Package 'stressor'

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Type Package

Title Algorithms for Testing Models under Stress

Version 0.2.0

Description Traditional model evaluation metrics fail to capture model performance under less than ideal conditions. This package employs techniques to evaluate models ``under-stress". This includes testing models' extrapolation ability, or testing accuracy on specific sub-samples of the overall model space. Details describing stress-testing methods in this package are provided in Haycock (2023) <doi:10.26076/2am5-9f67>. The other primary contribution of this package is provided to R users access to the 'Python' library 'PyCaret' https://pycaret.org/ for quick and easy access to auto-tuned machine learning models.

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Author Sam Haycock [aut, cre],

Brennan Bean [aut],

Utah State University [cph, fnd],

Thermo Fisher Scientific Inc. [fnd]

Maintainer Sam Haycock <haycock.sam@outlook.com>

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boston

Boston Housing Data

Description

A subset of data from the Housing data for 506 census tracts of Boston from the 1970 Census. Original data set can be found in the mlbench package.

Usage

data(boston)

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Format

```
A data.frame with 506 rows and 13 columns:

cmedv corrected median value of owner-occupied homes in USD 1000's

crim per capita crime rate by town

zn proportion of residential land zoned for lots over 25,000 sq.ft

indus proportion of non-retail business acres per town

nox nitric oxides concentration (parts per 10 million)

rm average number of rooms per dwelling

age proportion of owner-occupied units built prior to 1940

dis weighted distances to five Boston employment centres

rad index of accessibility to radial highways

tax full-value property-tax rate per USD 10,000

ptratio pupil-teacher ratio by town

chas Charles River dummy variable (= 1 if tract bounds river; 0 otherwise)

lstat percentage of lower status of the population
```

Source

mlbench package

create_groups

Create Groups for CV

Description

Create groups for the data by separating them either into 10 fold cross-validation, LOO cross-validation, or k-means grouping.

Usage

```
create_groups(
  formula,
  data,
  n_folds = 10,
  k_mult = NULL,
  repl = FALSE,
  grouping_formula = NULL
)
```

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Arguments

formula	A formula object that specifies the model to be fit.
data	The data that will be separated into each group.
n_folds	An integer value defaulted to 10 fold cross-validation. If NULL uses Leave One $\mathrm{Out}(\mathrm{LOO})$ instead.
k_mult	When specified, this is passed onto the cv_cluster to fit the data into k_groups.
repl	A Boolean value defaulted to 'FALSE', change to 'TRUE' when replicates need to be included in the same group.
grouping_formul	a

A formula object that specifies how the groups will be gathered.

Details

If 'k_mult' is specified as an integer, the formula object will be used to help determine the features specified by the user. This will be passed to the cv_cluster function, which takes a scaled matrix of features.

This function is called by the cv methods as it forms the groups necessary to perform the crossvalidation. If you want to use this, it is a nice function that separates the 'data' into groups for training and testing.

Value

A vector of the length equal to number of rows of data.frame from the data argument.

Examples

```
# data generation
lm_data <- data_gen_lm(1000)</pre>
# 10 Fold CV group
create_groups(Y ~ ., lm_data)
# Spatial CV
create_groups(Y ~ ., lm_data, n_folds = 10, k_mult = 5)
# LOO CV group
create_groups(Y ~ ., lm_data, n_folds = NULL)
```

create_virtualenv

Create 'Python' Virtual Environment

Description

Allows the user to create a stressor 'python' environment with 'PyCaret' installed in the environment. This function assumes that you have properly installed 'python'. We recommend version 3.8.10. It uses existing stressor environments.

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Usage

```
create_virtualenv(python = Sys.which("python"), delete_env = FALSE)
```

Arguments

python Defaults to your install of 'python'. We prefer version 3.8.10. This is assuming

that you installed python from python.org. Currently 'Anaconda' installations

of python are not implemented.

delete_env Boolean value to indicate if the environments need to be deleted.

