Package 'daltoolbox'

November 25, 2024

Title Leveraging Experiment Lines to Data Analytics

Version 1.1.727

Description
The natural increase in the complexity of current research experiments and data demands better tools to enhance productivity in Data Analytics. The package is a framework designed to address the modern challenges in data analytics workflows. The package is inspired by Experiment Line concepts. It aims to provide seamless support for users in developing their data mining workflows by offering a uniform data model and method API. It enables the integration of various data mining activities, including data preprocessing, classification, regression, clustering, and time series prediction. It also offers options for hyper-parameter tuning and supports integration with existing libraries and languages. Overall, the package provides researchers with a comprehensive set of functionalities for data science, promoting ease of use, extensibility, and integration with various tools and libraries. Information on Experiment Line is based on Ogasawara et al. (2009) <doi:10.1007/978-3-642-02279-1_20>.

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URL https://github.com/cefet-rj-dal/daltoolbox

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Imports FNN, MLmetrics, caret, class, cluster, dbscan, dplyr, e1071, elmNNRcpp, forecast, ggplot2, nnet, randomForest, reshape, tree, reticulate

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Contents

aae_encode *Adversarial Autoencoder - Encode*

Description

Creates an deep learning adversarial autoencoder to encode a sequence of observations. It wraps the pytorch library.

Usage

```
aae_encode(
  input_size,
  encoding_size,
  batch_size = 350,
  num_epochs = 1000,
  learning_rate = 0.001
)
```

Arguments

input_size	input size
encoding_size	encoding size
batch_size	size for batch learning
num_epochs	number of epochs for training
learning_rate	learning rate

Value

a aae_encode object. #See an example of using aae_encode at this #link

---

aae_encode_decode *Adversarial Autoencoder - Encode*

Description

Creates an deep learning adversarial autoencoder to encode a sequence of observations. It wraps the pytorch library.

Usage

```
aae_encode_decode(
  input_size,
  encoding_size,
  batch_size = 32,
  num_epochs = 1000,
  learning_rate = 0.001
)
```

Arguments

input_size	input size
encoding_size	encoding size
batch_size	size for batch learning
num_epochs	number of epochs for training
learning_rate	learning rate

Value

a aae_encode_decode object.

Examples

```
#See an example of using `aae_encode_decode` at this
#[link](https://github.com/cefet-rj-dal/daltoolbox/blob/main/transf/aae_enc_decode.ipynb)
```

---

action *Action*

Description

Executes the action of model applied in provided data

Usage

```
action(obj, ...)
```

Arguments

obj	object: a dal_base object to apply the transformation on the input dataset.
...	optional arguments.

Value

returns the result of an action of the model applied in provided data

Examples

```
data(iris)
# an example is minmax normalization
trans <- minmax()
trans <- fit(trans, iris)
tiris <- action(trans, iris)
```

action.dal_transform *Action implementation for transform*

Description

A default function that defines the action to proxy transform method

Usage

```
## S3 method for class 'dal_transform'
action(obj, ...)
```

Arguments

obj	object
...	optional arguments

Value

returns a transformed data

Examples

```
#See ?minmax for an example of transformation
```

adjust_class_label *Adjust categorical mapping*

Description

Converts a vector into a categorical mapping, where each category is represented by a specific value. By default, the values represent binary categories (true/false)

Usage

```
adjust_class_label(x, valTrue = 1, valFalse = 0)
```

Arguments

x	vector to be categorized
valTrue	value to represent true
valFalse	value to represent false

Value

returns an adjusted categorical mapping

adjust_data.frame *Adjust to data frame*

Description

Converts a dataset to a `data.frame` if it is not already in that format

Usage

```
adjust_data.frame(data)
```

Arguments

`data`	dataset

Value

returns a data.frame

Examples

```
data(iris)
df <- adjust_data.frame(iris)
```

adjust_factor *Adjust factors*

Description

Converts a vector into a factor with specified levels and labels

Usage

```
adjust_factor(value, ilevels, slevels)
```

Arguments

`value`	vector to be converted into factor
`ilevels`	order for categorical values
`slevels`	labels for categorical values

Value

returns an adjusted factor

adjust_matrix *Adjust to matrix*

Description

Converts a dataset to a matrix format if it is not already in that format

Usage

```
adjust_matrix(data)
```

Arguments

data	dataset

Value

returns an adjusted matrix

Examples

```
data(iris)
mat <- adjust_matrix(iris)
```

adjust_ts_data *Adjust* ts_data

Description

Converts a dataset to a ts_data object

Usage

```
adjust_ts_data(data)
```

Arguments

data	dataset

Value

returns an adjusted ts_data

autoenc_encode *Autoencoder - Encode*

Description

Creates an deep learning autoencoder to encode a sequence of observations. It wraps the pytorch and reticulate libraries.

Usage

```
autoenc_encode(
  input_size,
  encoding_size,
  batch_size = 32,
  num_epochs = 1000,
  learning_rate = 0.001
)
```

Arguments

input_size	input size
encoding_size	encoding size
batch_size	size for batch learning
num_epochs	number of epochs for training
learning_rate	learning rate

Value

returns a autoenc_encode object.

Examples

```
#See an example of using `autoenc_encode` at this
#[link](https://github.com/cefet-rj-dal/daltoolbox/blob/main/transf/van_encode.ipynb)
```

autoenc_encode_decode *Autoencoder - Encode-decode*

Description

Creates an deep learning autoencoder to encode-decode a sequence of observations. It wraps the pytorch and reticulate libraries.

Usage

```
autoenc_encode_decode(
  input_size,
  encoding_size,
  batch_size = 32,
  num_epochs = 1000,
  learning_rate = 0.001
)
```

Arguments

input_size	input size
encoding_size	encoding size
batch_size	size for batch learning
num_epochs	number of epochs for training
learning_rate	learning rate

Value

returns a autoenc_encode_decode object.

Examples

```
#See an example of using `autoenc_encode_decode` at this
#[link](https://github.com/cefet-rj-dal/daltoolbox/blob/main/transf/van_enc_decode.ipynb)
```

Boston *Boston Housing Data (Regression)*

Description

housing values in suburbs of Boston.

- 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
- chas: Charles River dummy variable (= 1 if tract bounds)
- 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 $10,000

- ptratio: pupil-teacher ratio by town
- black: 1000(Bk - 0.63)^2 where Bk is the proportion of blacks by town
- lstat: percentage of lower status of the population
- medv: Median value of owner-occupied homes in $1000's

Usage

```
data(Boston)
```

Format

Regression Dataset.

Source

This dataset was obtained from the MASS library.

References

Creator: Harrison, D. and Rubinfeld, D.L. Hedonic prices and the demand for clean air, J. Environ. Economics & Management, vol.5, 81-102, 1978.

Examples

```
data(Boston)
head(Boston)
```

---

cae2den_encode *Convolutional 2d Denoising Autoencoder - Encode*

Description

Creates an deep learning convolutional denoising autoencoder to encode a sequence of observations. It wraps the pytorch library.

Creates an deep learning convolutional autoencoder to encode a sequence of observations. It wraps the pytorch library.

Usage

```
cae2den_encode(
  input_size,
  encoding_size,
  batch_size = 32,
  num_epochs = 50,
  learning_rate = 0.001
)
```

```
cae2den_encode(
  input_size,
  encoding_size,
  batch_size = 32,
  num_epochs = 50,
  learning_rate = 0.001
)
```

Arguments

input_size	input size
encoding_size	encoding size
batch_size	size for batch learning
num_epochs	number of epochs for training
learning_rate	learning rate

Value

a c2den_encode_decode object.

a cae2den_encode object.

Examples

```
#See an example of using `c2den_encode_decode` at this
#[link](https://github.com/cefet-rj-dal/daltoolbox/blob/main/transf/c2den_encode.ipynb)
#See an example of using `cae2den_encode` at this
#[link](https://github.com/cefet-rj-dal/daltoolbox/blob/main/transf/cae2den_encode.ipynb)
```

---

cae2den_encode_decode *Convolutional 2d Denoising Autoencoder - Encode*

Description

Creates an deep learning convolutional denoising autoencoder to encode a sequence of observations. It wraps the pytorch library.

Usage

```
cae2den_encode_decode(
  input_size,
  encoding_size,
  batch_size = 32,
  num_epochs = 50,
  learning_rate = 0.001
)
```

Arguments

input_size	input size
encoding_size	encoding size
batch_size	size for batch learning
num_epochs	number of epochs for training
learning_rate	learning rate

Value

a c2den_encode_decode object.

Examples

```
#See an example of using `cae2den_encode_decode` at this
#[link](https://github.com/cefet-rj-dal/daltoolbox/blob/main/transf/cae2den_enc_decode.ipynb)
```

---

cae2d_encode_decode *Convolutional 2d Autoencoder - Encode*

Description

Creates an deep learning convolutional autoencoder to encode a sequence of observations. It wraps the pytorch library.

Usage

```
cae2d_encode_decode(
  input_size,
  encoding_size,
  batch_size = 32,
  num_epochs = 50,
  learning_rate = 0.001
)
```

Arguments

input_size	input size
encoding_size	encoding size
batch_size	size for batch learning
num_epochs	number of epochs for training
learning_rate	learning rate

Value

a cae2d_encode_decode object.

returns a cae2d_encode_decode object.

Examples

```
#See an example of using `cae2d_encode_decode` at this
#[link](https://github.com/cefet-rj-dal/daltoolbox/blob/main/transf/cae2d_enc_decode.ipynb)
```

---

cae_encode *Convolutional Autoencoder - Encode*

Description

Creates an deep learning convolutional autoencoder to encode a sequence of observations. It wraps the pytorch library.

