayer = 4L,
  per_feature = TRUE,
  NThreads = max(1L, parallel::detectCores() - 2L),
  MaxMem = "28G",
  H2OStart = TRUE,
  H2OShutdown = TRUE,
  ModelID = "TestModel",
  model_path = NULL
)
```

Arguments

data	The data.table with the columns you wish to have analyzed
Features	NULL Column numbers or column names
RemoveFeatures	Set to TRUE if you want the features you specify in the Features argument to be removed from the data returned
ModelObject	If NULL then the model will be loaded from file. Otherwise, it will use what is supplied
AnomalyDetection	Set to TRUE to run anomaly detection
DimensionReduction	Set to TRUE to run dimension reduction
ReturnLayer	Which layer of the NNet to return. Choose from 1-7 with 4 being the layer with the least amount of nodes
per_feature	Set to TRUE to have per feature anomaly detection generated. Otherwise and overall value will be generated

NThreads	max(1L, parallel::detectCores()-2L)
MaxMem	"28G"
H2OStart	TRUE to start H2O inside the function
H2OShutdown	Setting to TRUE will shutdown H2O when it done being used internally.
ModelID	"TestModel"
model_path	If NULL no model will be saved. If a valid path is supplied the model will be saved there

Value

A data.table

Author(s)

Adrian Antico

See Also

Other Feature Engineering: AutoDataPartition(), AutoDiffLagN(), AutoHierarchicalFourier(), AutoInteraction(), AutoLagRollMode(), AutoLagRollStatsScoring(), AutoLagRollStats(), AutoTransformationCreate(), AutoTransformationScore(), AutoWord2VecModeler(), AutoWord2VecScoring() CategoricalEncoding(), CreateCalendarVariables(), CreateHolidayVariables(), DummifyDT(), H2OAutoencoder(), ModelDataPrep(), PercRankScoring(), PercRank(), StandardizeScoring(), Standardize(), TimeSeriesFillRoll(), TimeSeriesFill()

Examples

```
## Not run:
############################
# Training
############################

# Create simulated data
data <- AutoQuant::FakeDataGenerator(
  Correlation = 0.70,
  N = 1000L,
  ID = 2L,
  FactorCount = 2L,
  AddDate = TRUE,
  AddComment = FALSE,
  ZIP = 2L,
  TimeSeries = FALSE,
  ChainLadderData = FALSE,
  Classification = FALSE,
  MultiClass = FALSE)

# Run algo
data <- AutoQuant::H2OAutoencoder(

  # Select the service
  AnomalyDetection = TRUE,
  DimensionReduction = TRUE,

  # Data related args
```

```
  data = data,
  ValidationData = NULL,
  Features = names(data)[2L:(ncol(data)-1L)],
  per_feature = FALSE,
  RemoveFeatures = TRUE,
  ModelID = "TestModel",
  model_path = getwd(),

  # H2O Environment
  NThreads = max(1L, parallel::detectCores()-2L),
  MaxMem = "28G",
  H2OStart = TRUE,
  H2OShutdown = TRUE,

  # H2O ML Args
  LayerStructure = NULL,
  ReturnLayer = 4L,
  Activation = "Tanh",
  Epochs = 5L,
  L2 = 0.10,
  ElasticAveraging = TRUE,
  ElasticAveragingMovingRate = 0.90,
  ElasticAveragingRegularization = 0.001)

############################
# Scoring
############################

# Create simulated data
data <- AutoQuant::FakeDataGenerator(
  Correlation = 0.70,
  N = 1000L,
  ID = 2L,
  FactorCount = 2L,
  AddDate = TRUE,
  AddComment = FALSE,
  ZIP = 2L,
  TimeSeries = FALSE,
  ChainLadderData = FALSE,
  Classification = FALSE,
  MultiClass = FALSE)

# Run algo
data <- AutoQuant::H2OAutoencoderScoring(

  # Select the service
  AnomalyDetection = TRUE,
  DimensionReduction = TRUE,

  # Data related args
  data = data,
  Features = names(data)[2L:ncol(data)],
  RemoveFeatures = TRUE,
  per_feature = FALSE,
  ModelObject = NULL,
  ModelID = "TestModel",
  model_path = getwd(),
```

```
  # H2O args
  NThreads = max(1L, parallel::detectCores()-2L),
  MaxMem = "28G",
  H2OStart = TRUE,
  H2OShutdown = TRUE,
  ReturnLayer = 4L)

## End(Not run)
```

`H2OIsolationForest` *H2OIsolationForest*

Description

H2OIsolationForestScoring for dimensionality reduction and / or anomaly detection

Usage

```
H2OIsolationForest(
  data,
  Features = NULL,
  IDcols = NULL,
  ModelID = "TestModel",
  SavePath = NULL,
  Threshold = 0.975,
  MaxMem = "28G",
  NThreads = -1,
  NTrees = 100,
  MaxDepth = 8,
  MinRows = 1,
  RowSampleRate = (sqrt(5) - 1)/2,
  ColSampleRate = 1,
  ColSampleRatePerLevel = 1,
  ColSampleRatePerTree = 1,
  CategoricalEncoding = c("AUTO"),
  Debug = FALSE
)
```

Arguments

`data`	The data.table with the columns you wish to have analyzed
`Features`	A character vector with the column names to utilize in the isolation forest
`IDcols`	A character vector with the column names to not utilize in the isolation forest but have returned with the data output. Otherwise those columns will be removed
`ModelID`	Name for model that gets saved to file if SavePath is supplied and valid
`SavePath`	Path directory to store saved model
`Threshold`	Quantile value to find the cutoff value for classifying outliers
`MaxMem`	Specify the amount of memory to allocate to H2O. E.g. "28G"
`NThreads`	Specify the number of threads (E.g. cores * 2)

NTrees	Specify the number of decision trees to build
MaxDepth	Max tree depth
MinRows	Minimum number of rows allowed per leaf
RowSampleRate	Number of rows to sample per tree
ColSampleRate	Sample rate for each split
ColSampleRatePerLevel	Sample rate for each level
ColSampleRatePerTree	Sample rate per tree
CategoricalEncoding	Choose from "AUTO", "Enum", "OneHotInternal", "OneHotExplicit", "Binary", "Eigen", "LabelEncoder", "SortByResponse", "EnumLimited"
Debug	Debugging

Value

Source data.table with predictions. Note that any columns not listed in Features nor IDcols will not be returned with data. If you want columns returned but not modeled, supply them as IDcols

Author(s)

Adrian Antico

See Also

Other Unsupervised Learning: AutoClusteringScoring(), AutoClustering(), GenTSAnomVars(), H2OIsolationForestScoring(), ResidualOutliers()

Examples

```
## Not run:
# Create simulated data
data <- AutoQuant::FakeDataGenerator(
  Correlation = 0.70,
  N = 50000,
  ID = 2L,
  FactorCount = 2L,
  AddDate = TRUE,
  ZIP = 0L,
  TimeSeries = FALSE,
  ChainLadderData = FALSE,
  Classification = FALSE,
  MultiClass = FALSE)

# Run algo
data <- AutoQuant::H2OIsolationForest(
  data,
  Features = names(data)[2L:ncol(data)],
  IDcols = c("Adrian", "IDcol_1", "IDcol_2"),
  ModelID = "Adrian",
  SavePath = getwd(),
  Threshold = 0.95,
  MaxMem = "28G",
```

```
  NThreads = -1,
  NTrees = 100,
  MaxDepth = 8,
  MinRows = 1,
  RowSampleRate = (sqrt(5)-1)/2,
  ColSampleRate = 1,
  ColSampleRatePerLevel = 1,
  ColSampleRatePerTree = 1,
  CategoricalEncoding = c("AUTO"),
  Debug = TRUE)

# Remove output from data and then score
data[, eval(names(data)[17:ncol(data)]) := NULL]

# Run algo
Outliers <- AutoQuant::H2OIsolationForestScoring(
  data,
  Features = names(data)[2:ncol(data)],
  IDcols = c("Adrian", "IDcol_1", "IDcol_2"),
  H2OStart = TRUE,
  H2OShutdown = TRUE,
  ModelID = "TestModel",
  SavePath = getwd(),
  Threshold = 0.95,
  MaxMem = "28G",
  NThreads = -1,
  Debug = FALSE)

## End(Not run)
```

`H2OIsolationForestScoring`

H2OIsolationForestScoring

Description

H2OIsolationForestScoring for dimensionality reduction and / or anomaly detection scoring on new data

Usage

```
H2OIsolationForestScoring(
  data,
  Features = NULL,
  IDcols = NULL,
  H2OStart = TRUE,
  H2OShutdown = TRUE,
  ModelID = "TestModel",
  SavePath = NULL,
  Threshold = 0.975,
  MaxMem = "28G",
  NThreads = -1,
  Debug = FALSE
)
```

Arguments

data	The data.table with the columns you wish to have analyzed
Features	A character vector with the column names to utilize in the isolation forest
IDcols	A character vector with the column names to not utilize in the isolation forest but have returned with the data output. Otherwise those columns will be removed
H2OStart	TRUE to have H2O started inside function
H2OShutdown	TRUE to shutdown H2O inside function
ModelID	Name for model that gets saved to file if SavePath is supplied and valid
SavePath	Path directory to store saved model
Threshold	Quantile value to find the cutoff value for classifying outliers
MaxMem	Specify the amount of memory to allocate to H2O. E.g. "28G"
NThreads	Specify the number of threads (E.g. cores * 2)
Debug	Debugging

Value

Source data.table with predictions. Note that any columns not listed in Features nor IDcols will not be returned with data. If you want columns returned but not modeled, supply them as IDcols

Author(s)

Adrian Antico

See Also

Other Unsupervised Learning: AutoClusteringScoring(), AutoClustering(), GenTSAnomVars(), H2OIsolationForest(), ResidualOutliers()

Examples

```
## Not run:
# Create simulated data
data <- AutoQuant::FakeDataGenerator(
  Correlation = 0.70,
  N = 50000,
  ID = 2L,
  FactorCount = 2L,
  AddDate = TRUE,
  ZIP = 0L,
  TimeSeries = FALSE,
  ChainLadderData = FALSE,
  Classification = FALSE,
  MultiClass = FALSE)

# Run algo
data <- AutoQuant::H2OIsolationForest(
  data,
  Features = names(data)[2L:ncol(data)],
  IDcols = c("Adrian", "IDcol_1", "IDcol_2"),
  ModelID = "Adrian",
  SavePath = getwd(),
```

```
  Threshold = 0.95,
  MaxMem = "28G",
  NThreads = -1,
  NTrees = 100,
  SampleRate = (sqrt(5)-1)/2,
  MaxDepth = 8,
  MinRows = 1,
  ColSampleRate = 1,
  ColSampleRatePerLevel = 1,
  ColSampleRatePerTree = 1,
  CategoricalEncoding = c("AUTO"),
  Debug = TRUE)