Details

To install 'python', it is recommended using 'python' version 3.8.10 from python.org. This is the same version recommended by 'PyCaret', as it is the most stable. Users have reported troubles using the 'Anaconda' distribution of 'python'.

For MacOS and Linux Users note that in order to run this package, 'LightGBM' package on python requires the install of an additional compiler 'cmake' and the 'libomp' (Open Multi-Processing interface). Troubleshoot link from the 'LightGBM'documentation here.

Value

A message indicating which environment is being used.

Troubleshoot

If 'python' is not being found properly, trying setting the 'RETICULATE_PYTHON' to blank string. Also ensure that you do not have other 'python' objects in your environment.

Also note that on some instances that a warning message may be displayed as to which version of 'python' is being used.

Examples

create_virtualenv()

cv Cross Validation

Description

This is the core of cross-validation- both standard and using k-mean groups. This method is called by other cv methods of classes.

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Usage

```
cv(
  object,
  data,
  n_folds = 10,
  k_mult = NULL,
  repl = FALSE,
  grouping_formula = NULL
## S3 method for class 'lm'
cv(
  object,
  data,
  n_folds = 10,
  k_mult = NULL,
  repl = FALSE,
  grouping_formula = NULL
)
## S3 method for class 'mlm_stressor'
cv(
  object,
  data,
  n_folds = 10,
  k_mult = NULL
  repl = FALSE,
  grouping_formula = NULL
)
## S3 method for class 'reg_asym'
cv(
  object,
  data,
  n_folds = 10,
  k_mult = NULL,
  repl = FALSE,
  grouping_formula = NULL
)
## S3 method for class 'reg_sine'
cv(
  object,
  data,
  n_folds = 10,
  k_mult = NULL,
  repl = FALSE,
  grouping_formula = NULL
```

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)

Arguments

object
One of the four objects that is accepted: mlm_stressor, reg_sine, reg_asym, or lm.

A data.frame object that contains all the entries to be cross-validated on.

An integer value for the number of folds defaulted to 10. If NULL, it will run LOO cross-validation.

k_mult
Used to specify if k-means clustering is to be used, defaulted to NULL.

repl A Boolean value defaulted to 'FALSE', change to 'TRUE' when replicates need

to be included in the same group.

grouping_formula

A formula object that specifies how the groups will be gathered.

Value

If the object is of class mlm_stressor, then a data.frame will be returned. Otherwise, a vector of the predictions will be returned.

Methods (by class)

- cv(lm): Cross-Validation for lm
- cv(mlm_stressor): Cross-Validation for mlm stressor
- cv(reg_asym): Cross-Validation for reg_asym
- cv(reg_sine): Cross-Validation for reg_sine

```
# lm example
lm_test <- data_gen_lm(20)</pre>
lm \leftarrow lm(Y \sim ., lm_test)
cv(lm, lm_test, n_folds = 2)
lm_test <- data_gen_lm(20)</pre>
create_virtualenv()
mlm_lm <- mlm_regressor(Y ~ ., lm_test)</pre>
cv(mlm_lm, lm_test, n_folds = 2)
# Asymptotic example
asym_data <- data_gen_asym(10)</pre>
asym_fit <- reg_asym(Y ~ ., asym_data)</pre>
cv(asym_fit, asym_data, n_folds = 2)
# Sine example
sine_data <- data_gen_sine(10)</pre>
sine_fit <- reg_sine(Y ~ ., sine_data)</pre>
cv(sine_fit, sine_data, n_folds = 2)
```

8 cv_cluster

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Spatial Cluster-Based Partitions for Cross-Validation

Description

This function creates cluster-based partitions of a sample space based on k-means clustering. Included in the function are algorithms that attempt to produce clusters of roughly equal size.