Usage

```
cae_encode(
  input_size,
  encoding_size,
  batch_size = 32,
  num_epochs = 1000,
  learning_rate = 0.001
)
```

Arguments

input_size	input size
encoding_size	encoding size
batch_size	size for batch learning
num_epochs	number of epochs for training
learning_rate	learning rate

Value

a cae_encode object.

Examples

```
#See an example of using `cae_encode` at this
#[link](https://github.com/cefet-rj-dal/daltoolbox/blob/main/transf/cae_encode.ipynb)
```

cae_encode_decode *Convolutional Autoencoder - Encode*

Description

Creates an deep learning convolutional autoencoder to encode a sequence of observations. It wraps the pytorch library.

Usage

```
cae_encode_decode(
  input_size,
  encoding_size,
  batch_size = 32,
  num_epochs = 1000,
  learning_rate = 0.001
)
```

Arguments

input_size	input size
encoding_size	encoding size
batch_size	size for batch learning
num_epochs	number of epochs for training
learning_rate	learning rate

Value

a cae_encode_decode object.

Examples

```
#See an example of using `cae_encode_decode` at this
#[link](https://github.com/cefet-rj-dal/daltoolbox/blob/main/transf/cae_enc_decode.ipynb)
```

categ_mapping *Categorical mapping*

Description

Categorical mapping provides a way to map the levels of a categorical variable to new values. Each possible value is converted to a binary attribute.

Usage

```
categ_mapping(attribute)
```

Arguments

attribute	attribute to be categorized.

Value

returns a data frame with binary attributes, one for each possible category.

Examples

```
cm <- categ_mapping("Species")
iris_cm <- transform(cm, iris)

# can be made in a single column
species <- iris[,"Species", drop=FALSE]
iris_cm <- transform(cm, species)
```

---

classification *classification*

Description

Ancestor class for classification problems using MLmetrics nnet

Usage

```
classification(attribute, slevels)
```

Arguments

attribute	attribute target to model building
slevels	possible values for the target classification

Value

returns a classification object

Examples

```
#See ?cla_dtree for a classification example using a decision tree
```

cla_dtree *Decision Tree for classification*

Description

Creates a classification object that uses the Decision Tree algorithm for classification. It wraps the tree library.

Usage

```
cla_dtree(attribute, slevels)
```

Arguments

attribute	attribute target to model building
slevels	the possible values for the target classification

Value

returns a classification object

Examples

```
data(iris)
slevels <- levels(iris$Species)
model <- cla_dtree("Species", slevels)

# preparing dataset for random sampling
sr <- sample_random()
sr <- train_test(sr, iris)
train <- sr$train
test <- sr$test

model <- fit(model, train)

prediction <- predict(model, test)
predictand <- adjust_class_label(test[,"Species"])
test_eval <- evaluate(model, predictand, prediction)
test_eval$metrics
```

cla_knn *K Nearest Neighbor Classification*

Description

Classifies using the K-Nearest Neighbor algorithm. It wraps the class library.

Usage

```
cla_knn(attribute, slevels, k = 1)
```

Arguments

attribute	attribute target to model building.
slevels	possible values for the target classification.
k	a vector of integers indicating the number of neighbors to be considered.

Value

returns a knn object.

Examples

```
data(iris)
slevels <- levels(iris$Species)
model <- cla_knn("Species", slevels, k=3)

# preparing dataset for random sampling
sr <- sample_random()
sr <- train_test(sr, iris)
train <- sr$train
test <- sr$test

model <- fit(model, train)

prediction <- predict(model, test)
predictand <- adjust_class_label(test[,"Species"])
test_eval <- evaluate(model, predictand, prediction)
test_eval$metrics
```

`cla_majority` *Majority Classification*

Description

This function creates a classification object that uses the majority vote strategy to predict the target attribute. Given a target attribute, the function counts the number of occurrences of each value in the dataset and selects the one that appears most often.

Usage

```
cla_majority(attribute, slevels)
```

Arguments

`attribute`	attribute target to model building.
`slevels`	possible values for the target classification.

Value

returns a classification object.

Examples

```
data(iris)
slevels <- levels(iris$Species)
model <- cla_majority("Species", slevels)

# preparing dataset for random sampling
sr <- sample_random()
sr <- train_test(sr, iris)
train <- sr$train
test <- sr$test

model <- fit(model, train)

prediction <- predict(model, test)
predictand <- adjust_class_label(test[,"Species"])
test_eval <- evaluate(model, predictand, prediction)
test_eval$metrics
```

cla_mlp *MLP for classification*

Description

Creates a classification object that uses the Multi-Layer Perceptron (MLP) method. It wraps the nnet library.

Usage

```
cla_mlp(attribute, slevels, size = NULL, decay = 0.1, maxit = 1000)
```

Arguments

attribute	attribute target to model building
slevels	possible values for the target classification
size	number of nodes that will be used in the hidden layer
decay	how quickly it decreases in gradient descent
maxit	maximum iterations

Value

returns a classification object

Examples

```
data(iris)
slevels <- levels(iris$Species)
model <- cla_mlp("Species", slevels, size=3, decay=0.03)

# preparing dataset for random sampling
sr <- sample_random()
sr <- train_test(sr, iris)
train <- sr$train
test <- sr$test

model <- fit(model, train)

prediction <- predict(model, test)
predictand <- adjust_class_label(test[,"Species"])
test_eval <- evaluate(model, predictand, prediction)
test_eval$metrics
```

cla_nb *Naive Bayes Classifier*

Description

Classification using the Naive Bayes algorithm It wraps the e1071 library.

Usage

```
cla_nb(attribute, slevels)
```

Arguments

attribute	attribute target to model building.
slevels	possible values for the target classification.

Value

returns a classification object.

Examples

```
data(iris)
slevels <- levels(iris$Species)
model <- cla_nb("Species", slevels)

# preparing dataset for random sampling
sr <- sample_random()
sr <- train_test(sr, iris)
train <- sr$train
test <- sr$test

model <- fit(model, train)

prediction <- predict(model, test)
predictand <- adjust_class_label(test[,"Species"])
test_eval <- evaluate(model, predictand, prediction)
test_eval$metrics
```

cla_rf *Random Forest for classification*

Description

Creates a classification object that uses the Random Forest method It wraps the randomForest library.

Usage

```
cla_rf(attribute, slevels, nodesize = 5, ntree = 10, mtry = NULL)
```

Arguments

attribute	attribute target to model building
slevels	possible values for the target classification
nodesize	node size
ntree	number of trees
mtry	number of attributes to build tree

Value

returns a classification object

Examples

```
data(iris)
slevels <- levels(iris$Species)
model <- cla_rf("Species", slevels, ntree=5)

# preparing dataset for random sampling
sr <- sample_random()
sr <- train_test(sr, iris)
train <- sr$train
test <- sr$test

model <- fit(model, train)

prediction <- predict(model, test)
predictand <- adjust_class_label(test[,"Species"])
test_eval <- evaluate(model, predictand, prediction)
test_eval$metrics
```

---

cla_svm *SVM for classification*

Description

Creates a classification object that uses the Support Vector Machine (SVM) method for classification It wraps the e1071 and svm library.

Usage

```
cla_svm(attribute, slevels, epsilon = 0.1, cost = 10, kernel = "radial")
```

Arguments

attribute	attribute target to model building
slevels	possible values for the target classification
epsilon	parameter that controls the width of the margin around the separating hyperplane
cost	parameter that controls the trade-off between having a wide margin and correctly classifying training data points
kernel	the type of kernel function to be used in the SVM algorithm (linear, radial, polynomial, sigmoid)

Value

returns a SVM classification object

Examples

```
data(iris)
slevels <- levels(iris$Species)
model <- cla_svm("Species", slevels, epsilon=0.0,cost=20.000)

# preparing dataset for random sampling
sr <- sample_random()
sr <- train_test(sr, iris)
train <- sr$train
test <- sr$test

model <- fit(model, train)

prediction <- predict(model, test)
predictand <- adjust_class_label(test[,"Species"])
test_eval <- evaluate(model, predictand, prediction)
test_eval$metrics
```

---

cla_tune *Classification Tune*

Description

This function performs a grid search or random search over specified hyperparameter values to optimize a base classification model

Usage

```
cla_tune(base_model, folds = 10, metric = "accuracy")
```

Arguments

base_model	base model for tuning
folds	number of folds for cross-validation
metric	metric used to optimize

Value

returns a cla_tune object

Examples

```
# preparing dataset for random sampling
sr <- sample_random()
sr <- train_test(sr, iris)
train <- sr$train
test <- sr$test

# hyper parameter setup
tune <- cla_tune(cla_mlp("Species", levels(iris$Species)))
ranges <- list(size=c(3:5), decay=c(0.1))

# hyper parameter optimization
model <- fit(tune, train, ranges)

# testing optimization
test_prediction <- predict(model, test)
test_predictand <- adjust_class_label(test[,"Species"])
test_eval <- evaluate(model, test_predictand, test_prediction)
test_eval$metrics
```

---

cluster *Cluster*

Description

Defines a cluster method

Usage

```
cluster(obj, ...)
```

Arguments

obj	a clusterer object
...	optional arguments

Value

clustered data

Examples

```
#See ?cluster_kmeans for an example of transformation
```

`clusterer` *Clusterer*

Description

Ancestor class for clustering problems

Usage

```
clusterer()
```

Value

returns a `clusterer` object

Examples

```
#See ?cluster_kmeans for an example of transformation
```

`cluster_dbscan` *DBSCAN*

Description

Creates a clusterer object that uses the DBSCAN method It wraps the dbscan library.