# Remove output from data and then score
data[, eval(names(data)[17:ncol(data)]) := NULL]

# Run algo
Outliers <- AutoQuant::H2OIsolationForestScoring(
  data,
  Features = names(data)[2:ncol(data)],
  IDcols = c("Adrian", "IDcol_1", "IDcol_2"),
  H2OStart = TRUE,
  H2OShutdown = TRUE,
  ModelID = "TestModel",
  SavePath = getwd(),
  Threshold = 0.95,
  MaxMem = "28G",
  NThreads = -1,
  Debug = FALSE)

## End(Not run)
```

HeatMapPlot *HeatMapPlot*

Description

Create heat maps with numeric or categorical dt

Usage

```
HeatMapPlot(
  dt,
  x = NULL,
  y = NULL,
  z = NULL,
  AggMethod = "mean",
  PercentileBuckets_X = 0.1,
  PercentileBuckets_Y = 0.1,
  NLevels_X = 33,
  NLevels_Y = 33
)
```

Arguments

dt	Source data.table
x	X-Axis variable
y	Y-Axis variable
z	Z-Axis variable
AggMethod	'mean', 'median', 'sum', 'sd', 'count'
PercentileBuckets_X	= 0.10
PercentileBuckets_Y	= 0.10
NLevels_X	= 20
NLevels_Y	= 20
RankLevels_X	= 'mean'

Author(s)

Adrian Antico

See Also

Other Graphics: AddFacet(), BarPlot(), BoxPlot(), ChartTheme(), CorrMatrixPlot(), DensityPlot(), HistPlot(), PlotlyConversion(), StockData(), StockPlot(), ViolinPlot(), multiplot()

HistPlot *HistPlot*

Description

Build a histogram plot by simply passing arguments to a single function. It will sample your data using SampleSize number of rows. Sampled data is randomized.

Usage

```
HistPlot(
  data = NULL,
  XVar = NULL,
  YVar = NULL,
  ColorVar = NULL,
  FacetVar1 = NULL,
  FacetVar2 = NULL,
  SampleSize = 1000000L,
  Bins = 30,
  FillColor = "gray",
  OutlierSize = 0.1,
  OutlierColor = "blue",
  YTicks = "Default",
  XTicks = "Default",
  TextSize = 12,
  AngleX = 90,
```

```
  AngleY = 0,
  ChartColor = "aliceblue",
  BorderColor = "darkblue",
  TextColor = "darkblue",
  GridColor = "#d3d3e0",
  BackGroundColor = "gray95",
  SubTitleColor = "blue",
  LegendPosition = "bottom",
  LegendBorderSize = 0.5,
  LegendLineType = "solid",
  Debug = FALSE
)
```

Arguments

data	Source data.table
XVar	Column name of X-Axis variable. If NULL then ignored
YVar	Column name of Y-Axis variable. If NULL then ignored
ColorVar	Column name of Group Variable for distinct colored histograms by group levels
FacetVar1	Column name of facet variable 1. If NULL then ignored
FacetVar2	Column name of facet variable 2. If NULL then ignored
SampleSize	An integer for the number of rows to use. Sampled data is randomized. If NULL then ignored
Bins	= 30
FillColor	'gray'
OutlierSize	0.10
OutlierColor	'blue'
YTicks	Choose from 'Default', 'Percentiles', 'Every 5th percentile', 'Deciles', 'Quantiles', 'Quartiles'
XTicks	Choose from 'Default', '1 year', '1 day', '3 day', '1 week', '2 week', '1 month', '3 month', '6 month', '2 year', '5 year', '10 year', '1 minute', '15 minutes', '30 minutes', '1 hour', '3 hour', '6 hour', '12 hour'
TextSize	14
AngleX	90
AngleY	0
ChartColor	'lightsteelblue'
BorderColor	'darkblue'
TextColor	'darkblue'
GridColor	'white'
BackGroundColor	'gray95'
SubTitleColor	'darkblue'
LegendPosition	'bottom'
LegendBorderSize	0.50
LegendLineType	'solid'
Debug	FALSE

Author(s)

Adrian Antico

See Also

Other Graphics: AddFacet(), BarPlot(), BoxPlot(), ChartTheme(), CorrMatrixPlot(), DensityPlot(), HeatMapPlot(), PlotlyConversion(), StockData(), StockPlot(), ViolinPlot(), multiplot()

Examples

```
## Not run:
# Load packages
library(AutoQuant)
library(data.table)

# Load data
data <- data.table::fread(file = file.path('C:/Users/Bizon/Documents/GitHub/BenchmarkData1.csv'))

# Run function
p1 <- AutoQuant:::HistPlot(
  data = data,
  XVar = NULL,
  YVar = 'Weekly_Sales',
  ColorVar = 'Region',
  FacetVar1 = 'Store',
  FacetVar2 = 'Dept',
  SampleSize = 1000000L,
  Bins = 20,
  FillColor = 'gray',
  YTicks = 'Default',
  XTicks = 'Default',
  TextSize = 12,
  AngleX = 90,
  AngleY = 0,
  ChartColor = 'lightsteelblue1',
  BorderColor = 'darkblue',
  TextColor = 'darkblue',
  GridColor = 'white',
  BackGroundColor = 'gray95',
  SubTitleColor = 'blue',
  LegendPosition = 'bottom',
  LegendBorderSize = 0.50,
  LegendLineType = 'solid',
  Debug = FALSE)

# Step through function
# # plotly::ggplotly(p1)
# XVar = NULL
# YVar = 'Weekly_Sales'
# AggMethod = 'mean'
# ColorVar = 'Region'
# FacetVar1 = NULL
# FacetVar2 = NULL
# Bins = 20
# SampleSize = 1000000L
# FillColor = 'gray'
```

```
# YTicks = 'Default'
# XTicks = 'Default'
# TextSize = 12
# AngleX = 90
# AngleY = 0
# ChartColor = 'lightsteelblue1'
# BorderColor = 'darkblue'
# TextColor = 'darkblue'
# GridColor = 'white'
# BackGroundColor = 'gray95'
# SubTitleColor = 'blue'
# LegendPosition = 'bottom'
# LegendBorderSize = 0.50
# LegendLineType = 'solid'
# Debug = FALSE
# Bins

## End(Not run)
```

Mode *Mode*

Description

Statistical mode. Only returns the first mode if there are many

Usage

```
Mode(x)
```

Arguments

x	vector

Author(s)

Adrian Antico

See Also

Other EDA: AutoWordFreq(), EDA_Histograms(), PlotGUI(), ScatterCopula(), UserBaseEvolution()

ModelDataPrep *ModelDataPrep*

Description

This function replaces inf values with NA, converts characters to factors, and imputes with constants

Usage

```
ModelDataPrep(
  data,
  Impute = TRUE,
  CharToFactor = TRUE,
  FactorToChar = FALSE,
  IntToNumeric = TRUE,
  LogicalToBinary = FALSE,
  DateToChar = FALSE,
  IDateConversion = FALSE,
  RemoveDates = FALSE,
  MissFactor = "0",
  MissNum = -1,
  IgnoreCols = NULL
)
```

Arguments

data	This is your source data you'd like to modify
Impute	Defaults to TRUE which tells the function to impute the data
CharToFactor	Defaults to TRUE which tells the function to convert characters to factors
FactorToChar	Converts to character
IntToNumeric	Defaults to TRUE which tells the function to convert integers to numeric
LogicalToBinary	Converts logical values to binary numeric values
DateToChar	Converts date columns into character columns
IDateConversion	Convert IDateTime to POSIXct and IDate to Date types
RemoveDates	Defaults to FALSE. Set to TRUE to remove date columns from your data.table
MissFactor	Supply the value to impute missing factor levels
MissNum	Supply the value to impute missing numeric values
IgnoreCols	Supply column numbers for columns you want the function to ignore

Value

Returns the original data table with corrected values

Author(s)

Adrian Antico

See Also

Other Feature Engineering: AutoDataPartition(), AutoDiffLagN(), AutoHierarchicalFourier(), AutoInteraction(), AutoLagRollMode(), AutoLagRollStatsScoring(), AutoLagRollStats(), AutoTransformationCreate(), AutoTransformationScore(), AutoWord2VecModeler(), AutoWord2VecScoring(), CategoricalEncoding(), CreateCalendarVariables(), CreateHolidayVariables(), DummifyDT(), H2OAutoencoderScoring(), H2OAutoencoder(), PercRankScoring(), PercRank(), StandardizeScoring(), Standardize(), TimeSeriesFillRoll(), TimeSeriesFill()

Examples

```
## Not run:
# Create fake data
data <- AutoQuant::FakeDataGenerator(
  Correlation = 0.75,
  N = 250000L,
  ID = 2L,
  ZIP = 0L,
  FactorCount = 6L,
  AddDate = TRUE,
  Classification = FALSE,
  MultiClass = FALSE)

# Check column types
str(data)

# Convert some factors to character
data <- AutoQuant::ModelDataPrep(
  data,
  Impute       = TRUE,
  CharToFactor = FALSE,
  FactorToChar = TRUE,
  IntToNumeric = TRUE,
  LogicalToBinary = FALSE,
  DateToChar   = FALSE,
  IDateConversion = FALSE,
  RemoveDates  = TRUE,
  MissFactor   = "0",
  MissNum      = -1,
  IgnoreCols   = c("Factor_1"))

# Check column types
str(data)

## End(Not run)
```

ModelInsightsReport *ModelInsightsReport*

Description

ModelInsightsReport is an Rmarkdown report for viewing the model insights generated by AutoQuant supervised learning functions

Usage