Usage

```
cv_cluster(features, k, k_mult = 5, ...)
```

Arguments

features	A scaled matrix of features to be used in the clustering. Scaling usually done with scale and should not include the predictor variable.
k	The number of partitions for k-fold cross-validation.
k_mult	k^*k_mult determines the number of subgroups that will be created as part of the balancing algorithm.
	Additional arguments passed to kmeans as needed.

Details

More information regarding spatial cross-validation can be found in Robin Lovelace's explanation of spatial cross-validation in his textbook.

Value

An integer vector that is number of rows of features with indices of each group.

```
# Creating a matrix of predictor variables
x_data <- base::scale(data_gen_lm(30)[, -1])
groups <- cv_cluster(x_data, 5, k_mult = 5)
groups</pre>
```

cv_core 9

cv_core Cross Validation Function

Description

This is the machinery to run cross validation. It subsets the test and train set based on the groups it receives.

Usage

```
cv_core(object, data, t_groups, ...)
```

Arguments

object Currently "reg_sine", "reg_asym", "lm", "mlm_stressor" objects are accepted.

A data.frame object that has the same formula that was fitted on the data.

The groups for cross validation: standard cross validation, LOO cross_validation, or spatial cross validation.

Additional arguments that are passed to the predict function.

Value

Either a vector of predictions for "reg_sine", "reg_asym", "lm" and a data frame for "mlm_stressor".

```
# lm example
lm_test <- data_gen_lm(20)</pre>
lm <- lm(Y \sim ., lm_test)
cv(lm, lm_test, n_folds = 2)
lm_test <- data_gen_lm(20)</pre>
create_virtualenv()
mlm_lm <- mlm_regressor(Y ~ ., lm_test)</pre>
cv(mlm_lm, lm_test, n_folds = 2)
# Asymptotic example
asym_data <- data_gen_asym(10)</pre>
asym_fit <- reg_asym(Y ~ ., asym_data)</pre>
cv(asym_fit, asym_data, n_folds = 2)
# Sine example
sine_data <- data_gen_sine(10)</pre>
sine_fit <- reg_sine(Y ~ ., sine_data)</pre>
cv(sine_fit, sine_data, n_folds = 2)
```

data_gen_asym

data_gen_asym

Data Generation Asymptotic

Description

Creates a synthetic data set for an additive asymptotic model. See the details section for clarification.

Usage

```
data_gen_asym(
   n,
   weight_mat = matrix(rlnorm(10), nrow = 2, ncol = 5),
   y_int = 0,
   resp_sd = 1,
   window = 1e-05,
   ...
)
```

Arguments

n	The number of observations for each parameter.
weight_mat	The parameter coefficients, where each column represents the coefficients and is two rows as each additive equation contains two parameters. Defaulted to be 10 random numbers from the log-normal distribution. The second row of the matrix needs to be positive.
y_int	The y-intercept term of the additive model.
resp_sd	The standard deviation of the epsilon term to be added for noise.
window	Used to determine for any given X variable to get you within distance to capture the asymptotic behavior.
	Additional arguments that are not currently implemented.

Details

Observations are generated from the following model:

$$y = \sum_{i=1}^{n} -\alpha_i e^{-\beta_i \cdot x_i} + y_{int}$$

Where 'n' is the number of parameters to be used, α_i 's are the scaling parameter and the β_i 's are the weights associated with each x_i . With the y_{int} being where it crosses the y-axis.

Value

A data frame object with the n rows and the response variable with the number of parameters being equal to the number of columns from the weight matrix.

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Examples

```
# Generates 10 observations
asym_data <- data_gen_asym(10)
asym_data</pre>
```

data_gen_lm

Data Generation for Linear Regression

Description

Creates a synthetic data set for an additive linear model. See details for clarification.

Usage

```
data_gen_lm(n, weight_vec = rep(1, 5), y_int = 0, resp_sd = 1, ...)
```

Arguments

n The number of observations for each parameter.

weight_vec The parameter coefficients where each entry represents the coefficients for the

additive linear model.

y_int The y-intercept term of the additive model.

resp_sd The standard deviation of the epsilon term to be added for noise.