Usage

```
cluster_dbscan(minPts = 3, eps = NULL)
```

Arguments

`minPts`	minimum number of points
`eps`	distance value

Value

returns a dbscan object

Examples

```
# setup clustering
model <- cluster_dbscan(minPts = 3)

#load dataset
data(iris)

# build model
model <- fit(model, iris[,1:4])
clu <- cluster(model, iris[,1:4])
table(clu)

# evaluate model using external metric
eval <- evaluate(model, clu, iris$Species)
eval
```

`cluster_kmeans` *k-means*

Description

Creates a clusterer object that uses the k-means method It wraps the stats library.

Usage

```
cluster_kmeans(k = 1)
```

Arguments

k	the number of clusters to form.

Value

returns a k-means object.

Examples

```
# setup clustering
model <- cluster_kmeans(k=3)

#load dataset
data(iris)

# build model
model <- fit(model, iris[,1:4])
clu <- cluster(model, iris[,1:4])
table(clu)

# evaluate model using external metric
eval <- evaluate(model, clu, iris$Species)
eval
```

cluster_pam *PAM*

Description

Creates a clusterer object that uses the Partition Around Medoids (PAM) method It wraps the cluster library.

Usage

```
cluster_pam(k = 1)
```

Arguments

k	the number of clusters to generate.

Value

returns PAM object.

Examples

```
# setup clustering
model <- cluster_pam(k = 3)

#load dataset
data(iris)

# build model
model <- fit(model, iris[,1:4])
clu <- cluster(model, iris[,1:4])
table(clu)

# evaluate model using external metric
eval <- evaluate(model, clu, iris$Species)
eval
```

clu_tune *Clustering Tune*

Description

Creates an object for tuning clustering models. This object can be used to fit and optimize clustering algorithms by specifying hyperparameter ranges

Usage

```
clu_tune(base_model)
```

Arguments

base_model	base model for tuning

Value

returns a clu_tune object.

Examples

```
data(iris)

# fit model
model <- clu_tune(cluster_kmeans(k = 0))
ranges <- list(k = 1:10)
model <- fit(model, iris[,1:4], ranges)
model$k
```

---

dal_base *Class dal_base*

Description

The dal_base class is an abstract class for all dal descendants classes. It provides both fit() and action() functions

Usage

```
dal_base()
```

Value

returns a dal_base object

Examples

```
trans <- dal_base()
```

dal_learner *DAL Learner*

Description

A ancestor class for clustering, classification, regression, and time series regression. It also provides the basis for specialized evaluation of learning performance.

An example of a learner is a decision tree (cla_dtree)

Usage

```
dal_learner()
```

Value

returns a learner

Examples

```
#See ?cla_dtree for a classification example using a decision tree
```

dal_transform *DAL Transform*

Description

A transformation method applied to a dataset. If needed, the fit can be called to adjust the transform.

Usage

```
dal_transform()
```

Value

returns a `dal_transform` object.

Examples

```
#See ?minmax for an example of transformation
```

dal_tune *DAL Tune*

Description

Creates an ancestor class for hyperparameter optimization, allowing the tuning of a base model using cross-validation.

Usage

```
dal_tune(base_model, folds = 10)
```

Arguments

base_model	base model for tuning
folds	number of folds for cross-validation

Value

returns a dal_tune object

Examples

```
#See ?cla_tune for classification tuning
#See ?reg_tune for regression tuning
#See ?ts_tune for time series tuning
```

data_sample *Data Sample*

Description

The data_sample function in R is used to randomly sample data from a given data frame. It can be used to obtain a subset of data for further analysis or modeling.

Two basic specializations of data_sample are sample_random and sample_stratified. They provide random sampling and stratified sampling, respectively.

Data sample provides both training and testing partitioning (train_test) and k-fold partitioning (k_fold) of data.

Usage

```
data_sample()
```

Value

returns an object of class data_sample

Examples

```
#using random sampling
sample <- sample_random()
tt <- train_test(sample, iris)

# distribution of train
table(tt$train$Species)

# preparing dataset into four folds
folds <- k_fold(sample, iris, 4)

# distribution of folds
tbl <- NULL
for (f in folds) {
 tbl <- rbind(tbl, table(f$Species))
}
head(tbl)
```

---

dns_encode *Denoising Autoencoder - Encode*

Description

Creates an deep learning denoising autoencoder to encode a sequence of observations. It wraps the pytorch library.

Usage

```
dns_encode(
  input_size,
  encoding_size,
  batch_size = 32,
  num_epochs = 1000,
  learning_rate = 0.001,
  noise_factor = 0.3
)
```

Arguments

input_size	input size
encoding_size	encoding size
batch_size	size for batch learning
num_epochs	number of epochs for training
learning_rate	learning rate
noise_factor	level of noise to be added to the data

Value

a dns_encode_decode object.

Examples

```
#See example at https://nbviewer.org/github/cefet-rj-dal/daltoolbox-examples
```

---

dns_encode_decode *Denoising Autoencoder - Encode*

Description

Creates an deep learning denoising autoencoder to encode a sequence of observations. It wraps the pytorch library.

Usage

```
dns_encode_decode(
  input_size,
  encoding_size,
  batch_size = 32,
  num_epochs = 1000,
  learning_rate = 0.001,
  noise_factor = 0.3
)
```

Arguments

input_size	input size
encoding_size	encoding size
batch_size	size for batch learning
num_epochs	number of epochs for training
learning_rate	learning rate
noise_factor	level of noise to be added to the data

Value

a dns_encode_decode object.

Examples

```
#See example at https://nbviewer.org/github/cefet-rj-dal/daltoolbox-examples
```

do_fit *Fit Time Series Model*

Description

The actual time series model fitting. This method should be override by descendants.

Usage

```
do_fit(obj, x, y = NULL)
```

Arguments

obj	an object representing the model or algorithm to be fitted
x	a matrix or data.frame containing the input features for training the model
y	a vector or matrix containing the output values to be predicted by the model

Value

returns a fitted object

do_predict *Predict Time Series Model*

Description

The actual time series model prediction. This method should be override by descendants.

Usage

```
do_predict(obj, x)
```

Arguments

obj	an object representing the fitted model or algorithm
x	a matrix or data.frame containing the input features for making predictions

Value

returns the predicted values

dt_pca *PCA*

Description

PCA (Principal Component Analysis) is an unsupervised dimensionality reduction technique used in data analysis and machine learning. It transforms a dataset of possibly correlated variables into a new set of uncorrelated variables called principal components.

Usage

```
dt_pca(attribute = NULL, components = NULL)
```

Arguments

attribute	target attribute to model building
components	number of components for PCA

Value

returns an object of class dt_pca

Examples

```
mypca <- dt_pca("Species")
# Automatically fitting number of components
mypca <- fit(mypca, iris)
iris.pca <- transform(mypca, iris)
head(iris.pca)
head(mypca$pca.transf)
# Manual establishment of number of components
mypca <- dt_pca("Species", 3)
mypca <- fit(mypca, datasets::iris)
iris.pca <- transform(mypca, iris)
head(iris.pca)
head(mypca$pca.transf)
```

evaluate *Evaluate*

Description

Evaluate learner performance. The actual evaluate varies according to the type of learner (clustering, classification, regression, time series regression)

Usage

```
evaluate(obj, ...)
```

Arguments

obj	object
...	optional arguments

Value

returns the evaluation

Examples

```
data(iris)
slevels <- levels(iris$Species)
model <- cla_dtree("Species", slevels)
model <- fit(model, iris)
prediction <- predict(model, iris)
predictand <- adjust_class_label(iris[,"Species"])
test_eval <- evaluate(model, predictand, prediction)
test_eval$metrics
```

---

fit *Fit*

Description

Applies the `fit` method to a model object to train or configure it using the provided data and optional arguments

Usage

```
fit(obj, ...)
```

Arguments

obj	object
...	optional arguments.

Value

returns a object after fitting

Examples

```
data(iris)
# an example is minmax normalization
trans <- minmax()
trans <- fit(trans, iris)
tiris <- action(trans, iris)
```

`fit.cla_tune` *tune hyperparameters of ml model*

Description

Tunes the hyperparameters of a machine learning model for classification

Usage

```
## S3 method for class 'cla_tune'
fit(obj, data, ranges, ...)
```

Arguments

`obj`	an object containing the model and tuning configuration
`data`	the dataset used for training and evaluation
`ranges`	a list of hyperparameter ranges to explore
`...`	optional arguments

Value

a fitted obj

`fit.cluster_dbscan` *fit dbscan model*

Description

Fits a DBSCAN clustering model by setting the `eps` parameter. If `eps` is not provided, it is estimated based on the k-nearest neighbor distances. It wraps dbscan library

Usage

```
## S3 method for class 'cluster_dbscan'
fit(obj, data, ...)
```

Arguments

obj	an object containing the DBSCAN model configuration, including minPts and optionally eps
data	the dataset to use for fitting the model
...	optional arguments

Value

returns a fitted obj with the eps parameter set

---

fit_curvature_max *maximum curvature analysis*

Description

Fitting a curvature model in a sequence of observations. It extracts the the maximum curvature computed.

Usage

```
fit_curvature_max()
```

Value

returns an object of class fit_curvature_max, which inherits from the fit_curvature and dal_transform classes. The object contains a list with the following elements:

- x: The position in which the maximum curvature is reached.
- y: The value where the the maximum curvature occurs.
- yfit: The value of the maximum curvature.