```
ModelInsightsReport(
  KeepOutput = NULL,
  TrainData = NULL,
  ValidationData = NULL,
  TestData = NULL,
  TargetColumnName = NULL,
  PredictionColumnName = "Predict",
  FeatureColumnNames = NULL,
  DateColumnName = NULL,
  TargetType = "regression",
  ModelID = "ModelTest",
  Algo = "catboost",
  SourcePath = NULL,
  OutputPath = NULL,
  ModelObject = NULL,
  Test_Importance_dt = NULL,
  Validation_Importance_dt = NULL,
  Train_Importance_dt = NULL,
  Test_Interaction_dt = NULL,
  Validation_Interaction_dt = NULL,
  Train_Interaction_dt = NULL,
  GlobalVars = ls()
)
```

Arguments

KeepOutput	NULL A list of output names to select. Pass in as a character vector. E.g. c('Test_VariableImportance', 'Train_VariableImportance')
TrainData	data.table or something that converts to data.table via as.data.table
ValidationData	data.table or something that converts to data.table via as.data.table
TestData	data.table or something that converts to data.table via as.data.table
TargetColumnName	NULL. Target variable column name as character
PredictionColumnName	NULL. Predicted value column name as character. 'p1' for AutoQuant functions
FeatureColumnNames	NULL. Feature column names as character vector.
DateColumnName	NULL. Date column name as character
TargetType	'regression', 'classification', or 'multiclass'
ModelID	ModelID used in the AutoQuant supervised learning function
Algo	'catboost' or 'other'. Use 'catboost' if using AutoQuant::AutoCatBoost_() functions. Otherwise, 'other'
SourcePath	Path to directory with AutoQuant Model Output
OutputPath	Path to directory where the html will be saved
ModelObject	Returned output from regression, classificaiton, and multiclass Remix Auto_() models. Currenly supports CatBoost, XGBoost, and LightGBM models

`Test_Importance_dt`
: NULL.. Ignore if using AutoQuant Models. Otherwise, supply a two column data.table with colnames 'Variable' and 'Importance'

`Validation_Importance_dt`
: NULL.. Ignore if using AutoQuant Models. Otherwise, supply a two column data.table with colnames 'Variable' and 'Importance'

`Train_Importance_dt`
: NULL.. Ignore if using AutoQuant Models. Otherwise, supply a two column data.table with colnames 'Variable' and 'Importance'

`Test_Interaction_dt`
: NULL.. Ignore if using AutoQuant Models. Otherwise, supply a three column data.table with colnames 'Features1', 'Features2' and 'score'

`Validation_Interaction_dt`
: NULL.. Ignore if using AutoQuant Models. Otherwise, supply a three column data.table with colnames 'Features1', 'Features2' and 'score'

`Train_Interaction_dt`
: NULL.. Ignore if using AutoQuant Models. Otherwise, supply a three column data.table with colnames 'Features1', 'Features2' and 'score'

`GlobalVars`
: ls() don't use

`Path`
: Path to Model Output if ModelObject is left NULL

Author(s)

Adrian Antico

See Also

Other Model Insights: `ShapImportancePlot()`

Examples

```
## Not run:

######################################################
# CatBoost
######################################################

# Create some dummy correlated data
data <- AutoQuant::FakeDataGenerator(
  Correlation = 0.85,
  N = 10000,
  ID = 2,
  ZIP = 0,
  AddDate = FALSE,
  Classification = FALSE,
  MultiClass = FALSE)

# Copy data
data1 <- data.table::copy(data)

# Run function
ModelObject <- AutoQuant::AutoCatBoostRegression(

  # GPU or CPU and the number of available GPUs
```

```
TrainOnFull = FALSE,
task_type = 'GPU',
NumGPUs = 1,
DebugMode = FALSE,

# Metadata args
OutputSelection = c('Importances','EvalPlots','EvalMetrics','Score_TrainData'),
ModelID = 'Test_Model_1',
model_path = getwd(),
metadata_path = getwd(),
SaveModelObjects = FALSE,
SaveInfoToPDF = FALSE,
ReturnModelObjects = TRUE,

# Data args
data = data1,
ValidationData = NULL,
TestData = NULL,
TargetColumnName = 'Adrian',
FeatureColNames = names(data1)[!names(data1) %in% c('IDcol_1','IDcol_2','Adrian')],
PrimaryDateColumn = NULL,
WeightsColumnName = NULL,
IDcols = c('IDcol_1','IDcol_2'),
TransformNumericColumns = 'Adrian',
Methods = c('Asinh','Asin','Log','LogPlus1','Sqrt','Logit'),

# Model evaluation
eval_metric = 'RMSE',
eval_metric_value = 1.5,
loss_function = 'RMSE',
loss_function_value = 1.5,
MetricPeriods = 10L,
NumOfParDepPlots = ncol(data1)-1L-2L,

# Grid tuning args
PassInGrid = NULL,
GridTune = FALSE,
MaxModelsInGrid = 30L,
MaxRunsWithoutNewWinner = 20L,
MaxRunMinutes = 60*60,
BaselineComparison = 'default',

# ML args
langevin = FALSE,
diffusion_temperature = 10000,
Trees = 500,
Depth = 9,
L2_Leaf_Reg = NULL,
RandomStrength = 1,
BorderCount = 128,
LearningRate = NULL,
RSM = 1,
BootStrapType = NULL,
GrowPolicy = 'SymmetricTree',
model_size_reg = 0.5,
feature_border_type = 'GreedyLogSum',
sampling_unit = 'Object',
```

```
  subsample = NULL,
  score_function = 'Cosine',
  min_data_in_leaf = 1)

# Create Model Insights Report
AutoQuant::ModelInsightsReport(

  # Items to keep in global environment when
  #   function finishes execution
  KeepOutput = 'Test_VariableImportance',

  # DataSets
  TrainData = NULL,
  ValidationData = NULL,
  TestData = NULL,

  # Meta info
  TargetColumnName = NULL,
  PredictionColumnName = NULL,
  FeatureColumnNames = NULL,
  DateColumnName = NULL,

  # Variable Importance
  Test_Importance_dt = NULL,
  Validation_Importance_dt = NULL,
  Train_Importance_dt = NULL,
  Test_Interaction_dt = NULL,
  Validation_Interaction_dt = NULL,
  Train_Interaction_dt = NULL,

  # Control options
  TargetType = 'regression',
  ModelID = 'ModelTest',
  Algo = 'catboost',
  SourcePath = getwd(),
  OutputPath = getwd(),
  ModelObject = ModelObject)

## End(Not run)
```

`multiplot` *multiplot*

Description

Sick of copying this one into your code? Well, not anymore.

Usage

```
multiplot(plotlist = NULL)
```

Arguments

`plotlist`	This is the list of your charts

Value

Multiple ggplots on a single image

Author(s)

Adrian Antico

See Also

Other Graphics: AddFacet(), BarPlot(), BoxPlot(), ChartTheme(), CorrMatrixPlot(), DensityPlot(), HeatMapPlot(), HistPlot(), PlotlyConversion(), StockData(), StockPlot(), ViolinPlot()

Examples

```
## Not run:
Correl <- 0.85
data <- data.table::data.table(Target = runif(100))
data[, x1 := qnorm(Target)]
data[, x2 := runif(100)]
data[, Independent_Variable1 := log(
  pnorm(Correl * x1 + sqrt(1-Correl^2) * qnorm(x2)))]
data[, Predict := (
  pnorm(Correl * x1 + sqrt(1-Correl^2) * qnorm(x2)))]
p1 <- AutoQuant::ParDepCalPlots(
  data,
  PredictionColName = "Predict",
  TargetColName = "Target",
  IndepVar = "Independent_Variable1",
  GraphType = "calibration",
  PercentileBucket = 0.20,
  FactLevels = 10,
  Function = function(x) mean(x, na.rm = TRUE))
p2 <- AutoQuant::ParDepCalPlots(
  data,
  PredictionColName = "Predict",
  TargetColName = "Target",
  IndepVar = "Independent_Variable1",
  GraphType = "boxplot",
  PercentileBucket = 0.20,
  FactLevels = 10,
  Function = function(x) mean(x, na.rm = TRUE))
AutoQuant::multiplot(plotlist = list(p1,p2))

## End(Not run)
```

ParDepCalPlots *ParDepCalPlots*

Description

This function automatically builds partial dependence calibration plots and partial dependence calibration boxplots for model evaluation using regression, quantile regression, and binary and multinomial classification

Usage

```
ParDepCalPlots(
  data,
  PredictionColName = NULL,
  TargetColName = NULL,
  IndepVar = NULL,
  GraphType = "calibration",
  PercentileBucket = 0.05,
  FactLevels = 10,
  Function = function(x) mean(x, na.rm = TRUE),
  DateColumn = NULL,
  DateAgg_3D = NULL,
  PlotYMeanColor = "black",
  PlotXMeanColor = "chocolate",
  PlotXLowColor = "purple",
  PlotXHighColor = "purple"
)
```

Arguments

`data`	Data containing predicted values and actual values for comparison
`PredictionColName`	Predicted values column names
`TargetColName`	Target value column names
`IndepVar`	Independent variable column names
`GraphType`	calibration or boxplot - calibration aggregated data based on summary statistic; boxplot shows variation
`PercentileBucket`	Number of buckets to partition the space on (0,1) for evaluation
`FactLevels`	The number of levels to show on the chart (1. Levels are chosen based on frequency; 2. all other levels grouped and labeled as "Other")
`Function`	Supply the function you wish to use for aggregation.
`DateColumn`	Add date column for 3D scatterplot
`DateAgg_3D`	Aggregate date column by 'day', 'week', 'month', 'quarter', 'year'

Value

Partial dependence calibration plot or boxplot

Author(s)

Adrian Antico

See Also

Other Model Evaluation and Interpretation: `AutoShapeShap()`, `CumGainsChart()`, `EvalPlot()`, `ROCPlot()`, `RedYellowGreen()`, `ResidualPlots()`, `SingleRowShapeShap()`, `threshOptim()`

Examples

```
## Not run:
# Create fake data
data <- AutoQuant::FakeDataGenerator(
  Correlation = 0.70, N = 10000000, Classification = FALSE)
data.table::setnames(data, "Independent_Variable2", "Predict")

# Build plot
Plot <- AutoQuant::ParDepCalPlots(
  data,
  PredictionColName = "Predict",
  TargetColName = "Adrian",
  IndepVar = "Independent_Variable1",
  GraphType = "calibration",
  PercentileBucket = 0.20,
  FactLevels = 10,
  Function = function(x) mean(x, na.rm = TRUE),
  DateColumn = NULL,
  DateAgg_3D = NULL)

# Step through function
# PredictionColName = "Predict"
# TargetColName = "Adrian"
# IndepVar = "Independent_Variable1"
# GraphType = "calibration"
# PercentileBucket = 0.20
# FactLevels = 10
# Function = function(x) mean(x, na.rm = TRUE)
# DateColumn = NULL
# DateAgg_3D = NULL

## End(Not run)
```

PercRank *PercRank*

Description

Generate percent ranks for multiple variables, by groups if provided, and with a selected granularity

Usage

```
PercRank(
  data,
  ColNames,
  GroupVars = NULL,
  Granularity = 0.001,
  ScoreTable = FALSE
)
```

Arguments

data	Source data.table

ColNames	Character vector of column names
GroupVars	Character vector of column names to have percent ranks by the group levels
Granularity	Provide a value such that data.table::frank(Variable) * (1 / Granularity) / .N * Granularity. Default is 0.001
ScoreTable	= FALSE. Set to TRUE to get the reference values for applying to new data. Pass to scoring version of this function

Author(s)

Adrian Antico

See Also

Other Feature Engineering: AutoDataPartition(), AutoDiffLagN(), AutoHierarchicalFourier(), AutoInteraction(), AutoLagRollMode(), AutoLagRollStatsScoring(), AutoLagRollStats(), AutoTransformationCreate(), AutoTransformationScore(), AutoWord2VecModeler(), AutoWord2VecScoring() CategoricalEncoding(), CreateCalendarVariables(), CreateHolidayVariables(), DummifyDT(), H2OAutoencoderScoring(), H2OAutoencoder(), ModelDataPrep(), PercRankScoring(), StandardizeScoring(), Standardize(), TimeSeriesFillRoll(), TimeSeriesFill()

Examples