... Additional arguments that are not currently implemented.

Details

Observations are generated from the following model:

$$y = \sum_{i=1}^{n} \alpha_i \cdot x_i + y_{int}$$

Where 'n' is the number of parameters to be used and the α_i 's are the weights associated with each x_i . With the y_{int} being where it crosses the y-axis.

Value

A data frame object with the n rows and the response variable with the number of parameters being equal to the number of columns from the weight matrix.

```
# Generates 10 observations
lm_data <- data_gen_lm(10)
lm_data</pre>
```

data_gen_sine

data_gen_sine

Data Generation for Sinusoidal Regression

Description

Creates a synthetic data set for an additive sinusoidal regression model. See the details section for clarification.

Usage

```
data_gen_sine(
   n,
   weight_mat = matrix(rnorm(15), nrow = 3, ncol = 5),
   y_int = 0,
   resp_sd = 1,
   ...
)
```

Arguments

n The number of observations for each parameter.

weight_mat The parameter coefficients, where each column represents the coefficients and is three rows as each additive equation contains three parameters. Defaulted to be 15 random numbers from the normal distribution.

y_int The y-intercept term of the additive model.

resp_sd The standard deviation of the epsilon term to be added for noise.

Additional arguments that are not currently implemented.

Details

Observations are generated from the following model:

$$y = \sum_{i=1}^{n} \alpha_i \sin(\beta_i(x_i - \gamma_i))) + y_{int}$$

Where 'n' is the number of parameters to be used, α_i 's are the amplitude of each sine wave, β_i 's are the periods for each sine wave and indirectly the weight on each x_i , and the γ_i 's are the phase shift associated with each sine wave. With the y_{int} being where it crosses the y-axis.

Value

A data frame object with the n rows and the response variable with the number of parameters being equal to the number of columns from the weight matrix.

dist_cent 13

Examples

```
# Generates 10 observations
sine_data <- data_gen_sine(10)
sine_data</pre>
```

dist_cent

Distance to Center

Description

Calculates the distance from center of the matrix of predictor variables using a euclidean distance, or the average of all x-dimensions.

Usage

```
dist_cent(formula, data)
```

Arguments

formula A formula object.
data A data.frame object.

Details

Formula used to calculate the center point:

$$\bar{x} = \frac{1}{N} \sum_{j=1}^{N} x_{ij}$$

Where \bar{x} is a vector of the center of the x-dimensions, N is the number of rows in the matrix, and x_{ij} is the i, j^{th} entry in the matrix.

Value

A vector of distances from the center.

```
data <- data_gen_lm(10)
dist <- dist_cent(Y ~ ., data)
dist</pre>
```

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kappa_class

Kappa function

Description

A function to calculate the Kappa of binary classification.

Usage

```
kappa_class(confusion_matrix)
```

Arguments

confusion_matrix

A matrix or table that is the confusion matrix.

Value

A numeric value representing the kappa value.

mlm_classification

Fit Machine Learning Classification Models

Description

Through the PyCaret module from 'python', this function fits many machine learning models simultaneously without requiring any 'python' programming on the part of the user. This function is specifically designed for the classification models fitted by 'PyCaret'.