Examples

```
x <- seq(from=1,to=10,by=0.5)
dat <- data.frame(x = x, value = -log(x), variable = "log")
myfit <- fit_curvature_max()
res <- transform(myfit, dat$value)
head(res)
```

fit_curvature_min *minimum curvature analysis*

Description

Fitting a curvature model in a sequence of observations. It extracts the the minimum curvature computed.

Usage

```
fit_curvature_min()
```

Value

Returns an object of class fit_curvature_max, which inherits from the fit_curvature and dal_transform classes. The object contains a list with the following elements:

- x: The position in which the minimum curvature is reached.
- y: The value where the the minimum curvature occurs.
- yfit: The value of the minimum curvature.

Examples

```
x <- seq(from=1,to=10,by=0.5)
dat <- data.frame(x = x, value = log(x), variable = "log")
myfit <- fit_curvature_min()
res <- transform(myfit, dat$value)
head(res)
```

inverse_transform *Inverse Transform*

Description

Reverses the transformation applied to data.

Usage

```
inverse_transform(obj, ...)
```

Arguments

obj	a dal_transform object.
...	optional arguments.

Value

dataset inverse transformed.

Examples

```
#See ?minmax for an example of transformation
```

`k_fold` *K-fold sampling*

Description

k-fold partition of a dataset using a sampling method

Usage

```
k_fold(obj, data, k)
```

Arguments

`obj`	an object representing the sampling method
`data`	dataset to be partitioned
`k`	number of folds

Value

returns a list of k data frames

Examples

```
#using random sampling
sample <- sample_random()

# preparing dataset into four folds
folds <- k_fold(sample, iris, 4)

# distribution of folds
tbl <- NULL
for (f in folds) {
 tbl <- rbind(tbl, table(f$Species))
}
head(tbl)
```

lae_encode *LSTM Autoencoder - Encode*

Description

Creates an deep learning LSTM autoencoder to encode a sequence of observations. It wraps the pytorch library.

Usage

```
lae_encode(
  input_size,
  encoding_size,
  batch_size = 32,
  num_epochs = 50,
  learning_rate = 0.001
)
```

Arguments

input_size	input size
encoding_size	encoding size
batch_size	size for batch learning
num_epochs	number of epochs for training
learning_rate	learning rate

Value

returns a lae_encode object.

Examples

```
#See an example of using `lae_encode` at this
#[link](https://github.com/cefet-rj-dal/daltoolbox/blob/main/transf/lae_encode.ipynb)
```

lae_encode_decode *LSTM Autoencoder - Decode*

Description

Creates an deep learning LSTM autoencoder to encode a sequence of observations. It wraps the pytorch library.

Usage

```
lae_encode_decode(
  input_size,
  encoding_size,
  batch_size = 32,
  num_epochs = 50,
  learning_rate = 0.001
)
```

Arguments

input_size	input size
encoding_size	encoding size
batch_size	size for batch learning
num_epochs	number of epochs for training
learning_rate	learning rate

Value

returns a lae_encode_decode object.

Examples

```
#See an example of using `lae_encode_decode` at this
#[link](https://github.com/cefet-rj-dal/daltoolbox/blob/main/transf/lae_enc_decode.ipynb)
```

---

minmax *Min-max normalization*

Description

The minmax performs scales data between [0,1].

$minmax = (x - min(x))/(max(x) - min(x))$

Usage

```
minmax()
```

Value

returns an object of class minmax

Examples

```
data(iris)
head(iris)

trans <- minmax()
trans <- fit(trans, iris)
tiris <- transform(trans, iris)
head(tiris)

itiris <- inverse_transform(trans, tiris)
head(itiris)
```

`MSE.ts` *MSE*

Description

Compute the mean squared error (MSE) between actual values and forecasts of a time series

Usage

```
MSE.ts(actual, prediction)
```

Arguments

`actual`	real observations
`prediction`	predicted observations

Value

returns a number, which is the calculated MSE

`outliers` *Outliers*

Description

The outliers class uses box-plot definition for outliers. An outlier is a value that is below than $Q_1 - 1.5 \cdot IQR$ or higher than $Q_3 + 1.5 \cdot IQR$. The class remove outliers for numeric attributes. Users can set alpha to 3 to remove extreme values.

Usage

```
outliers(alpha = 1.5)
```

Arguments

alpha	boxplot outlier threshold (default 1.5, but can be 3.0 to remove extreme values)

Value

returns an outlier object

Examples

```
# code for outlier removal
out_obj <- outliers() # class for outlier analysis
out_obj <- fit(out_obj, iris) # computing boundaries
iris.clean <- transform(out_obj, iris) # returning cleaned dataset

#inspection of cleaned dataset
nrow(iris.clean)

idx <- attr(iris.clean, "idx")
table(idx)
iris.outliers <- iris[idx,]
iris.outliers
```

---

plot_bar *Plot bar graph*

Description

this function displays a bar graph from a data frame containing x-axis categories using ggplot2.

Usage

```
plot_bar(data, label_x = "", label_y = "", colors = NULL, alpha = 1)
```

Arguments

data	data.frame contain x, value, and variable
label_x	x-axis label
label_y	y-axis label
colors	color vector
alpha	level of transparency

Value

returns a ggplot graphic

Examples

```
#summarizing iris dataset
data <- iris |> dplyr::group_by(Species) |>
 dplyr::summarize(Sepal.Length=mean(Sepal.Length))
head(data)

#ploting data
grf <- plot_bar(data, colors="blue")
plot(grf)
```

`plot_boxplot` *Plot boxplot*

Description

this function displays a boxplot graph from a data frame containing x-axis categories and numeric values using ggplot2.

Usage

```
plot_boxplot(data, label_x = "", label_y = "", colors = NULL, barwidth = 0.25)
```

Arguments

`data`	data.frame contain x, value, and variable
`label_x`	x-axis label
`label_y`	y-axis label
`colors`	color vector
`barwidth`	width of bar

Value

returns a ggplot graphic

Examples

```
grf <- plot_boxplot(iris, colors="white")
plot(grf)
```

`plot_boxplot_class` *Boxplot per class*

Description

This function generates boxplots grouped by a specified class label from a data frame containing numeric values using ggplot2.

Usage

```
plot_boxplot_class(
  data,
  class_label,
  label_x = "",
  label_y = "",
  colors = NULL
)
```

Arguments

`data`	data.frame contain x, value, and variable
`class_label`	name of attribute for class label
`label_x`	x-axis label
`label_y`	y-axis label
`colors`	color vector

Value

returns a ggplot graphic

Examples

```
grf <- plot_boxplot_class(iris |> dplyr::select(Sepal.Width, Species),
 class = "Species", colors=c("red", "green", "blue"))
plot(grf)
```

plot_density *Plot density*

Description

This function generates a density plot from a data frame containing numeric values using ggplot2. If the data frame has multiple columns, densities can be grouped and plotted.

Usage

```
plot_density(
  data,
  label_x = "",
  label_y = "",
  colors = NULL,
  bin = NULL,
  alpha = 0.25
)
```

Arguments

data	data.frame contain x, value, and variable
label_x	x-axis label
label_y	y-axis label
colors	color vector
bin	bin width for density estimation
alpha	level of transparency

Value

returns a ggplot graphic

Examples

```
grf <- plot_density(iris |> dplyr::select(Sepal.Width), colors="blue")
plot(grf)
```

plot_density_class *Plot density per class*

Description

This function generates density plots using ggplot2 grouped by a specified class label from a data frame containing numeric values.

Usage

```
plot_density_class(
  data,
  class_label,
  label_x = "",
  label_y = "",
  colors = NULL,
  bin = NULL,
  alpha = 0.5
)
```

Arguments

data	data.frame contain x, value, and variable
class_label	name of attribute for class label
label_x	x-axis label
label_y	y-axis label
colors	color vector
bin	bin width for density estimation
alpha	level of transparency

Value

returns a ggplot graphic

Examples

```
grf <- plot_density_class(iris |> dplyr::select(Sepal.Width, Species),
 class = "Species", colors=c("red", "green", "blue"))
plot(grf)
```

plot_groupedbar *Plot grouped bar*

Description

This function generates a grouped bar plot from a given data frame using ggplot2.

Usage

```
plot_groupedbar(data, label_x = "", label_y = "", colors = NULL, alpha = 1)
```

Arguments

data	data.frame contain x, value, and variable
label_x	x-axis label
label_y	y-axis label
colors	color vector
alpha	level of transparency

Value

returns a ggplot graphic

Examples

```
#summarizing iris dataset
data <- iris |> dplyr::group_by(Species) |>
 dplyr::summarize(Sepal.Length=mean(Sepal.Length), Sepal.Width=mean(Sepal.Width))
head(data)

#ploting data
grf <- plot_groupedbar(data, colors=c("blue", "red"))
plot(grf)
```

plot_hist *Plot histogram*

Description

This function generates a histogram from a specified data frame using ggplot2.

Usage

```
plot_hist(data, label_x = "", label_y = "", color = "white", alpha = 0.25)
```

Arguments

data	data.frame contain x, value, and variable
label_x	x-axis label
label_y	y-axis label
color	color vector
alpha	transparency level

Value

returns a ggplot graphic

Examples

```
grf <- plot_hist(iris |> dplyr::select(Sepal.Width), color=c("blue"))
plot(grf)
```

---

plot_lollipop *Plot lollipop*

Description

This function creates a lollipop chart using ggplot2.