```
## Not run:
data <- data.table::fread(file.choose())
x <- PercRank(data, ColNames = c('Weekly_Sales', 'XREG1'), GroupVars = c('Region','Store','Dept'), Granularity

## End(Not run)
```

PercRankScoring *PercRankScoring*

Description

Generate percent ranks for multiple variables, by groups if provided, and with a selected granularity, via list passed from PercRank

Usage

```
PercRankScoring(data, ScoreTable, GroupVars = NULL, RollDirection = "forward")
```

Arguments

data	Source data.table
ScoreTable	list of values returned from PercRank
GroupVars	Character vector of column names to have percent ranks by the group levels
RollDirection	"forward" or "backward"

Author(s)

Adrian Antico

See Also

Other Feature Engineering: AutoDataPartition(), AutoDiffLagN(), AutoHierarchicalFourier(), AutoInteraction(), AutoLagRollMode(), AutoLagRollStatsScoring(), AutoLagRollStats(), AutoTransformationCreate(), AutoTransformationScore(), AutoWord2VecModeler(), AutoWord2VecScoring(), CategoricalEncoding(), CreateCalendarVariables(), CreateHolidayVariables(), DummifyDT(), H2OAutoencoderScoring(), H2OAutoencoder(), ModelDataPrep(), PercRank(), StandardizeScoring(), Standardize(), TimeSeriesFillRoll(), TimeSeriesFill()

PlotGUI *PlotGUI*

Description

Spin up the esquisse plotting gui

Usage

```
PlotGUI()
```

See Also

Other EDA: AutoWordFreq(), EDA_Histograms(), Mode(), ScatterCopula(), UserBaseEvolution()

PosteGRE_CreateDatabase *PostGRE_CreateDatabase*

Description

PostGRE_CreateDatabase will create a database with a name supplied by user

Usage

```
PosteGRE_CreateDatabase(
  DBName = NULL,
  Connection = NULL,
  CloseConnection = TRUE,
  Host = "localhost",
  Port = 5432,
  User = "postgres",
  Password = ""
)
```

Arguments

DBName	See args from related functions
Connection	See args from related functions
CloseConnection	See args from related functions
Host	See args from related functions
Port	See args from related functions
User	See args from related functions
Password	See args from related functions

Author(s)

Adrian Antico

See Also

Other Database: AutoDataDictionaries(), PostGRE_AppendData(), PostGRE_CreateTable(), PostGRE_GetTableNames(), PostGRE_ListTables(), PostGRE_Query(), PostGRE_RemoveCreateAppend(), PostGRE_RemoveTable(), PosteGRE_DropDB(), PosteGRE_ListDatabases(), SQL_ClearTable(), SQL_DropTable(), SQL_Query_Push(), SQL_Query(), SQL_SaveTable(), SQL_Server_DBConnection()

PosteGRE_DropDB *PosteGRE_DropDB*

Description

PosteGRE_DropDB Drop selected database if it exists

Usage

```
PosteGRE_DropDB(
  DBName = NULL,
  Host = "localhost",
  Port = 5432,
  User = "postgres",
  Password = "",
  Connection = NULL,
  CloseConnection = TRUE
)
```

Arguments

DBName	name of db
Host	See args from related functions
Port	See args from related functions
User	See args from related functions
Password	See args from related functions
Connection	See args from related functions
CloseConnection	See args from related functions

Author(s)

Adrian Antico

See Also

Other Database: AutoDataDictionaries(), PostGRE_AppendData(), PostGRE_CreateTable(), PostGRE_GetTableNames(), PostGRE_ListTables(), PostGRE_Query(), PostGRE_RemoveCreateAppend(), PostGRE_RemoveTable(), PosteGRE_CreateDatabase(), PosteGRE_ListDatabases(), SQL_ClearTable(), SQL_DropTable(), SQL_Query_Push(), SQL_Query(), SQL_SaveTable(), SQL_Server_DBConnection()

PosteGRE_ListDatabases

PosteGRE_ListDatabases

Description

PosteGRE_ListDatabases list of available databases

Usage

```
PosteGRE_ListDatabases(
  Host = "localhost",
  Port = 5432,
  User = "postgres",
  Password = "",
  Connection = NULL,
  CloseConnection = TRUE
)
```

Arguments

Host	See args from related functions
Port	See args from related functions
User	See args from related functions
Password	See args from related functions
Connection	See args from related functions
CloseConnection	See args from related functions

Author(s)

Adrian Antico

See Also

Other Database: AutoDataDictionaries(), PostGRE_AppendData(), PostGRE_CreateTable(), PostGRE_GetTableNames(), PostGRE_ListTables(), PostGRE_Query(), PostGRE_RemoveCreateAppend(), PostGRE_RemoveTable(), PosteGRE_CreateDatabase(), PosteGRE_DropDB(), SQL_ClearTable(), SQL_DropTable(), SQL_Query_Push(), SQL_Query(), SQL_SaveTable(), SQL_Server_DBConnection()

PostGRE_AppendData *PostGRE_AppendData*

Description

PostGRE_AppendData get data from a database table

Usage

```
PostGRE_AppendData(
  data = NULL,
  TableName = NULL,
  Append = FALSE,
  Connection = NULL,
  CloseConnection = FALSE,
  Host = NULL,
  DBName = NULL,
  User = NULL,
  Port = NULL,
  Password = NULL
)
```

Arguments

data	Source data.table
Append	Set to TRUE to append data, FALSE to overwrite data
Connection	db connection
CloseConnection	= FALSE
Host	If Connection is NULL then this must be supplied. host
DBName	If Connection is NULL then this must be supplied. dbname
User	If Connection is NULL then this must be supplied. user
Port	If Connection is NULL then this must be supplied. port
Password	If Connection is NULL then this must be supplied. password

Author(s)

Adrian Antico

See Also

Other Database: AutoDataDictionaries(), PostGRE_CreateTable(), PostGRE_GetTableNames(), PostGRE_ListTables(), PostGRE_Query(), PostGRE_RemoveCreateAppend(), PostGRE_RemoveTable(), PosteGRE_CreateDatabase(), PosteGRE_DropDB(), PosteGRE_ListDatabases(), SQL_ClearTable(), SQL_DropTable(), SQL_Query_Push(), SQL_Query(), SQL_SaveTable(), SQL_Server_DBConnection()

Examples

```
## Not run:
AutoQuant::PostGRE_AppendData(
  data = data,
  TableName = 'somename',
  Append = FALSE,
  CloseConnection = FALSE,
  Host = 'localhost',
  DBName = 'AutoQuant',
  User = 'postgres',
  Port = 5432,
  Password = 'Aa...')

# data = data
# CloseConnection = FALSE,
# Host = 'localhost'
# DBName = 'Testing'
# User = 'postgres'
# Port = 5432
# Password = 'Aa...'

## End(Not run)
```

PostGRE_CreateTable *PostGRE_CreateTable*

Description

PostGRE_CreateTable get data from a database table

Usage

```
PostGRE_CreateTable(
  data = NULL,
  DBName = NULL,
  Schema = NULL,
  TableName = NULL,
  Connection = NULL,
  CloseConnection = FALSE,
  Temporary = FALSE,
  Host = NULL,
  User = NULL,
  Port = NULL,
  Password = NULL
)
```

Arguments

data	Source data.table. If you supply a Schema, data will be ignored.
DBName	If Connection is NULL then this must be supplied. database name
Schema	Optional. Advised to use if type inference is fuzzy

TableName	Name of table you want created
Connection	NULL. If supplied, use this: Connection <- DBI::dbConnect(RPostgres::Postgres(), host = Host, dbname = DBName, user = User, port = Port, password = Password)
CloseConnection	= FALSE
Temporary	If Connection is NULL then this must be supplied. FALSE
Host	If Connection is NULL then this must be supplied. host name
User	If Connection is NULL then this must be supplied. user name
Port	If Connection is NULL then this must be supplied. port name
Password	user password

Author(s)

Adrian Antico

See Also

Other Database: AutoDataDictionaries(), PostGRE_AppendData(), PostGRE_GetTableNames(), PostGRE_ListTables(), PostGRE_Query(), PostGRE_RemoveCreateAppend(), PostGRE_RemoveTable(), PosteGRE_CreateDatabase(), PosteGRE_DropDB(), PosteGRE_ListDatabases(), SQL_ClearTable(), SQL_DropTable(), SQL_Query_Push(), SQL_Query(), SQL_SaveTable(), SQL_Server_DBConnection()

Examples

```
## Not run:
AutoQuant::PostGRE_CreateTable(
  data,
  DBName = 'Testing',
  Schema = NULL,
  TableName = NULL,
  Temporary = FALSE,
  Connection = NULL,
  CloseConnection = FALSE,
  Host = 'localhost',
  User = 'postgres',
  Port = 5432,
  Password = 'Aa...')

## End(Not run)
```

PostGRE_GetTableNames *PostGRE_GetTableNames*

Description

PostGRE_GetTableNames will list all column names from a table

Usage

```
PostGRE_GetTableNames(
  Host = NULL,
  CloseConnection = FALSE,
  DBName = NULL,
  TableName = NULL,
  User = NULL,
  Port = NULL,
  Password = NULL
)
```

Arguments

Host	See args from related functions
CloseConnection	See args from related functions
DBName	See args from related functions
TableName	Name of postgres table
User	See args from related functions
Port	See args from related functions
Password	See args from related functions

Value

A character vector of names. Exactly like names R base function for a data.frame

Author(s)

Adrian Antico

See Also

Other Database: AutoDataDictionaries(), PostGRE_AppendData(), PostGRE_CreateTable(), PostGRE_ListTables(), PostGRE_Query(), PostGRE_RemoveCreateAppend(), PostGRE_RemoveTable(), PosteGRE_CreateDatabase(), PosteGRE_DropDB(), PosteGRE_ListDatabases(), SQL_ClearTable(), SQL_DropTable(), SQL_Query_Push(), SQL_Query(), SQL_SaveTable(), SQL_Server_DBConnection()

PostGRE_ListTables *PostGRE_ListTables*

Description

PostGRE_ListTables will list all tables with an associated db

Usage

```
PostGRE_ListTables(
  DBName = NULL,
  Connection = NULL,
  CloseConnection = TRUE,
  Host = NULL,
  Port = NULL,
  User = NULL,
  Password = NULL
)
```

Arguments

DBName	See args from related functions
Connection	See args from related functions
CloseConnection	See args from related functions
Host	See args from related functions
Port	See args from related functions
User	See args from related functions
Password	See args from related functions
Temporary	See args from related functions

Author(s)

Adrian Antico

See Also

Other Database: AutoDataDictionaries(), PostGRE_AppendData(), PostGRE_CreateTable(), PostGRE_GetTableNames(), PostGRE_Query(), PostGRE_RemoveCreateAppend(), PostGRE_RemoveTable(), PosteGRE_CreateDatabase(), PosteGRE_DropDB(), PosteGRE_ListDatabases(), SQL_ClearTable(), SQL_DropTable(), SQL_Query_Push(), SQL_Query(), SQL_SaveTable(), SQL_Server_DBConnection()

PostGRE_Query *PostGRE_Query*

Description

PostGRE_Query get data from a database table

Usage