Usage

```
mlm_classification(
  formula,
  train_data,
  fit_models = c("ada", "et", "lightgbm", "dummy", "lr", "rf", "ridge", "knn", "dt",
        "gbc", "svm", "lda", "nb", "qda"),
  sort_v = c("Accuracy", "AUC", "Recall", "Precision", "F1", "Kappa", "MCC"),
  n_models = 9999,
  seed = NULL,
  ...
)
```

mlm_classification 15

Arguments

formula The classification formula, as a formula object.

train_data A data.frame object that includes data to be trained on.

fit_models A character vector with all the possible Machine Learning classifiers that are

currently being fit, the user may specify a subset of them using a character vec-

tor.

ada AdaBoost Classifier

dt Decision Tree Classifier

dummy Dummy Classifier

et Extra Trees Classifier

gbc Gradient Boosting Classifier

knn K Neighbors Classifier

lda Linear Discriminant Analysis

lightgbm Light Gradient Boosting Machine

lr Logistic Regression

nb Naive Bayes

qda Quadratic Discriminant Analysis

rf Random Forest Classifier

ridge Ridge Classifier svm SVM - Linear Kernel

sort_v A character vector indicating what to sort the tuned models on.

n_models An integer value defaulted to a large integer value to return all possible models.

seed An integer value to set the seed of the 'python' environment. Default value is

set to 'NULL'.

... Additional arguments passed onto mlm_init.

Details

'PyCaret' is a 'python' module where machine learning models can be fitted with little coding by the user. The pipeline that 'PyCaret' uses is a setup function to parameterize the data that is easy for all the models to fit on. Then the compare models function is executed, which fits all the models that are currently available. This process takes less than five minutes for data.frame objects that are less than 10,000 rows.

Value

A list object where the first entry is the models fitted and the second is the initial predictive accuracy on the random test data. Returns as two classes "mlm_stressor" and "classifier".

```
lm_test <- data_gen_lm(20)
binary_response <- sample(c(0, 1), 20, replace = TRUE)
lm_test$Y <- binary_response</pre>
```

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```
mlm_class <- mlm_classification(Y ~ ., lm_test)</pre>
```

mlm_init

Compare Machine Learning Models

Description

Through the PyCaret module from 'python', this function fits many machine learning models simultaneously without requiring any 'python' programming on the part of the user. This is the core function to fitting the initial models. This function is the backbone to fitting all the models.

Usage

```
mlm_init(
  formula,
  train_data,
  fit_models,
  sort_v = NULL,
  n_models = 9999,
  classification = FALSE,
  seed = NULL,
  ...
)
```

Arguments

formula The regression formula or classification formula. This formula should be linear.

train_data A data.frame object that includes data to be trained on.

fit_models A character vector with all the possible Machine Learning regressors that are currently being fit. The user may specify a subset of them using a character

vector.

ada AdaBoost Regressor

br Bayesian Ridge

dt Decision Tree Regressor

dummy Dummy Regressor

en Elastic Net

et Extra Trees Regressor

gbr Gradient Boosting Regressor

huber Huber Regressor

knn K Neighbors Regressor

lar Least Angle Regression

lasso Lasso Regression

lightgbm Light Gradient Boosting Machine

llar Lasso Least Angle Regression

lr Linear Regression

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omp Orthogonal Matching Pursuit
par Passive Aggressive Regressor
rf Random Forest Regressor
ridge Ridge Regression

If classification is set to 'TRUE', these models can be used depending on user. These are the default values for classification:

ada AdaBoost Classifier
dt Decision Tree Classifier
dummy Dummy Classifier
et Extra Trees Classifier
gbc Gradient Boosting Classifier
knn K Neighbors Classifier

lda Linear Discriminant Analysis lightgbm Light Gradient Boosting Machine

lr Logistic Regressionnb Naive Bayes

qda Quadratic Discriminant Analysis

rf Random Forest Classifier

ridge Ridge Classifier svm SVM - Linear Kernel

sort_v A character vector indicating what to sort the tuned models on. Default value is

'NULL'.

n_models A defaulted integer to return the maximum number of models.

classification A Boolean value tag to indicate if classification methods should be used.

seed An integer value to set the seed of the python environment. Default value is set

to 'NULL'.

... Additional arguments passed to the setup function in 'PyCaret'.

Details

The formula should be linear. However, that does not imply a linear fit. The formula is a convenient way to separate predictor variables from explanatory variables.

'PyCaret' is a 'python' module where machine learning models can be fitted with little coding by the user. The pipeline that 'PyCaret' uses has a setup function to parameterize the data that is easy for all the models to fit on. Then compare models function is executed which fits all the models that are currently available. This process takes less than five minutes for data.frame objects that are less than 10,000 rows.

Value

A list object that contains all the fitted models and the CV predictive accuracy. With a class attribute of "mlm_stressor".

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Examples