Usage

```
plot_lollipop(
  data,
  label_x = "",
  label_y = "",
  colors = NULL,
  color_text = "black",
  size_text = 3,
  size_ball = 8,
  alpha_ball = 0.2,
  min_value = 0,
  max_value_gap = 1
)
```

Arguments

data	data.frame contain x, value, and variable
label_x	x-axis label
label_y	y-axis label
colors	color vector
color_text	color of text inside ball

size_text	size of text inside ball
size_ball	size of ball
alpha_ball	transparency of ball
min_value	minimum value
max_value_gap	maximum value gap

Value

returns a ggplot graphic

Examples

```
#summarizing iris dataset
data <- iris |> dplyr::group_by(Species) |>
 dplyr::summarize(Sepal.Length=mean(Sepal.Length))
head(data)

#ploting data
grf <- plot_lollipop(data, colors="blue", max_value_gap=0.2)
plot(grf)
```

---

plot_pieplot *Plot pie*

Description

This function creates a pie chart using ggplot2.

Usage

```
plot_pieplot(
  data,
  label_x = "",
  label_y = "",
  colors = NULL,
  textcolor = "white",
  bordercolor = "black"
)
```

Arguments

data	data.frame contain x, value, and variable
label_x	x-axis label
label_y	y-axis label
colors	color vector
textcolor	text color
bordercolor	border color

Value

returns a ggplot graphic

Examples

```
#summarizing iris dataset
data <- iris |> dplyr::group_by(Species) |>
 dplyr::summarize(Sepal.Length=mean(Sepal.Length))
head(data)

#ploting data
grf <- plot_pieplot(data, colors=c("red", "green", "blue"))
plot(grf)
```

---

plot_points *Plot points*

Description

This function creates a scatter plot using ggplot2.

Usage

```
plot_points(data, label_x = "", label_y = "", colors = NULL)
```

Arguments

data	data.frame contain x, value, and variable
label_x	x-axis label
label_y	y-axis label
colors	color vector

Value

returns a ggplot graphic

Examples

```
x <- seq(0, 10, 0.25)
data <- data.frame(x, sin=sin(x), cosine=cos(x)+5)
head(data)

grf <- plot_points(data, colors=c("red", "green"))
plot(grf)
```

plot_radar *Plot radar*

Description

This function creates a radar chart using ggplot2.

Usage

```
plot_radar(data, label_x = "", label_y = "", colors = NULL)
```

Arguments

data	data.frame contain x, value, and variable
label_x	x-axis label
label_y	y-axis label
colors	color vector

Value

returns a ggplot graphic

Examples

```
data <- data.frame(name = "Petal.Length", value = mean(iris$Petal.Length))
data <- rbind(data, data.frame(name = "Petal.Width", value = mean(iris$Petal.Width)))
data <- rbind(data, data.frame(name = "Sepal.Length", value = mean(iris$Sepal.Length)))
data <- rbind(data, data.frame(name = "Sepal.Width", value = mean(iris$Sepal.Width)))

grf <- plot_radar(data, colors="red") + ggplot2::ylim(0, NA)
plot(grf)
```

plot_scatter *Scatter graph*

Description

This function creates a scatter plot using ggplot2.

Usage

```
plot_scatter(data, label_x = "", label_y = "", colors = NULL)
```

Arguments

data	data.frame contain x, value, and variable
label_x	x-axis label
label_y	y-axis label
colors	color vector

Value

return a ggplot graphic

Examples

```
grf <- plot_scatter(iris |> dplyr::select(x = Sepal.Length,
 value = Sepal.Width, variable = Species),
 label_x = "Sepal.Length", label_y = "Sepal.Width",
 colors=c("red", "green", "blue"))
 plot(grf)
```

---

plot_series *Plot series*

Description

This function creates a time series plot using ggplot2.

Usage

```
plot_series(data, label_x = "", label_y = "", colors = NULL)
```

Arguments

data	data.frame contain x, value, and variable
label_x	x-axis label
label_y	y-axis label
colors	color vector

Value

returns a ggplot graphic

Examples

```
x <- seq(0, 10, 0.25)
data <- data.frame(x, sin=sin(x))
head(data)

grf <- plot_series(data, colors=c("red"))
plot(grf)
```

plot_stackedbar *Plot stacked bar*

Description

this function creates a stacked bar chart using ggplot2.

Usage

```
plot_stackedbar(data, label_x = "", label_y = "", colors = NULL, alpha = 1)
```

Arguments

data	data.frame contain x, value, and variable
label_x	x-axis label
label_y	y-axis label
colors	color vector
alpha	level of transparency

Value

returns a ggplot graphic

Examples

```
#summarizing iris dataset
data <- iris |> dplyr::group_by(Species) |>
 dplyr::summarize(Sepal.Length=mean(Sepal.Length), Sepal.Width=mean(Sepal.Width))

#plotting data
grf <- plot_stackedbar(data, colors=c("blue", "red"))
plot(grf)
```

plot_ts *Plot time series chart*

Description

This function plots a time series chart with points and a line using ggplot2.

Usage

```
plot_ts(x = NULL, y, label_x = "", label_y = "", color = "black")
```

Arguments

x	input variable
y	output variable
label_x	x-axis label
label_y	y-axis label
color	color for time series

Value

returns a ggplot graphic

Examples

```
x <- seq(0, 10, 0.25)
data <- data.frame(x, sin=sin(x))
head(data)

grf <- plot_ts(x = data$x, y = data$sin, color=c("red"))
plot(grf)
```

---

plot_ts_pred *Plot a time series chart with predictions*

Description

This function plots a time series chart with three lines: the original series, the adjusted series, and the predicted series using ggplot2.

Usage

```
plot_ts_pred(
  x = NULL,
  y,
  yadj,
  ypred = NULL,
  label_x = "",
  label_y = "",
  color = "black",
  color_adjust = "blue",
  color_prediction = "green"
)
```

Arguments

x	time index
y	time series
yadj	adjustment of time series
ypred	prediction of the time series
label_x	x-axis title
label_y	y-axis title
color	color for the time series
color_adjust	color for the adjusted values
color_prediction	color for the predictions

Value

returns a ggplot graphic

Examples

```
data(sin_data)
ts <- ts_data(sin_data$y, 0)
ts_head(ts, 3)


samp <- ts_sample(ts, test_size= 5)
io_train <- ts_projection(samp$train)
io_test <- ts_projection(samp$test)

model <- ts_arima()
model <- fit(model, x=io_train$input, y=io_train$output)
adjust <- predict(model, io_train$input)

prediction <- predict(model, x=io_test$input, steps_ahead=5)
prediction <- as.vector(prediction)

yvalues <- c(io_train$output, io_test$output)
grf <- plot_ts_pred(y=yvalues, yadj=adjust, ypre=prediction)
plot(grf)
```

---

predictor *DAL Predict*

Description

Ancestor class for regression and classification It provides basis for fit and predict methods. Besides, action method proxies to predict.

An example of learner is a decision tree (cla_dtree)

Usage

```
predictor()
```

Value

returns a predictor object

Examples

```
#See ?cla_dtree for a classification example using a decision tree
```

R2.ts *R2*

Description

Compute the R-squared (R2) between actual values and forecasts of a time series

Usage

```
R2.ts(actual, prediction)
```

Arguments

actual	real observations
prediction	predicted observations

Value

returns a number, which is the calculated R2

---

regression *Regression*

Description

Ancestor class for regression problems. This ancestor class is used to define and manage the target attribute for regression tasks.

Usage

```
regression(attribute)
```

Arguments

attribute	attribute target to model building

Value

returns a regression object

Examples

```
#See ?reg_dtree for a regression example using a decision tree
```

---

reg_dtree *Decision Tree for regression*

Description

Creates a regression object that uses the Decision Tree method for regression It wraps the tree library.

Usage

```
reg_dtree(attribute)
```

Arguments

attribute	attribute target to model building.

Value

returns a decision tree regression object

Examples

```
data(Boston)
model <- reg_dtree("medv")

# preparing dataset for random sampling
sr <- sample_random()
sr <- train_test(sr, Boston)
train <- sr$train
test <- sr$test

model <- fit(model, train)

test_prediction <- predict(model, test)
test_predictand <- test[,"medv"]
test_eval <- evaluate(model, test_predictand, test_prediction)
test_eval$metrics
```

reg_knn *knn regression*

Description

Creates a regression object that uses the K-Nearest Neighbors (knn) method for regression

Usage

```
reg_knn(attribute, k)
```

Arguments

attribute	attribute target to model building
k	number of k neighbors

Value

returns a knn regression object

Examples

```
data(Boston)
model <- reg_knn("medv", k=3)

# preparing dataset for random sampling
sr <- sample_random()
sr <- train_test(sr, Boston)
train <- sr$train
test <- sr$test

model <- fit(model, train)

test_prediction <- predict(model, test)
test_predictand <- test[,"medv"]
test_eval <- evaluate(model, test_predictand, test_prediction)
test_eval$metrics
```

reg_mlp *MLP for regression*

Description

Creates a regression object that uses the Multi-Layer Perceptron (MLP) method. It wraps the nnet library.

Usage

```
reg_mlp(attribute, size = NULL, decay = 0.05, maxit = 1000)
```

Arguments

attribute	attribute target to model building
size	number of neurons in hidden layers
decay	decay learning rate
maxit	number of maximum iterations for training

Value

returns a object of class reg_mlp

Examples

```
data(Boston)
model <- reg_mlp("medv", size=5, decay=0.54)

# preparing dataset for random sampling
sr <- sample_random()
sr <- train_test(sr, Boston)
train <- sr$train
test <- sr$test

model <- fit(model, train)

test_prediction <- predict(model, test)
test_predictand <- test[,"medv"]
test_eval <- evaluate(model, test_predictand, test_prediction)
test_eval$metrics
```

---

reg_rf *Random Forest for regression*

Description

Creates a regression object that uses the Random Forest method. It wraps the randomForest library.