```
PostGRE_Query(
  Query = NULL,
  Connection = NULL,
  CloseConnection = FALSE,
  Host = NULL,
  DBName = NULL,
```

```
  User = NULL,
  Port = NULL,
  Password = NULL
)
```

Arguments

Query	SQL Statement in quotes
Connection	db connection
CloseConnection	= FALSE
Host	If Connection is NULL then this must be supplied. host
DBName	If Connection is NULL then this must be supplied. dbname
User	If Connection is NULL then this must be supplied. user
Port	If Connection is NULL then this must be supplied. port
Password	If Connection is NULL then this must be supplied. password

Author(s)

Adrian Antico

See Also

Other Database: AutoDataDictionaries(), PostGRE_AppendData(), PostGRE_CreateTable(), PostGRE_GetTableNames(), PostGRE_ListTables(), PostGRE_RemoveCreateAppend(), PostGRE_RemoveTable(), PosteGRE_CreateDatabase(), PosteGRE_DropDB(), PosteGRE_ListDatabases(), SQL_ClearTable(), SQL_DropTable(), SQL_Query_Push(), SQL_Query(), SQL_SaveTable(), SQL_Server_DBConnection()

Examples

```
## Not run:

# Query data from table with Uppercase name
data <- AutoQuant::PostGRE_Query(
  Query = paste0("SELECT * FROM ", shQuote('Devices')),
  Host = 'localhost',
  CloseConnection = FALSE,
  DBName = 'Testing',
  User = 'postgres',
  Port = 5432,
  Password = 'Aa...')

# Query = 'Select * from static_data'
# Host = 'localhost'
# DBName = 'Testing'
# CloseConnection = FALSE,
# User = 'postgres'
# Port = 5432
# Password = 'Aa...'

# Create Schema
query <- "CREATE SCHEMA AutoQuant AUTHORIZATION postgres;"
AutoQuant::PostGRE_Query(
```

```
  Query = query,
  Host = 'localhost',
  CloseConnection = FALSE,
  DBName = 'Testing',
  User = 'postgres',
  Port = 5432,
  Password = 'Aa...')

## End(Not run)
```

PostGRE_RemoveCreateAppend *PostGRE_RemoveCreateAppend*

Description

PostGRE_RemoveCreateAppend will DROP the table specified

Usage

```
PostGRE_RemoveCreateAppend(
  data = NULL,
  TableName = NULL,
  CloseConnection = TRUE,
  CreateSchema = NULL,
  Host = NULL,
  DBName = NULL,
  User = NULL,
  Port = NULL,
  Password = NULL,
  Temporary = FALSE,
  Connection = NULL,
  Append = TRUE
)
```

Arguments

data	See args from related functions
TableName	See args from related functions
CloseConnection	See args from related functions
CreateSchema	See args from related functions
Host	See args from related functions
DBName	See args from related functions
User	See args from related functions
Port	See args from related functions
Password	See args from related functions
Temporary	See args from related functions
Connection	See args from related functions
Append	See args from related functions

Author(s)

Adrian Antico

See Also

Other Database: AutoDataDictionaries(), PostGRE_AppendData(), PostGRE_CreateTable(), PostGRE_GetTableNames(), PostGRE_ListTables(), PostGRE_Query(), PostGRE_RemoveTable(), PosteGRE_CreateDatabase(), PosteGRE_DropDB(), PosteGRE_ListDatabases(), SQL_ClearTable(), SQL_DropTable(), SQL_Query_Push(), SQL_Query(), SQL_SaveTable(), SQL_Server_DBConnection()

PostGRE_RemoveTable *PostGRE_RemoveTable*

Description

PostGRE_RemoveTable will DROP the table specified

Usage

```
PostGRE_RemoveTable(
  TableName = NULL,
  Connection = NULL,
  CloseConnection = FALSE,
  Host = NULL,
  DBName = NULL,
  User = NULL,
  Port = NULL,
  Password = NULL
)
```

Arguments

TableName	Name of table you want created
Connection	NULL. If supplied, use this: Connection <- DBI::dbConnect(RPostgres::Postgres(), host = Host, dbname = DBName, user = User, port = Port, password = Password)
CloseConnection	= FALSE
Host	If Connection is NULL then this must be supplied. Host name
DBName	If Connection is NULL then this must be supplied. database name
User	If Connection is NULL then this must be supplied. user name
Port	If Connection is NULL then this must be supplied. port name
Password	If Connection is NULL then this must be supplied. user password

Author(s)

Adrian Antico

See Also

Other Database: AutoDataDictionaries(), PostGRE_AppendData(), PostGRE_CreateTable(), PostGRE_GetTableNames(), PostGRE_ListTables(), PostGRE_Query(), PostGRE_RemoveCreateAppend(), PosteGRE_CreateDatabase(), PosteGRE_DropDB(), PosteGRE_ListDatabases(), SQL_ClearTable(), SQL_DropTable(), SQL_Query_Push(), SQL_Query(), SQL_SaveTable(), SQL_Server_DBConnection()

Examples

```
## Not run:
AutoQuant::PostGRE_RemoveTable(
  TableName = 'static_data',
  Connection = NULL,
  CloseConnection = FALSE,
  Host = 'localhost',
  DBName = 'Testing',
  User = 'postgres',
  Port = 5432,
  Password = 'Aa...')

# Host = 'localhost'
# TableName = 'static_data'
# Connection = NULL
# DBName = 'Testing'
# User = 'postgres'
# Port = 5432
# Password = 'Aa...'

## End(Not run)
```

RedYellowGreen *RedYellowGreen*

Description

This function will find the optimial thresholds for applying the main label and for finding the optimial range for doing nothing when you can quantity the cost of doing nothing

Usage

```
RedYellowGreen(
  data,
  PredictColNumber = 2,
  ActualColNumber = 1,
  TruePositiveCost = 0,
  TrueNegativeCost = 0,
  FalsePositiveCost = -10,
  FalseNegativeCost = -50,
  MidTierCost = -2,
  Cores = 8,
  Precision = 0.01,
  Boundaries = c(0.05, 0.75)
)
```

Arguments

data	data is the data table with your predicted and actual values from a classification model
PredictColNumber	The column number where the prediction variable is located (in binary form)
ActualColNumber	The column number where the target variable is located
TruePositiveCost	This is the utility for generating a true positive prediction
TrueNegativeCost	This is the utility for generating a true negative prediction
FalsePositiveCost	This is the cost of generating a false positive prediction
FalseNegativeCost	This is the cost of generating a false negative prediction
MidTierCost	This is the cost of doing nothing (or whatever it means to not classify in your case)
Cores	Number of cores on your machine
Precision	Set the decimal number to increment by between 0 and 1
Boundaries	Supply a vector of two values c(lower bound, upper bound) where the first value is the smallest threshold you want to test and the second value is the largest value you want to test. Note, if your results are at the boundaries you supplied, you should extent the boundary that was reached until the values is within both revised boundaries.

Value

A data table with all evaluated strategies, parameters, and utilities, along with a 3d scatterplot of the results

Author(s)

Adrian Antico

See Also

Other Model Evaluation and Interpretation: AutoShapeShap(), CumGainsChart(), EvalPlot(), ParDepCalPlots(), ROCPlot(), ResidualPlots(), SingleRowShapeShap(), threshOptim()

Examples

```
## Not run:
data <- data.table::data.table(Target = runif(10))
data[, x1 := qnorm(Target)]
data[, x2 := runif(10)]
data[, Predict := log(pnorm(0.85 * x1 +
  sqrt(1-0.85^2) * qnorm(x2)))]
data[, ':=' (x1 = NULL, x2 = NULL)]
data <- RedYellowGreen(
  data,
  PredictColNumber  = 2,
```

```
  ActualColNumber   = 1,
  TruePositiveCost  = 0,
  TrueNegativeCost  = 0,
  FalsePositiveCost = -1,
  FalseNegativeCost = -2,
  MidTierCost = -0.5,
  Precision = 0.01,
  Cores = 1,
  Boundaries = c(0.05,0.75))

## End(Not run)
```

`ResidualOutliers` *ResidualOutliers*

Description

ResidualOutliers is an automated time series outlier detection function that utilizes tsoutliers and auto.arima. It looks for five types of outliers: "AO" Additive outliter - a singular extreme outlier that surrounding values aren't affected by; "IO" Innovational outlier - Initial outlier with subsequent anomalous values; "LS" Level shift - An initial outlier with subsequent observations being shifted by some constant on average; "TC" Transient change - initial outlier with lingering effects that dissapate exponentially over time; "SLS" Seasonal level shift - similar to level shift but on a seasonal scale.

Usage

```
ResidualOutliers(
  data,
  DateColName = NULL,
  TargetColName = NULL,
  PredictedColName = NULL,
  TimeUnit = "day",
  Lags = 5,
  Diff = 1,
  MA = 5,
  SLags = 0,
  SDiff = 1,
  SMA = 0,
  tstat = 2,
  FixedParams = FALSE
)
```

Arguments

`data`	the source residuals data.table
`DateColName`	The name of your data column to use in reference to the target variable
`TargetColName`	The name of your target variable column
`PredictedColName`	The name of your predicted value column. If you supply this, you will run anomaly detection of the difference between the target variable and your predicted value. If you leave PredictedColName NULL then you will run anomaly detection over the target variable.

TimeUnit	The time unit of your date column: hour, day, week, month, quarter, year
Lags	the largest lag or moving average (seasonal too) values for the arima fit
Diff	The largest d value for differencing
MA	Max moving average
SLags	Max seasonal lags
SDiff	The largest d value for seasonal differencing
SMA	Max seasonal moving averages
tstat	the t-stat value for tsoutliers
FixedParams	Set to TRUE or FALSE. If TRUE, a stats::Arima() model if fitted with those parameter values. If FALSE, then an auto.arima is built with the parameter values representing the max those values can be.

Value

A named list containing FullData = original data.table with outliers data and ARIMA_MODEL = the arima model object

Author(s)

Adrian Antico

See Also

Other Unsupervised Learning: AutoClusteringScoring(), AutoClustering(), GenTSAnomVars(), H2OIsolationForestScoring(), H2OIsolationForest()

Examples

```
## Not run:
data <- data.table::data.table(
  DateTime = as.Date(Sys.time()),
  Target = as.numeric(
    stats::filter(
      rnorm(1000, mean = 50, sd = 20),
      filter=rep(1,10),
      circular=TRUE)))
data[, temp := seq(1:1000)][, DateTime := DateTime - temp][, temp := NULL]
data.table::setorderv(x = data, cols = 'DateTime', 1)
data[, Predicted := as.numeric(
  stats::filter(
    rnorm(1000, mean = 50, sd = 20),
    filter=rep(1,10),
    circular=TRUE))]
Output <- ResidualOutliers(
  data = data,
  DateColName = "DateTime",
  TargetColName = "Target",
  PredictedColName = NULL,
  TimeUnit = "day",
  Lags = 5,
  Diff = 1,
  MA = 5,
  SLags = 0,
```