```
lm_test <- data_gen_lm(20)
create_virtualenv()
mlm_lm <- mlm_regressor(Y ~ ., lm_test)</pre>
```

mlm_refit

Refit Machine Learning Models

Description

Refits models fitted in the mlm_init, and returns the predictions.

Usage

```
mlm_refit(mlm_object, train_data, test_data, classification = FALSE)
```

Arguments

mlm_object A "mlm_stressor" object.

train_data A data.frame object used for refitting excludes the test data. Can be 'NULL' to

allow for predictions to be used on the current model.

test_data A data.frame object used for predictions.

classification A Boolean value used to represent if classification methods need to be used to

refit the data.

Value

A matrix with the predictions of the various machine learning methods.

```
lm_train <- data_gen_lm(20)
train_idx <- sample.int(20, 5)
train <- lm_train[train_idx, ]
test <- lm_train[-train_idx, ]
create_virtualenv()
mlm_lm <- mlm_regressor(Y ~ ., lm_train)
mlm_refit(mlm_lm, train, test, classification = FALSE)</pre>
```

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mlm_regressor

Fit Machine Learning Regressor Models

Description

Through the PyCaret module from 'python', this function fits many machine learning models simultaneously with without requiring any 'python' programming on the part of the user. This function is specifically designed for the regression models.

Usage

```
mlm_regressor(
   formula,
   train_data,
   fit_models = c("ada", "et", "lightgbm", "gbr", "lr", "rf", "ridge", "knn", "dt",
        "dummy", "lar", "br", "huber", "omp", "lasso", "en", "llar", "par"),
   sort_v = c("MAE", "MSE", "RMSE", "R2", "RMSLE", "MAPE"),
   n_models = 9999,
   seed = NULL,
   ...
)
```

Arguments

formula A linear formula object.

train_data A data.frame object that includes data to be trained on.

fit_models A character vector with all the possible Machine Lea

A character vector with all the possible Machine Learning regressors that are currently being fit. The user may specify a subset of them using a character

vector.

ada AdaBoost Regressor

br Bayesian Ridge

dt Decision Tree Regressor

dummy Dummy Regressor

en Elastic Net

et Extra Trees Regressor

gbr Gradient Boosting Regressor

huber Huber Regressor

knn K Neighbors Regressor

lar Least Angle Regression

lasso Lasso Regression

lightgbm Light Gradient Boosting Machine

llar Lasso Least Angle Regression

lr Linear Regression

omp Orthogonal Matching Pursuit

par Passive Aggressive Regressor

rf Random Forest Regressor

ridge Ridge Regression

20 predict

sort_v	A character vector indicating what to sort the tuned models on.
n_models	An integer value defaulted to a large integer value to return all possible models.
seed	An integer value to set the seed of the 'python' environment. Default value is set to 'NULL'.
	Additional arguments passed onto mlm_init.

Details

'PyCaret' is a 'python' module where machine learning models can be fitted with little coding by the user. The pipeline that 'PyCaret' uses is a setup function to parameterize the data that is easy for all the models to fit on. Then the compare models function is executed, which fits all the models that are currently available. This process takes less than five minutes for data.frame objects that are less than 10,000 rows.

Value

A list object where the first entry is the models fitted and the second is the initial predictive accuracy on the random test data. Returns as two classes "mlm_stressor" and "regressor".

Examples