Usage

```
reg_rf(attribute, nodesize = 1, ntree = 10, mtry = NULL)
```

Arguments

attribute	attribute target to model building
nodesize	node size
ntree	number of trees
mtry	number of attributes to build tree

Value

returns an object of class reg_rfobj

Examples

```
data(Boston)
model <- reg_rf("medv", ntree=10)

# preparing dataset for random sampling
sr <- sample_random()
sr <- train_test(sr, Boston)
train <- sr$train
test <- sr$test

model <- fit(model, train)

test_prediction <- predict(model, test)
test_predictand <- test[,"medv"]
test_eval <- evaluate(model, test_predictand, test_prediction)
test_eval$metrics
```

---

reg_svm *SVM for regression*

Description

Creates a regression object that uses the Support Vector Machine (SVM) method for regression It wraps the e1071 and svm library.

Usage

```
reg_svm(attribute, epsilon = 0.1, cost = 10, kernel = "radial")
```

Arguments

attribute	attribute target to model building
epsilon	parameter that controls the width of the margin around the separating hyperplane
cost	parameter that controls the trade-off between having a wide margin and correctly classifying training data points
kernel	the type of kernel function to be used in the SVM algorithm (linear, radial, polynomial, sigmoid)

Value

returns a SVM regression object

Examples

```
data(Boston)
model <- reg_svm("medv", epsilon=0.2,cost=40.000)

# preparing dataset for random sampling
sr <- sample_random()
sr <- train_test(sr, Boston)
train <- sr$train
test <- sr$test

model <- fit(model, train)

test_prediction <- predict(model, test)
test_predictand <- test[,"medv"]
test_eval <- evaluate(model, test_predictand, test_prediction)
test_eval$metrics
```

`reg_tune` *Regression Tune*

Description

Creates an object for tuning regression models

Usage

```
reg_tune(base_model, folds = 10)
```

Arguments

`base_model`	base model for tuning
`folds`	number of folds for cross-validation

Value

returns a `reg_tune` object.

Examples

```
# preparing dataset for random sampling
data(Boston)
sr <- sample_random()
sr <- train_test(sr, Boston)
train <- sr$train
test <- sr$test

# hyper parameter setup
tune <- reg_tune(reg_mlp("medv"))
ranges <- list(size=c(3), decay=c(0.1,0.5))
```

```
# hyper parameter optimization
model <- fit(tune, train, ranges)

test_prediction <- predict(model, test)
test_predictand <- test[,"medv"]
test_eval <- evaluate(model, test_predictand, test_prediction)
test_eval$metrics
```

---

sae_encode *Stacked Autoencoder - Encode*

Description

Creates an deep learning stacked autoencoder to encode a sequence of observations. The autoencoder layers are based on DAL Toolbox Vanilla Autoencoder It wraps the pytorch library.

Usage

```
sae_encode(
  input_size,
  encoding_size,
  batch_size = 32,
  num_epochs = 1000,
  learning_rate = 0.001,
  k = 3
)
```

Arguments

input_size	input size
encoding_size	encoding size
batch_size	size for batch learning
num_epochs	number of epochs for training
learning_rate	learning rate
k	number of AE layers in the stack

Value

a sae_encode_decode object.

Examples

```
#See example at https://nbviewer.org/github/cefet-rj-dal/daltoolbox-examples
```

sae_encode_decode *Stacked Autoencoder - Encode*

Description

Creates an deep learning stacked autoencoder to encode a sequence of observations. The autoencoder layers are based on DAL Toolbox Vanilla Autoencoder It wraps the pytorch library.

Usage

```
sae_encode_decode(
  input_size,
  encoding_size,
  batch_size = 32,
  num_epochs = 1000,
  learning_rate = 0.001,
  k = 3
)
```

Arguments

input_size	input size
encoding_size	encoding size
batch_size	size for batch learning
num_epochs	number of epochs for training
learning_rate	learning rate
k	number of AE layers in the stack

Value

a sae_encode_decode object.

Examples

```
#See example at https://nbviewer.org/github/cefet-rj-dal/daltoolbox-examples
```

sample_random *Sample Random*

Description

The sample_random function in R is used to generate a random sample of specified size from a given data set.

Usage

```
sample_random()
```

Value

returns an object of class 'sample_random

Examples

```
#using random sampling
sample <- sample_random()
tt <- train_test(sample, iris)

# distribution of train
table(tt$train$Species)

# preparing dataset into four folds
folds <- k_fold(sample, iris, 4)

# distribution of folds
tbl <- NULL
for (f in folds) {
 tbl <- rbind(tbl, table(f$Species))
}
head(tbl)
```

sample_stratified *Stratified Random Sampling*

Description

The sample_stratified function in R is used to generate a stratified random sample from a given dataset. Stratified sampling is a statistical method that is used when the population is divided into non-overlapping subgroups or strata, and a sample is selected from each stratum to represent the entire population. In stratified sampling, the sample is selected in such a way that it is representative of the entire population and the variability within each stratum is minimized.

Usage

```
sample_stratified(attribute)
```

Arguments

attribute	attribute target to model building

Value

returns an object of class sample_stratified

Examples

```
#using stratified sampling
sample <- sample_stratified("Species")
tt <- train_test(sample, iris)

# distribution of train
table(tt$train$Species)

# preparing dataset into four folds
folds <- k_fold(sample, iris, 4)

# distribution of folds
tbl <- NULL
for (f in folds) {
 tbl <- rbind(tbl, table(f$Species))
}
head(tbl)
```

---

select_hyper *Selection hyper parameters*

Description

Selects the optimal hyperparameters from a dataset resulting from k-fold cross-validation

Usage

```
select_hyper(obj, hyperparameters)
```

Arguments

obj	the object or model used for hyperparameter selection.
hyperparameters	data set with hyper parameters and quality measure from execution

Value

returns the index of selected hyper parameter

select_hyper.cla_tune *selection of hyperparameters*

Description

Selects the optimal hyperparameter by maximizing the average classification metric. It wraps dplyr library.

Usage

```
## S3 method for class 'cla_tune'
select_hyper(obj, hyperparameters)
```

Arguments

obj	an object representing the model or tuning process
hyperparameters	a dataframe with columns key (hyperparameter configuration) and metric (classification metric)

Value

returns a optimized key number of hyperparameters

select_hyper.ts_tune *Select Optimal Hyperparameters for Time Series Models*

Description

Identifies the optimal hyperparameters by minimizing the error from a dataset of hyperparameters. The function selects the hyperparameter configuration that results in the lowest average error. It wraps the dplyr library.

Usage

```
## S3 method for class 'ts_tune'
select_hyper(obj, hyperparameters)
```

Arguments

obj	a ts_tune object containing the model and tuning settings
hyperparameters	hyperparameters dataset

Value

returns the optimized key number of hyperparameters

set_params *Assign parameters*

Description

set_params function assigns all parameters to the attributes presented in the object.

Usage

```
set_params(obj, params)
```

Arguments

obj	object of class dal_base
params	parameters to set obj

Value

returns an object with parameters set

Examples

```
obj <- set_params(dal_base(), list(x = 0))
```

set_params.default *Default Assign parameters*

Description

Default method for set_params which returns the object unchanged

Usage

```
## Default S3 method:
set_params(obj, params)
```

Arguments

obj	object
params	parameters

Value

returns the object unchanged

sin_data *Time series example dataset*

Description

Synthetic dataset of sine function.

- x: correspond time from 0 to 10.
- y: dependent variable for time series modeling.

Usage

```
data(sin_data)
```

Format

`data.frame`.

Source

This dataset was generated for examples.

Examples

```
data(sin_data)
head(sin_data)
```

sMAPE.ts *sMAPE*

Description

Compute the symmetric mean absolute percent error (sMAPE)

Usage

```
sMAPE.ts(actual, prediction)
```

Arguments

`actual`	real observations
`prediction`	predicted observations

Value

returns the sMAPE between the actual and prediction vectors

smoothing *Smoothing*

Description

Smoothing is a statistical technique used to reduce the noise in a signal or a dataset by removing the high-frequency components. The smoothing level is associated with the number of bins used. There are alternative methods to establish the smoothing: equal interval, equal frequency, and clustering.

Usage

```
smoothing(n)
```

Arguments

n	number of bins

Value

returns an object of class smoothing

Examples

```
data(iris)
obj <- smoothing_inter(n = 2)
obj <- fit(obj, iris$Sepal.Length)
sl.bi <- transform(obj, iris$Sepal.Length)
table(sl.bi)
obj$interval

entro <- evaluate(obj, as.factor(names(sl.bi)), iris$Species)
entro$entropy
```

smoothing_cluster *Smoothing by cluster*

Description

Uses clustering method to perform data smoothing. The input vector is divided into clusters using the k-means algorithm. The mean of each cluster is then calculated and used as the smoothed value for all observations within that cluster.

Usage

```
smoothing_cluster(n)
```

Arguments

n	number of bins

Value

returns an object of class smoothing_cluster

Examples

```
data(iris)
obj <- smoothing_cluster(n = 2)
obj <- fit(obj, iris$Sepal.Length)
sl.bi <- transform(obj, iris$Sepal.Length)
table(sl.bi)
obj$interval

entro <- evaluate(obj, as.factor(names(sl.bi)), iris$Species)
entro$entropy
```

---

smoothing_freq *Smoothing by Freq*

Description

The 'smoothing_freq' function is used to smooth a given time series data by aggregating observations within a fixed frequency.