```
  SDiff = 0,
  SMA = 0,
  tstat = 4)
data <- Output[['FullData']]
model <- Output[['ARIMA_MODEL']]
outliers <- data[type != "<NA>"]

## End(Not run)
```

ResidualPlots *ResidualPlots*

Description

Residual plots for regression models

Usage

```
ResidualPlots(
  TestData = NULL,
  Target = "Adrian",
  Predicted = "Independent_Variable1",
  DateColumnName = NULL,
  Gam_Fit = FALSE
)
```

Arguments

TestData	= NULL,
Target	= "Adrian",
Predicted	= "Independent_Variable1",
DateColumnName	"DateTime"
Gam_Fit	= TRUE

Author(s)

Adrian Antico

See Also

Other Model Evaluation and Interpretation: AutoShapeShap(), CumGainsChart(), EvalPlot(), ParDepCalPlots(), ROCPlot(), RedYellowGreen(), SingleRowShapeShap(), threshOptim()

Examples

```
## Not run:
# Create fake data
test_data <- AutoQuant::FakeDataGenerator(
  Correlation = 0.80,
  N = 250000,
  ID = 0,
  FactorCount = 0,
```

```
  AddDate = TRUE,
  AddComment = FALSE,
  AddWeightsColumn = FALSE,
  ZIP = 0)

# Build Plots
output <- AutoQuant::ResidualPlots(
  TestData = test_data,
  Target = "Adrian",
  Predicted = "Independent_Variable1",
  DateColumnName = "DateTime",
  Gam_Fit = TRUE)

## End(Not run)
```

ROCPlot *ROCPlot*

Description

Internal usage for classification methods. Returns an ROC plot

Usage

```
ROCPlot(
  data = ValidationData,
  TargetName = TargetColumnName,
  SavePlot = SaveModelObjects,
  Name = ModelID,
  metapath = metadata_path,
  modelpath = model_path
)
```

Arguments

data	validation data
TargetName	Target variable name
SavePlot	TRUE or FALSE
Name	Name for saving
metapath	Passthrough
modelpath	Passthrough

Value

ROC Plot for classification models

Author(s)

Adrian Antico

See Also

Other Model Evaluation and Interpretation: AutoShapeShap(), CumGainsChart(), EvalPlot(), ParDepCalPlots(), RedYellowGreen(), ResidualPlots(), SingleRowShapeShap(), threshOptim()

ScatterCopula *ScatterCopula*

Description

Dual plot. One on original scale and one using empirical copula data

Usage

```
ScatterCopula(
  data = NULL,
  x_var = NULL,
  y_var = NULL,
  Marginals = FALSE,
  MarginalType = "density",
  GroupVariable = NULL,
  FacetCol = NULL,
  FacetRow = NULL,
  SizeVar1 = NULL,
  SampleCount = 100000L,
  FitGam = TRUE,
  color = "darkblue",
  point_size = 0.5,
  text_size = 12,
  x_axis_text_angle = 35,
  y_axis_text_angle = 0,
  chart_color = "lightsteelblue1",
  border_color = "darkblue",
  text_color = "darkblue",
  grid_color = "white",
  background_color = "gray95",
  legend_position = "bottom",
  Debug = FALSE
)
```

Arguments

data	Source data.table
x_var	Numeric variable
y_var	Numeric variable
Marginals	= FALSE,
MarginalType	= 'density',
GroupVariable	Color options
FacetCol	NULL or string

FacetRow	NULL or string
SizeVar1	NULL. Use to size the dots by a variable
SampleCount	Number of randomized rows to utilize. For speedup and memory purposes
FitGam	Add gam fit to scatterplot and copula plot
color	= "darkblue"
point_size	= 0.50
text_size	= 12
x_axis_text_angle	= 35
y_axis_text_angle	= 0
chart_color	= "lightsteelblue1"
border_color	= "darkblue"
text_color	= "darkblue"
grid_color	= "white"
background_color	= "gray95"
legend_position	= "bottom
Debug	= FALSE

Author(s)

Adrian Antico

See Also

Other EDA: AutoWordFreq(), EDA_Histograms(), Mode(), PlotGUI(), UserBaseEvolution()

Examples

```
## Not run:
# Create data
data <- AutoQuant::FakeDataGenerator()

# Build plot
AutoQuant::ScatterCopula(
  data = data,
  x_var = 'Independent_Variable1',
  y_var = 'Independent_Variable2',
  Marginals = FALSE,
  MarginalType = 'density',
  GroupVariable = NULL, #'Factor_1',
  FacetCol = 'Factor_1',
  FacetRow = NULL,
  SizeVar1 = 'Independent_Variable1',
  SampleCount = 100000L,
  FitGam = FALSE,
  color = "darkblue",
  point_size = 0.50,
  text_size = 12,
```

```
  x_axis_text_angle = 35,
  y_axis_text_angle = 0,
  chart_color = "lightsteelblue1",
  border_color = "darkblue",
  text_color = "darkblue",
  grid_color = "white",
  background_color = "gray95",
  legend_position = "bottom",
  Debug = FALSE)

## End(Not run)
```

ShapImportancePlot *ShapImportancePlot*

Description

Generate Variable Importance Plots using Shapely Values of given data set

Usage

```
ShapImportancePlot(
  data,
  ShapColNames = NULL,
  FacetVar1 = NULL,
  FacetVar2 = NULL,
  AggMethod = "mean",
  TopN = 25,
  Debug = FALSE
)
```

Arguments

data	Source data.table
ShapColNames	Names of the columns that contain shap values you want included
FacetVar1	Column name
FacetVar2	Column name
AggMethod	A string for aggregating shapely values for importances. Choices include, 'mean', 'absmean', 'meanabs', 'sd', 'median', 'absmedian', 'medianabs'
TopN	The number of variables to plot
Debug	= FALSE

Author(s)

Adrian Antico

See Also

Other Model Insights: ModelInsightsReport()

SingleRowShapeShap *SingleRowShapeShap*

Description

SingleRowShapeShap will convert a single row of your shap data into a table

Usage

```
SingleRowShapeShap(ShapData = NULL, EntityID = NULL, DateColumnName = NULL)
```

Arguments

ShapData	Scoring data from AutoCatBoostScoring with classification or regression

Author(s)

Adrian Antico

See Also

Other Model Evaluation and Interpretation: AutoShapeShap(), CumGainsChart(), EvalPlot(), ParDepCalPlots(), ROCPlot(), RedYellowGreen(), ResidualPlots(), threshOptim()

SQL_ClearTable *SQL_ClearTable*

Description

SQL_ClearTable remove all rows from a database table

Usage

```
SQL_ClearTable(
  DBConnection,
  SQLTableName = "",
  CloseChannel = TRUE,
  Errors = TRUE
)
```

Arguments

DBConnection	AutoQuant::SQL_Server_DBConnection()
SQLTableName	The SQL statement you want to run
CloseChannel	TRUE to close when done, FALSE to leave the channel open
Errors	Set to TRUE to halt, FALSE to return -1 in cases of errors

Author(s)

Adrian Antico

See Also

Other Database: AutoDataDictionaries(), PostGRE_AppendData(), PostGRE_CreateTable(), PostGRE_GetTableNames(), PostGRE_ListTables(), PostGRE_Query(), PostGRE_RemoveCreateAppend(), PostGRE_RemoveTable(), PosteGRE_CreateDatabase(), PosteGRE_DropDB(), PosteGRE_ListDatabases(), SQL_DropTable(), SQL_Query_Push(), SQL_Query(), SQL_SaveTable(), SQL_Server_DBConnection()

SQL_DropTable *SQL_DropTable*

Description

SQL_DropTable drop a database table

Usage

```
SQL_DropTable(
  DBConnection,
  SQLTableName = "",
  CloseChannel = TRUE,
  Errors = TRUE
)
```

Arguments

DBConnection	AutoQuant::SQL_Server_DBConnection()
SQLTableName	The SQL statement you want to run
CloseChannel	TRUE to close when done, FALSE to leave the channel open
Errors	Set to TRUE to halt, FALSE to return -1 in cases of errors

Author(s)

Adrian Antico

See Also

Other Database: AutoDataDictionaries(), PostGRE_AppendData(), PostGRE_CreateTable(), PostGRE_GetTableNames(), PostGRE_ListTables(), PostGRE_Query(), PostGRE_RemoveCreateAppend(), PostGRE_RemoveTable(), PosteGRE_CreateDatabase(), PosteGRE_DropDB(), PosteGRE_ListDatabases(), SQL_ClearTable(), SQL_Query_Push(), SQL_Query(), SQL_SaveTable(), SQL_Server_DBConnection()

SQL_Query *SQL_Query*

Description

SQL_Query get data from a database table

Usage

```
SQL_Query(
  DBConnection,
  Query,
  ASIS = FALSE,
  CloseChannel = TRUE,
  RowsPerBatch = 1024
)
```

Arguments

DBConnection	AutoQuant::SQL_Server_DBConnection()
Query	The SQL statement you want to run
ASIS	Auto column typing
CloseChannel	TRUE to close when done, FALSE to leave the channel open
RowsPerBatch	Rows default is 1024

Author(s)

Adrian Antico

See Also

Other Database: AutoDataDictionaries(), PostGRE_AppendData(), PostGRE_CreateTable(), PostGRE_GetTableNames(), PostGRE_ListTables(), PostGRE_Query(), PostGRE_RemoveCreateAppend(), PostGRE_RemoveTable(), PosteGRE_CreateDatabase(), PosteGRE_DropDB(), PosteGRE_ListDatabases(), SQL_ClearTable(), SQL_DropTable(), SQL_Query_Push(), SQL_SaveTable(), SQL_Server_DBConnection()

SQL_Query_Push *SQL_Query_Push*

Description

SQL_Query_Push push data to a database table

Usage

```
SQL_Query_Push(DBConnection, Query, CloseChannel = TRUE)
```

Arguments

DBConnection	AutoQuant::SQL_Server_DBConnection()
Query	The SQL statement you want to run
CloseChannel	TRUE to close when done, FALSE to leave the channel open

Author(s)

Adrian Antico

See Also

Other Database: AutoDataDictionaries(), PostGRE_AppendData(), PostGRE_CreateTable(), PostGRE_GetTableNames(), PostGRE_ListTables(), PostGRE_Query(), PostGRE_RemoveCreateAppend(), PostGRE_RemoveTable(), PosteGRE_CreateDatabase(), PosteGRE_DropDB(), PosteGRE_ListDatabases(), SQL_ClearTable(), SQL_DropTable(), SQL_Query(), SQL_SaveTable(), SQL_Server_DBConnection()

SQL_SaveTable *SQL_SaveTable*

Description

SQL_SaveTable create a database table

Usage