```
lm_test <- data_gen_lm(20)
create_virtualenv()
mlm_lm <- mlm_regressor(Y ~ ., lm_test)</pre>
```

predict

Prediction Methods for Various Models

Description

Predict values on 'mlm_stressor', 'reg_asym', or 'reg_sine' objects. This expands the predict function.

Usage

```
## S3 method for class 'mlm_stressor'
predict(object, newdata, train_data = NULL, ...)
## S3 method for class 'reg_asym'
predict(object, newdata, ...)
## S3 method for class 'reg_sine'
predict(object, newdata, ...)
```

python_avail 21

Arguments

object A 'mlm_stressor', 'reg_asym', or 'reg_sine' object.

A data.frame object that is the data to be predicted on.

A data.frame object defaulted to 'NULL'. This is only used when an 'mlm_stressor' object needs to be refitted.

Extending the predict function default. In this case, it is ignored.

Value

A data.frame of predictions if 'mlm_stressor' object or vector of predicted values.

Examples

```
# mlm_stressor example
lm_test <- data_gen_lm(20)
create_virtualenv()
mlm_lm <- mlm_regressor(Y ~ ., lm_test)
predict(mlm_lm, lm_test)

# Asymptotic Examples
asym_data <- data_gen_asym(10)
asym_fit <- reg_asym(Y ~ ., asym_data)
predict(asym_fit, asym_data)
# Sinusoidal Examples
sine_data <- data_gen_sine(10)
sine_fit <- reg_sine(Y ~ ., sine_data)
predict(sine_fit, sine_data)</pre>
```

python_avail

Check if 'Python' is Available

Description

A function that allows examples to run when appropriate.

Usage

```
python_avail()
```

Value

A Boolean value is returned.

```
python_avail()
```

22 reg_asym

reg_asym

Asymptotic Regression

Description

A simple example of asymptotic regression that is in the form of $y=-e^{-x}$ and is the sum of multiple of these exponential functions with a common intercept term.

Usage

```
reg_asym(
  formula,
  data,
  method = "BFGS",
  init_guess = rep(1, ncol(data) * 2 - 1),
  ...
)
```

Arguments

formula	A formula object to describe the relationship.
data	The response and predictor variables.
method	The method that is passed to the optim function. By default, it is the BFGS method which uses a gradient.
init_guess	The initial parameter guesses for the optim function. By default, it is all ones.
	Additional arguments passed to the optim function.

Value

A "reg_asym" object is returned which contains the results from the optim function that was returned.

```
asym_data <- data_gen_asym(10)
reg_asym(Y ~ ., asym_data)</pre>
```

reg_sine 23

reg_sine Sinusoidal Regression

Description

A simple example of sinusoidal regression that is in the form of y = asin(b(x-c)) and is the sum of of multiple of these sine functions with a common intercept term.

Usage

```
reg_sine(
  formula,
  data,
  method = "BFGS",
  init_guess = rep(1, ncol(data) * 3 - 2),
  ...
)
```

Arguments

formula	A formula object to describe the relationship.
data	The response and predictor variables.
method	The method that is passed to the optim function. By default, it is the BFGS method which uses a gradient.
init_guess	The initial parameter guesses for the optim function. By default, it is all ones.
	Additional arguments passed to the optim function.

Value

A "reg_sine" object is returned which contains the results from the optim function that was returned.

```
sine_data <- data_gen_sine(10)
reg_sine(Y ~ ., sine_data)</pre>
```

24 score

rmse	Root Mean Squarred Error (RMSE)
1 11130	Root Mean Squarrea Error (Rinst)

Description

A function to calculate the RMSE.

Usage

```
rmse(predicted, observed)
```

Arguments

predicted A data frame or vector object that is the same number of rows or length as the

length of observed values.

observed A vector of the observed results.

score Score Function for Metrics

Description

A score function takes the observed and predicted values and returns a vector or data.frame of the various metrics that are reported from 'PyCaret'. For regression, the following metrics are available: 'RMSE', 'MAE', 'MSE', 'R2', 'RMSLE', and 'MAPE'. For classification, the following metrics are available: 'Accuracy', 'AUC', 'Recall', 'Prec.', 'F1', 'MCC', and 'Kappa'.

Usage