Usage

```
smoothing_freq(n)
```

Arguments

n	number of bins

Value

returns an object of class smoothing_freq

Examples

```
data(iris)
obj <- smoothing_freq(n = 2)
obj <- fit(obj, iris$Sepal.Length)
sl.bi <- transform(obj, iris$Sepal.Length)
table(sl.bi)
obj$interval

entro <- evaluate(obj, as.factor(names(sl.bi)), iris$Species)
entro$entropy
```

smoothing_inter *Smoothing by interval*

Description

The "smoothing by interval" function is used to apply a smoothing technique to a vector or time series data using a moving window approach.

Usage

```
smoothing_inter(n)
```

Arguments

n	number of bins

Value

returns an object of class smoothing_inter

Examples

```
data(iris)
obj <- smoothing_inter(n = 2)
obj <- fit(obj, iris$Sepal.Length)
sl.bi <- transform(obj, iris$Sepal.Length)
table(sl.bi)
obj$interval

entro <- evaluate(obj, as.factor(names(sl.bi)), iris$Species)
entro$entropy
```

train_test *Train-Test Partition*

Description

Partitions a dataset into training and test sets using a specified sampling method

Usage

```
train_test(obj, data, perc = 0.8, ...)
```

Arguments

obj	an object of a class that supports the train_test method
data	dataset to be partitioned
perc	a numeric value between 0 and 1 specifying the proportion of data to be used for training
...	additional optional arguments passed to specific methods.

Value

returns an list with two elements:

- train: A data frame containing the training set
- test: A data frame containing the test set

Examples

```
#using random sampling
sample <- sample_random()
tt <- train_test(sample, iris)

# distribution of train
table(tt$train$Species)
```

---

train_test_from_folds *k-fold training and test partition object*

Description

Splits a dataset into training and test sets based on k-fold cross-validation. The function takes a list of data partitions (folds) and a specified fold index k. It returns the data corresponding to the k-th fold as the test set, and combines all other folds to form the training set.

Usage

```
train_test_from_folds(folds, k)
```

Arguments

folds	data partitioned into folds
k	k-fold for test set, all reminder for training set

Value

returns a list with two elements:

- train: A data frame containing the combined data from all folds except the k-th fold, used as the training set.
- test: A data frame corresponding to the k-th fold, used as the test set.

Examples

```
# Create k-fold partitions of a dataset (e.g., iris)
folds <- k_fold(sample_random(), iris, k = 5)

# Use the first fold as the test set and combine the remaining folds for the training set
train_test_split <- train_test_from_folds(folds, k = 1)

# Display the training set
head(train_test_split$train)

# Display the test set
head(train_test_split$test)
```

`transform` *Transform*

Description

Defines a transformation method.

Usage

```
transform(obj, ...)
```

Arguments

`obj`	a `dal_transform` object.
`...`	optional arguments.

Value

returns a transformed data.

Examples

```
#See ?minmax for an example of transformation
```

ts_arima *ARIMA*

Description

Creates a time series prediction object that uses the AutoRegressive Integrated Moving Average (ARIMA). It wraps the forecast library.

Usage

```
ts_arima()
```

Value

returns a `ts_arima` object.

Examples

```
data(sin_data)
ts <- ts_data(sin_data$y, 0)
ts_head(ts, 3)

samp <- ts_sample(ts, test_size = 5)
io_train <- ts_projection(samp$train)
io_test <- ts_projection(samp$test)

model <- ts_arima()
model <- fit(model, x=io_train$input, y=io_train$output)

prediction <- predict(model, x=io_test$input[1,], steps_ahead=5)
prediction <- as.vector(prediction)
output <- as.vector(io_test$output)

ev_test <- evaluate(model, output, prediction)
ev_test
```

ts_conv1d *Conv1D*

Description

Creates a time series prediction object that uses the Conv1D. It wraps the pytorch library.

Usage

```
ts_conv1d(preprocess = NA, input_size = NA, epochs = 10000L)
```

Arguments

preprocess	normalization
input_size	input size for machine learning model
epochs	maximum number of epochs

Value

returns a ts_conv1d object.

Examples

```
#See an example of using `ts_conv1d` at this
#[link](https://github.com/cefet-rj-dal/daltoolbox/blob/main/timeseries/ts_conv1d.ipynb)
```

---

ts_data *ts_data*

Description

Time series data structure used in DAL Toolbox. It receives a vector (representing a time series) or a matrix y (representing a sliding windows). Internal ts_data is matrix of sliding windows with size sw. If sw equals to zero, it store a time series as a single matrix column.

Usage

```
ts_data(y, sw = 1)
```

Arguments

y	output variable
sw	integer: sliding window size.

Value

returns a ts_data object.

Examples

```
data(sin_data)
head(sin_data)

data <- ts_data(sin_data$y)
ts_head(data)

data10 <- ts_data(sin_data$y, 10)
ts_head(data10)
```

ts_elm *ELM*

Description

Creates a time series prediction object that uses the Extreme Learning Machine (ELM). It wraps the elmNNRcpp library.

Usage

```
ts_elm(preprocess = NA, input_size = NA, nhid = NA, actfun = "purelin")
```

Arguments

preprocess	normalization
input_size	input size for machine learning model
nhid	ensemble size
actfun	defines the type to use, possible values: 'sig', 'radbas', 'tribas', 'relu', 'purelin' (default).

Value

returns a ts_elm object.

Examples

```
data(sin_data)
ts <- ts_data(sin_data$y, 10)
ts_head(ts, 3)

samp <- ts_sample(ts, test_size = 5)
io_train <- ts_projection(samp$train)
io_test <- ts_projection(samp$test)

model <- ts_elm(ts_norm_gminmax(), input_size=4, nhid=3, actfun="purelin")
model <- fit(model, x=io_train$input, y=io_train$output)

prediction <- predict(model, x=io_test$input[1,], steps_ahead=5)
prediction <- as.vector(prediction)
output <- as.vector(io_test$output)

ev_test <- evaluate(model, output, prediction)
ev_test
```

ts_head *Extract the First Observations from a* ts_data *Object*

Description

Returns the first n observations from a ts_data

Usage

```
ts_head(x, n = 6L, ...)
```

Arguments

x	ts_data object
n	number of rows to return
...	optional arguments

Value

returns the first n observations of a ts_data

Examples

```
data(sin_data)
data10 <- ts_data(sin_data$y, 10)
ts_head(data10)
```

ts_knn *KNN time series prediction*

Description

Creates a prediction object that uses the K-Nearest Neighbors (KNN) method for time series regression

Usage

```
ts_knn(preprocess = NA, input_size = NA, k = NA)
```

Arguments

preprocess	normalization
input_size	input size for machine learning model
k	number of k neighbors

Value

returns a ts_knn object.

Examples

```
data(sin_data)
ts <- ts_data(sin_data$y, 10)
ts_head(ts, 3)

samp <- ts_sample(ts, test_size = 5)
io_train <- ts_projection(samp$train)
io_test <- ts_projection(samp$test)

model <- ts_knn(ts_norm_gminmax(), input_size=4, k=3)
model <- fit(model, x=io_train$input, y=io_train$output)

prediction <- predict(model, x=io_test$input[1,], steps_ahead=5)
prediction <- as.vector(prediction)
output <- as.vector(io_test$output)

ev_test <- evaluate(model, output, prediction)
ev_test
```

---

ts_lstm *LSTM*

Description

Creates a time series prediction object that uses the LSTM. It wraps the pytorch library.

Usage

```
ts_lstm(preprocess = NA, input_size = NA, epochs = 10000L)
```

Arguments

preprocess	normalization
input_size	input size for machine learning model
epochs	maximum number of epochs

Value

returns a ts_lstm object.

Examples

```
#See an example of using `ts_ts_lstmconv1d` at this
#[link](https://github.com/cefet-rj-dal/daltoolbox/blob/main/timeseries/ts_lstm.ipynb)
```

ts_mlp *MLP*

Description

Creates a time series prediction object that uses the Multilayer Perceptron (MLP). It wraps the nnet library.

Usage

```
ts_mlp(preprocess = NA, input_size = NA, size = NA, decay = 0.01, maxit = 1000)
```

Arguments

preprocess	normalization
input_size	input size for machine learning model
size	number of neurons inside hidden layer
decay	decay parameter for MLP
maxit	maximum number of iterations

Value

returns a ts_mlp object.

Examples

```
data(sin_data)
ts <- ts_data(sin_data$y, 10)
ts_head(ts, 3)

samp <- ts_sample(ts, test_size = 5)
io_train <- ts_projection(samp$train)
io_test <- ts_projection(samp$test)

model <- ts_mlp(ts_norm_gminmax(), input_size=4, size=4, decay=0)
model <- fit(model, x=io_train$input, y=io_train$output)

prediction <- predict(model, x=io_test$input[1,], steps_ahead=5)
prediction <- as.vector(prediction)
output <- as.vector(io_test$output)

ev_test <- evaluate(model, output, prediction)
ev_test
```

ts_norm_an *Time Series Adaptive Normalization*

Description

Transform data to a common scale while taking into account the changes in the statistical properties of the data over time.

Usage

```
ts_norm_an(remove_outliers = TRUE, nw = 0)
```

Arguments

remove_outliers	logical: if TRUE (default) outliers will be removed.
nw	integer: window size.

Value

returns a ts_norm_an object.