```
SQL_SaveTable(
  DataToPush,
  DBConnection,
  SQLTableName = "",
  RowNames = NULL,
  ColNames = TRUE,
  CloseChannel = TRUE,
  AppendData = FALSE,
  AddPK = TRUE,
  Safer = TRUE
)
```

Arguments

DataToPush	data to be sent to warehouse
DBConnection	AutoQuant::SQL_Server_DBConnection()
SQLTableName	The SQL statement you want to run
RowNames	c("Segment","Date")
ColNames	Column names in first row
CloseChannel	TRUE to close when done, FALSE to leave the channel open
AppendData	TRUE or FALSE
AddPK	Add a PK column to table
Safer	TRUE

Author(s)

Adrian Antico

See Also

Other Database: AutoDataDictionaries(), PostGRE_AppendData(), PostGRE_CreateTable(), PostGRE_GetTableNames(), PostGRE_ListTables(), PostGRE_Query(), PostGRE_RemoveCreateAppend(), PostGRE_RemoveTable(), PosteGRE_CreateDatabase(), PosteGRE_DropDB(), PosteGRE_ListDatabases(), SQL_ClearTable(), SQL_DropTable(), SQL_Query_Push(), SQL_Query(), SQL_Server_DBConnection()

`SQL_Server_DBConnection`

SQL_Server_DBConnection

Description

SQL_Server_DBConnection makes a connection to a sql server database

Usage

```
SQL_Server_DBConnection(DataBaseName = "", Server = "")
```

Arguments

`DataBaseName`	Name of the database
`Server`	Name of the server to use

Author(s)

Adrian Antico

See Also

Other Database: AutoDataDictionaries(), PostGRE_AppendData(), PostGRE_CreateTable(), PostGRE_GetTableNames(), PostGRE_ListTables(), PostGRE_Query(), PostGRE_RemoveCreateAppend(), PostGRE_RemoveTable(), PosteGRE_CreateDatabase(), PosteGRE_DropDB(), PosteGRE_ListDatabases(), SQL_ClearTable(), SQL_DropTable(), SQL_Query_Push(), SQL_Query(), SQL_SaveTable()

Standardize *Standardize*

Description

Generate standardized values for multiple variables, by groups if provided, and with a selected granularity

Usage

```
Standardize(
  data,
  ColNames,
  GroupVars = NULL,
  Center = TRUE,
  Scale = TRUE,
  ScoreTable = FALSE
)
```

Arguments

data	Source data.table
ColNames	Character vector of column names
GroupVars	Character vector of column names to have percent ranks by the group levels
Center	TRUE
Scale	TRUE
ScoreTable	FALSE. Set to TRUE to return a data.table that can be used to apply or back-transform via StandardizeScoring

Author(s)

Adrian Antico

See Also

Other Feature Engineering: AutoDataPartition(), AutoDiffLagN(), AutoHierarchicalFourier(), AutoInteraction(), AutoLagRollMode(), AutoLagRollStatsScoring(), AutoLagRollStats(), AutoTransformationCreate(), AutoTransformationScore(), AutoWord2VecModeler(), AutoWord2VecScoring() CategoricalEncoding(), CreateCalendarVariables(), CreateHolidayVariables(), DummifyDT(), H2OAutoencoderScoring(), H2OAutoencoder(), ModelDataPrep(), PercRankScoring(), PercRank(), StandardizeScoring(), TimeSeriesFillRoll(), TimeSeriesFill()

Examples

```
## Not run:
data <- data.table::fread(file.choose())
x <- Standardize(data = data, ColNames = c('Weekly_Sales', 'XREG3'), GroupVars = c('Region','Store','Dept'), Ce

## End(Not run)
```

StandardizeScoring *StandardizeScoring*

Description

Generate standardized values for multiple variables, by groups if provided, and with a selected granularity

Usage

```
StandardizeScoring(data, ScoreTable, Apply = "apply", GroupVars = NULL)
```

Arguments

data	Source data.table
Apply	'apply' or 'backtransform'
GroupVars	Character vector of column names to have percent ranks by the group levels
ColNames	Character vector of column names
Center	TRUE
Scale	TRUE

Author(s)

Adrian Antico

See Also

Other Feature Engineering: AutoDataPartition(), AutoDiffLagN(), AutoHierarchicalFourier(), AutoInteraction(), AutoLagRollMode(), AutoLagRollStatsScoring(), AutoLagRollStats(), AutoTransformationCreate(), AutoTransformationScore(), AutoWord2VecModeler(), AutoWord2VecScoring() CategoricalEncoding(), CreateCalendarVariables(), CreateHolidayVariables(), DummifyDT(), H2OAutoencoderScoring(), H2OAutoencoder(), ModelDataPrep(), PercRankScoring(), PercRank(), Standardize(), TimeSeriesFillRoll(), TimeSeriesFill()

Examples

```
## Not run:
x <- Standardize(data = data, ColNames = c('Weekly_Sales', 'XREG1'), GroupVars = c('Region','Store','Dept'), Ce

## End(Not run)
```

StockData *StockData*

Description

Create stock data for plotting using StockPlot()

Usage

```
StockData(
  PolyOut = NULL,
  Symbol = "TSLA",
  CompanyName = "Tesla Inc. Common Stock",
  Metric = "Stock Price",
  TimeAgg = "days",
  StartDate = "2022-01-01",
  EndDate = "2022-01-01",
  APIKey = NULL
)
```

Arguments

PolyOut	NULL. If NULL, data is pulled. If supplied, data is not pulled.
Symbol	ticker symbol string
CompanyName	company name if you have it. ends up in title, that is all
Metric	Stock Price, Percent Returns (use symbol for percent), Percent Log Returns (use symbol for percent), Index, Quadratic Variation
TimeAgg	= 'days', 'weeks', 'months'
StartDate	Supply a start date. E.g. '2022-01-01'
EndDate	Supply an end date. E.g. 'Sys.Date()'
APIKey	Supply your polygon API key
Type	'candlestick', 'ohlc'

Author(s)

Adrian Antico

See Also

Other Graphics: AddFacet(), BarPlot(), BoxPlot(), ChartTheme(), CorrMatrixPlot(), DensityPlot(), HeatMapPlot(), HistPlot(), PlotlyConversion(), StockPlot(), ViolinPlot(), multiplot()

StockPlot *StockPlot*

Description

Create a candlestick plot for stocks. See https://plotly.com/r/figure-labels/

Usage

```
StockPlot(StockDataOutput, Type = "candlestick")
```

Arguments

StockDataOutput	PolyOut returned from StockData()
Type	'candlestick', 'ohlc'

Author(s)

Adrian Antico

See Also

Other Graphics: AddFacet(), BarPlot(), BoxPlot(), ChartTheme(), CorrMatrixPlot(), DensityPlot(), HeatMapPlot(), HistPlot(), PlotlyConversion(), StockData(), ViolinPlot(), multiplot()

threshOptim *threshOptim*

Description

threshOptim will return the utility maximizing threshold for future predictions along with the data generated to estimate the threshold

Usage

```
threshOptim(
  data,
  actTar = "target",
  predTar = "p1",
  tpProfit = 0,
  tnProfit = 0,
  fpProfit = -1,
  fnProfit = -2,
  MinThresh = 0.001,
  MaxThresh = 0.999,
  ThresholdPrecision = 0.001
)
```

Arguments

data	data is the data table you are building the modeling on
actTar	The column name where the actual target variable is located (in binary form)
predTar	The column name where the predicted values are located
tpProfit	This is the utility for generating a true positive prediction
tnProfit	This is the utility for generating a true negative prediction
fpProfit	This is the cost of generating a false positive prediction
fnProfit	This is the cost of generating a false negative prediction
MinThresh	Minimum value to consider for model threshold
MaxThresh	Maximum value to consider for model threshold
ThresholdPrecision	Incrementing value in search

Value

Optimal threshold and corresponding utilities for the range of thresholds tested

Author(s)

Adrian Antico

See Also

Other Model Evaluation and Interpretation: AutoShapeShap(), CumGainsChart(), EvalPlot(), ParDepCalPlots(), ROCPlot(), RedYellowGreen(), ResidualPlots(), SingleRowShapeShap()

Examples

```
## Not run:
data <- data.table::data.table(Target = runif(10))
data[, x1 := qnorm(Target)]
data[, x2 := runif(10)]
data[, Predict := log(pnorm(0.85 * x1 + sqrt(1-0.85^2) * qnorm(x2)))]
data[, ':=' (x1 = NULL, x2 = NULL)]
data <- threshOptim(data     = data,
                    actTar   = "Target",
                    predTar  = "Predict",
                    tpProfit = 0,
                    tnProfit = 0,
                    fpProfit = -1,
                    fnProfit = -2,
                    MinThresh = 0.001,
                    MaxThresh = 0.999,
                    ThresholdPrecision = 0.001)
optimalThreshold <- data$Thresholds
allResults <- data$EvaluationTable

## End(Not run)
```

`TimeSeriesDataPrepare` *TimeSeriesDataPrepare*

Description

TimeSeriesDataPrepare is a function that takes raw data and returns the necessary time series data and objects for model building. It also fills any time gaps with zeros. Use this before you run any time series model functions.

Usage

```
TimeSeriesDataPrepare(
  data,
  TargetName,
  DateName,
  Lags,
  SeasonalLags,
  MovingAverages,
  SeasonalMovingAverages,
  TimeUnit,
  FCPeriods,
  HoldOutPeriods,
  TSClean = TRUE,
  ModelFreq = TRUE,
  FinalBuild = FALSE
)
```

Arguments

`data`	Source data.table for forecasting
`TargetName`	Name of your target variable
`DateName`	Name of your date variable
`Lags`	The max number of lags you want to test
`SeasonalLags`	The max number of seasonal lags you want to test
`MovingAverages`	The max number of moving average terms
`SeasonalMovingAverages`	The max number of seasonal moving average terms
`TimeUnit`	The level of aggregation your dataset comes in. Choices include: 1Min, 5Min, 10Min, 15Min, and 30Min, hour, day, week, month, quarter, year
`FCPeriods`	The number of forecast periods you want to have forecasted
`HoldOutPeriods`	The number of holdout samples to compare models against
`TSClean`	TRUE or FALSE. TRUE will kick off a time series cleaning operation. Outliers will be smoothed and imputation will be conducted.
`ModelFreq`	TRUE or FALSE. TRUE will enable a model-based time frequency calculation for an alternative frequency value to test models on.
`FinalBuild`	Set to TRUE to create data sets with full data

Value

Time series data sets to pass onto auto modeling functions

Author(s)

Adrian Antico

Examples

```
## Not run:
data <- data.table::fread(
  file.path(PathNormalizer(
    "C:\\Users\\aantico\\Documents\\Package\\data"),
    "tsdata.csv"))
TimeSeriesDataPrepare(
  data = data,
  TargetName = "Weekly_Sales",
  DateName = "Date",
  Lags = 5,
  MovingAverages,
  SeasonalMovingAverages,
  SeasonalLags = 1,
  TimeUnit = "week",
  FCPeriods = 10,
  HoldOutPeriods = 10,
  TSClean = TRUE,
  ModelFreq = TRUE,
  FinalBuild = FALSE)