```
score(observed, predicted, ...)
```

Arguments

observed A vector of the observed results.

A data.frame or vector object that is the same number of rows or length as the length of observed values.

Arguments passed on to score_classification, score_regression metrics A character vector of the metrics to be fitted. This is defaulted to be

the metrics from 'PyCaret'.

Value

A matrix with the various metrics reported.

score_classification 25

Examples

```
lm_data <- data_gen_lm(100)
indices <- split_data_prob(lm_data, .2)
train <- lm_data[!indices,]
test <- lm_data[indices,]
model <- lm(Y ~ ., train)
pred_lm <- predict(model, test)
score(test$Y, pred_lm)</pre>
```

Description

This function takes the observed and predicted values and computes metrics that are found in 'Py-Caret' such as: 'Accuracy', 'AUC', 'Recall', 'Prec.', 'F1', 'MCC', and 'Kappa'.

Usage

```
score_classification(
  observed,
  predicted,
  metrics = c("Accuracy", "AUC", "Recall", "Prec.", "F1", "MCC", "Kappa")
)
```

Arguments

observed A vector of the observed results.

predicted A data frame or vector object that is the same number of rows or length as the

length of observed values.

metrics A character vector of the metrics to be fitted. This is defaulted to be the metrics

from 'PyCaret'.

Value

A vector or data.frame of the methods and metrics.

26 split_data_prob

score_regression	Score Function for Regression

Description

This function takes the observed and predicted values and computes metrics that are found in 'Py-Caret' such as: 'RMSE', 'MAE', 'MSE', 'RYSLE', and 'MAPE'.

Usage

```
score_regression(
  observed,
  predicted,
  metrics = c("RMSE", "MAE", "MSE", "R2", "RMSLE", "MAPE")
)
```

Arguments

observed A vector of the observed results.

predicted A data frame or vector object that is the same number of rows or length as the

length of observed values.

metrics A character vector of the metrics to be fitted. This is defaulted to be the metrics

from 'PyCaret'.

Value

A vector or data.frame of the methods and metrics.

split_data_prob	Create Train Index Set		
-----------------	------------------------	--	--

Description

This function takes in a data.frame object and the training size and returns a logical vector indicating which entries to include.

Usage

```
split_data_prob(data, test_prop)
```

Arguments

data A data.frame object used to determine the length of the vector.

test_prop A numeric that is between zero and one that represents the proportion of obser-

vations to be included in the test data.

thinning 27

Value

A logical vector is returned that is the same length as the number of rows of the data.

Examples

```
lm_data <- data_gen_lm(10)
indices <- split_data_prob(lm_data, .8)
train <- lm_data[indices, ]
test <- lm_data[!indices, ]</pre>
```

thinning

Thinning Algorithm for Models with Predict Function

Description

Fits various train size and test sizes.

Usage

```
thinning(
  model,
  data,
  max = 0.95,
  min = 0.05,
  iter = 0.05,
  classification = FALSE
)
```

Arguments

```
model A model that is currently of class type "reg_sine", "reg_asym", "lm", or "mlm_stressor".

data A data frame with all the data.

max A numeric value in (0, 1] and greater than 'min', defaulted to .95.

min A numeric value in (0, 1) and less than 'max', defaulted to .05.

iter A numeric value to indicate the step size, defaulted to .05.

classification A Boolean value defaulted 'FALSE', used for 'mlm_classification'.
```

Value

A list of objects, where the first element is the RMSE values at each iteration and the second element is the predictions.

```
lm_data <- data_gen_lm(1000)
lm_model <- lm(Y ~ ., lm_data)
thin_results <- thinning(lm_model, lm_data)</pre>
```

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