## End(Not run)
```

TimeSeriesFill *TimeSeriesFill*

Description

TimeSeriesFill For Completing Time Series Data For Single Series or Time Series by Group

Usage

```
TimeSeriesFill(
  data = NULL,
  TargetColumn = NULL,
  DateColumnName = NULL,
  GroupVariables = NULL,
  TimeUnit = "days",
  FillType = "maxmax",
  MaxMissingPercent = 0.05,
  SimpleImpute = FALSE
)
```

Arguments

data	Supply your full series data set here
TargetColumn	= NULL
DateColumnName	Supply the name of your date column
GroupVariables	Supply the column names of your group variables. E.g. "Group" or c("Group1","Group2")
TimeUnit	Choose from "second", "minute", "hour", "day", "week", "month", "quarter", "year"
FillType	Choose from maxmax - Fill from the absolute min date to the absolute max date, minmax - Fill from the max date of the min set to the absolute max date, maxmin - Fill from the absolute min date to the min of the max dates, or minmin - Fill from the max date of the min dates to the min date of the max dates
MaxMissingPercent	The maximum amount of missing values an individual series can have to remain and be imputed. Otherwise, they are discarded.
SimpleImpute	Set to TRUE or FALSE. With TRUE numeric cols will fill NAs with a 0 and non-numeric cols with a "0"

Value

Returns a data table with missing time series records filled (currently just zeros)

Author(s)

Adrian Antico

See Also

Other Feature Engineering: AutoDataPartition(), AutoDiffLagN(), AutoHierarchicalFourier(), AutoInteraction(), AutoLagRollMode(), AutoLagRollStatsScoring(), AutoLagRollStats(), AutoTransformationCreate(), AutoTransformationScore(), AutoWord2VecModeler(), AutoWord2VecScoring() CategoricalEncoding(), CreateCalendarVariables(), CreateHolidayVariables(), DummifyDT(), H2OAutoencoderScoring(), H2OAutoencoder(), ModelDataPrep(), PercRankScoring(), PercRank(), StandardizeScoring(), Standardize(), TimeSeriesFillRoll()

Examples

```
## Not run:

# Pull in data
data <- data.table::fread("https://www.dropbox.com/s/2str3ek4f4cheqi/walmart_train.csv?dl=1")

# Run function
data <- TimeSeriesFill(
  data,
  DateColumnName = "Date",
  GroupVariables = c("Store","Dept"),
  TimeUnit = "weeks",
  FillType = "maxmax",
  SimpleImpute = FALSE)

# data <- data.table::fread("https://www.dropbox.com/s/2str3ek4f4cheqi/walmart_train.csv?dl=1")
# DateColumnName = "Date"
```

```
# GroupVariables = c("Store","Dept")
# TimeUnit = "weeks"
# FillType = "maxmax" # "minmin" # "maxmin" # "dynamic:method" # "minmax" #
# SimpleImpute = FALSE


## End(Not run)
```

`TimeSeriesFillRoll` *TimeSeriesFillRoll*

Description

TimeSeriesFillRoll For Completing Time Series Data For Single Series or Time Series by Group

Usage

```
TimeSeriesFillRoll(
  data = NULL,
  DateColumnName = NULL,
  RollVars = NULL,
  NonRollVars = NULL,
  GroupVariables = NULL,
  RollDirection = "backward",
  TimeUnit = "days",
  SimpleImpute = FALSE
)
```

Arguments

`data`	Supply your full series data set here
`DateColumnName`	Supply the name of your date column
`RollVars`	= NULL,
`NonRollVars`	= NULL,
`GroupVariables`	Supply the column names of your group variables. E.g. "Group" or c("Group1","Group2")
`RollDirection`	'backward' or 'forward'
`TimeUnit`	Choose from "second", "minute", "hour", "day", "week", "month", "quarter", "year"
`SimpleImpute`	Set to TRUE or FALSE. With TRUE numeric cols will fill NAs with a 0 and non-numeric cols with a "0"

Value

Returns a data table with missing time series records filled (currently just zeros)

Author(s)

Adrian Antico

See Also

Other Feature Engineering: AutoDataPartition(), AutoDiffLagN(), AutoHierarchicalFourier(), AutoInteraction(), AutoLagRollMode(), AutoLagRollStatsScoring(), AutoLagRollStats(), AutoTransformationCreate(), AutoTransformationScore(), AutoWord2VecModeler(), AutoWord2VecScoring(), CategoricalEncoding(), CreateCalendarVariables(), CreateHolidayVariables(), DummifyDT(), H2OAutoencoderScoring(), H2OAutoencoder(), ModelDataPrep(), PercRankScoring(), PercRank(), StandardizeScoring(), Standardize(), TimeSeriesFill()

Examples

```
## Not run:

# Pull in data
data <- data <- data.table::fread("https://www.dropbox.com/s/2str3ek4f4cheqi/walmart_train.csv?dl=1")

# Run function
data <- TimeSeriesFillRoll(
  data,
  RollVars = c('Net_Revenue', 'Units', 'SIZE_UNITS', 'Liters', 'Accum_Units'),
 NonRollVars = c('Diff_1_DATE_ISO','Net_Revenue_PerDay','Liters_PerDay','Units_PerDay'),
  DateColumnName = "Date",
  GroupVariables = c("Store","Dept"),
  RollDirection = 'backward',
  TimeUnit = "weeks",
  SimpleImpute = FALSE)

## End(Not run)
```

UserBaseEvolution *UserBaseEvolution*

Description

This function creates a table of user counts over time for accumulated unique users, active unique users, new unique users, retained unique users, churned unique users, and reactivated unique users. You can run this with several specifications. You can request monthly, weekly, or daily counts and you can specify a churn window for the computations. If you want to compare how many churned users also churned from another segment of sorts, provide a list in the Cross parameter.

Usage

```
UserBaseEvolution(
  data,
  Cross = NULL,
  Entity = NULL,
  DateColumnName = NULL,
  TimeAgg = NULL,
  ChurnPeriods = 1
)
```

Arguments

data	Source data.table
Cross	Can be NULL. User base from non source. Must be a named list. Names of list are used to name columns in output table. Entity and DateColumnName must be identical across data sets.
Entity	Column name of the entity / user
DateColumnName	Name of the date column used for inclusion of users in time periods
TimeAgg	Choose from 'Month', 'Week', or 'Day'. Do not lowercase
ChurnPeriods	Defaults to 1. This means for TimeAgg = 'Month' a one month churn period is used. For TimeAgg = 'Week' you will have a one week churn period. If you set ChurnPeriods to 2 then it will be a 2 month churn or a 2 week churn. Same logic applies for daily.

Author(s)

Adrian Antico

See Also

Other EDA: AutoWordFreq(), EDA_Histograms(), Mode(), PlotGUI(), ScatterCopula()

ViolinPlot *ViolinPlot*

Description

Build a violin plot by simply passing arguments to a single function. It will sample your data using SampleSize number of rows. Sampled data is randomized.

Usage

```
ViolinPlot(
  data = NULL,
  XVar = NULL,
  YVar = NULL,
  FacetVar1 = NULL,
  FacetVar2 = NULL,
  SampleSize = 1000000L,
  FillColor = "gray",
  YTicks = "Default",
  XTicks = "Default",
  TextSize = 12,
  AngleX = 90,
  AngleY = 0,
  ChartColor = "lightsteelblue1",
  BorderColor = "darkblue",
  TextColor = "darkblue",
  GridColor = "white",
  BackGroundColor = "gray95",
```

```
  SubTitleColor = "blue",
  LegendPosition = "bottom",
  LegendBorderSize = 0.5,
  LegendLineType = "solid",
  Debug = FALSE
)
```

Arguments

data	Source data.table
XVar	Column name of X-Axis variable. If NULL then ignored
YVar	Column name of Y-Axis variable. If NULL then ignored
FacetVar1	Column name of facet variable 1. If NULL then ignored
FacetVar2	Column name of facet variable 2. If NULL then ignored
SampleSize	An integer for the number of rows to use. Sampled data is randomized. If NULL then ignored
FillColor	'gray'
YTicks	Choose from 'Default', 'Percentiles', 'Every 5th percentile', 'Deciles', 'Quantiles', 'Quartiles'
XTicks	Choose from 'Default', '1 year', '1 day', '3 day', '1 week', '2 week', '1 month', '3 month', '6 month', '2 year', '5 year', '10 year', '1 minute', '15 minutes', '30 minutes', '1 hour', '3 hour', '6 hour', '12 hour'
TextSize	14
AngleX	90
AngleY	0
ChartColor	'lightsteelblue'
BorderColor	'darkblue'
TextColor	'darkblue'
GridColor	'white'
BackGroundColor	'gray95'
SubTitleColor	'darkblue'
LegendPosition	'bottom'
LegendBorderSize	0.50
LegendLineType	'solid'
Debug	FALSE

Author(s)

Adrian Antico

See Also

Other Graphics: AddFacet(), BarPlot(), BoxPlot(), ChartTheme(), CorrMatrixPlot(), DensityPlot(), HeatMapPlot(), HistPlot(), PlotlyConversion(), StockData(), StockPlot(), multiplot()

Examples

```
## Not run:
# Load packages
library(AutoQuant)
library(data.table)

# Load data
data <- data.table::fread(file = file.path('C:/Users/Bizon/Documents/GitHub/BenchmarkData1.csv'))

# Run function
AutoQuant:::ViolinPlot(
  data = data,
  XVar = 'Region',
  YVar = 'Weekly_Sales',
  FacetVar1 = 'Store',
  FacetVar2 = NULL,
  SampleSize = 1000000L,
  FillColor = 'gray',
  YTicks = 'Default',
  XTicks = 'Default',
  TextSize = 12,
  AngleX = 90,
  AngleY = 0,
  ChartColor = 'lightsteelblue1',
  BorderColor = 'darkblue',
  TextColor = 'darkblue',
  GridColor = 'white',
  BackGroundColor = 'gray95',
  SubTitleColor = 'blue',
  LegendPosition = 'bottom',
  LegendBorderSize = 0.50,
  LegendLineType = 'solid',
  Debug = FALSE)

# Step through function
# XVar = 'Region'
# YVar = 'Weekly_Sales'
# FacetVar1 = 'Store'
# FacetVar2 = NULL
# SampleSize = 1000000L
# FillColor = 'gray'
# YTicks = 'Default'
# XTicks = 'Default'
# TextSize = 12
# AngleX = 90
# AngleY = 0
# ChartColor = 'lightsteelblue1'
# BorderColor = 'darkblue'
# TextColor = 'darkblue'
# GridColor = 'white'
# BackGroundColor = 'gray95'
# SubTitleColor = 'blue'
# LegendPosition = 'bottom'
# LegendBorderSize = 0.50
# LegendLineType = 'solid'
# Debug = FALSE
```

```
## End(Not run)
```

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