Examples

```
# time series to normalize
data(sin_data)

# convert to sliding windows
ts <- ts_data(sin_data$y, 10)
ts_head(ts, 3)
summary(ts[,10])

# normalization
preproc <- ts_norm_an()
preproc <- fit(preproc, ts)
tst <- transform(preproc, ts)
ts_head(tst, 3)
summary(tst[,10])
```

ts_norm_diff *Time Series Diff*

Description

This function calculates the difference between the values of a time series.

Usage

```
ts_norm_diff(remove_outliers = TRUE)
```

Arguments

remove_outliers	logical: if TRUE (default) outliers will be removed.

Value

returns a ts_norm_diff object.

Examples

```
# time series to normalize
data(sin_data)

# convert to sliding windows
ts <- ts_data(sin_data$y, 10)
ts_head(ts, 3)
summary(ts[,10])

# normalization
preproc <- ts_norm_diff()
preproc <- fit(preproc, ts)
tst <- transform(preproc, ts)
ts_head(tst, 3)
summary(tst[,9])
```

ts_norm_ean *Time Series Adaptive Normalization (Exponential Moving Average - EMA)*

Description

Creates a normalization object for time series data using an Exponential Moving Average (EMA) method. This normalization approach adapts to changes in the time series and optionally removes outliers.

Usage

```
ts_norm_ean(remove_outliers = TRUE, nw = 0)
```

Arguments

remove_outliers	logical: if TRUE (default) outliers will be removed.
nw	windows size

Value

returns a ts_norm_ean object.

Examples

```
# time series to normalize
data(sin_data)

# convert to sliding windows
ts <- ts_data(sin_data$y, 10)
ts_head(ts, 3)
summary(ts[,10])

# normalization
preproc <- ts_norm_ean()
preproc <- fit(preproc, ts)
tst <- transform(preproc, ts)
ts_head(tst, 3)
summary(tst[,10])
```

---

ts_norm_gminmax *Time Series Global Min-Max*

Description

Rescales data, so the minimum value is mapped to 0 and the maximum value is mapped to 1.

Usage

```
ts_norm_gminmax(remove_outliers = TRUE)
```

Arguments

remove_outliers	logical: if TRUE (default) outliers will be removed.

Value

returns a ts_norm_gminmax object.

Examples

```
# time series to normalize
data(sin_data)

# convert to sliding windows
ts <- ts_data(sin_data$y, 10)
ts_head(ts, 3)
summary(ts[,10])

# normalization
preproc <- ts_norm_gminmax()
preproc <- fit(preproc, ts)
tst <- transform(preproc, ts)
ts_head(tst, 3)
summary(tst[,10])
```

---

ts_norm_swminmax *Time Series Sliding Window Min-Max*

Description

The ts_norm_swminmax function creates an object for normalizing a time series based on the "sliding window min-max scaling" method

Usage

```
ts_norm_swminmax(remove_outliers = TRUE)
```

Arguments

remove_outliers	logical: if TRUE (default) outliers will be removed.

Value

returns a `ts_norm_swminmax` object.

Examples

```
# time series to normalize
data(sin_data)

# convert to sliding windows
ts <- ts_data(sin_data$y, 10)
ts_head(ts, 3)
summary(ts[,10])

# normalization
preproc <- ts_norm_swminmax()
```

```
preproc <- fit(preproc, ts)
tst <- transform(preproc, ts)
ts_head(tst, 3)
summary(tst[,10])
```

`ts_projection` *Time Series Projection*

Description

Separates a `ts_data` object into input and output components for time series analysis. This function is useful for preparing data for modeling, where the input and output variables are extracted from a time series dataset.

Usage

```
ts_projection(ts)
```

Arguments

`ts`	matrix or data.frame containing the time series.

Value

returns a `ts_projection` object.

Examples

```
#setting up a ts_data
data(sin_data)
ts <- ts_data(sin_data$y, 10)

io <- ts_projection(ts)

#input data
ts_head(io$input)

#output data
ts_head(io$output)
```

ts_reg *TSReg*

Description

Time Series Regression directly from time series Ancestral class for non-sliding windows implementation.

Usage

```
ts_reg()
```

Value

returns `ts_reg` object

Examples

```
#See ?ts_arima for an example using Auto-regressive Integrated Moving Average
```

ts_regsw *TSRegSW*

Description

Time Series Regression from Sliding Windows. Ancestral class for Machine Learning Implementation.

Usage

```
ts_regsw(preprocess = NA, input_size = NA)
```

Arguments

`preprocess`	normalization
`input_size`	input size for machine learning model

Value

returns a `ts_regsw` object

Examples

```
#See ?ts_elm for an example using Extreme Learning Machine
```

ts_rf *Random Forest*

Description

Creates a time series prediction object that uses the Random Forest. It wraps the randomForest library.

Usage

```
ts_rf(preprocess = NA, input_size = NA, nodesize = 1, ntree = 10, mtry = NULL)
```

Arguments

preprocess	normalization
input_size	input size for machine learning model
nodesize	node size
ntree	number of trees
mtry	number of attributes to build tree

Value

returns a ts_rf object.

Examples

```
data(sin_data)
ts <- ts_data(sin_data$y, 10)
ts_head(ts, 3)

samp <- ts_sample(ts, test_size = 5)
io_train <- ts_projection(samp$train)
io_test <- ts_projection(samp$test)

model <- ts_rf(ts_norm_gminmax(), input_size=4, nodesize=3, ntree=50)
model <- fit(model, x=io_train$input, y=io_train$output)

prediction <- predict(model, x=io_test$input[1,], steps_ahead=5)
prediction <- as.vector(prediction)
output <- as.vector(io_test$output)

ev_test <- evaluate(model, output, prediction)
ev_test
```

`ts_sample` *Time Series Sample*

Description

Separates the `ts_data` into training and test. It separates the test size from the last observations minus an offset. The offset is important to allow replication under different recent origins. The data for train uses the number of rows of a `ts_data` minus the test size and offset.

Usage

```
ts_sample(ts, test_size = 1, offset = 0)
```

Arguments

`ts`	time series.
`test_size`	integer: size of test data (default = 1).
`offset`	integer: starting point (default = 0).

Value

returns a list with the two samples

Examples

```
#setting up a ts_data
data(sin_data)
ts <- ts_data(sin_data$y, 10)

#separating into train and test
test_size <- 3
samp <- ts_sample(ts, test_size)

#first five rows from training data
ts_head(samp$train, 5)

#last five rows from training data
ts_head(samp$train[-c(1:(nrow(samp$train)-5)),])

#testing data
ts_head(samp$test)
```

ts_svm *SVM*

Description

Creates a time series prediction object that uses the Support Vector Machine (SVM). It wraps the e1071 library.

Usage

```
ts_svm(
  preprocess = NA,
  input_size = NA,
  kernel = "radial",
  epsilon = 0,
  cost = 10
)
```

Arguments

preprocess	normalization
input_size	input size for machine learning model
kernel	SVM kernel (linear, radial, polynomial, sigmoid)
epsilon	error threshold
cost	this parameter controls the trade-off between achieving a low error on the training data and minimizing the model complexity

Value

returns a ts_svm object.

Examples

```
data(sin_data)
ts <- ts_data(sin_data$y, 10)
ts_head(ts, 3)

samp <- ts_sample(ts, test_size = 5)
io_train <- ts_projection(samp$train)
io_test <- ts_projection(samp$test)

model <- ts_svm(ts_norm_gminmax(), input_size=4)
model <- fit(model, x=io_train$input, y=io_train$output)

prediction <- predict(model, x=io_test$input[1,], steps_ahead=5)
prediction <- as.vector(prediction)
output <- as.vector(io_test$output)
```

```
ev_test <- evaluate(model, output, prediction)
ev_test
```

---

ts_tune *Time Series Tune*

Description

Creates a ts_tune object for tuning hyperparameters of a time series model. This function sets up a tuning process for the specified base model by exploring different configurations of hyperparameters using cross-validation.

Usage

```
ts_tune(input_size, base_model, folds = 10)
```

Arguments

input_size	input size for machine learning model
base_model	base model for tuning
folds	number of folds for cross-validation

Value

returns a ts_tune object

Examples

```
data(sin_data)
ts <- ts_data(sin_data$y, 10)
ts_head(ts, 3)

samp <- ts_sample(ts, test_size = 5)
io_train <- ts_projection(samp$train)
io_test <- ts_projection(samp$test)

tune <- ts_tune(input_size=c(3:5), base_model = ts_elm(ts_norm_gminmax()))
ranges <- list(nhid = 1:5, actfun=c('purelin'))

# Generic model tunning
model <- fit(tune, x=io_train$input, y=io_train$output, ranges)

prediction <- predict(model, x=io_test$input[1,], steps_ahead=5)
prediction <- as.vector(prediction)
output <- as.vector(io_test$output)

ev_test <- evaluate(model, output, prediction)
ev_test
```

varae_encode *Variational Autoencoder - Encode*

Description

Creates an deep learning variational autoencoder to encode a sequence of observations. It wraps the pytorch library.

Usage

```
varae_encode(
  input_size,
  encoding_size,
  batch_size = 32,
  num_epochs = 1000,
  learning_rate = 0.001
)
```

Arguments

input_size	input size
encoding_size	encoding size
batch_size	size for batch learning
num_epochs	number of epochs for training
learning_rate	learning rate

Value

returns a varae_encode object.

Examples

```
#See an example of using `varae_encode` at this
#[link](https://github.com/cefet-rj-dal/daltoolbox/blob/main/transf/varae_encode.ipynb)
```

varae_encode_decode *Variational Autoencoder - Encode*

Description

Creates an deep learning variational autoencoder to encode a sequence of observations. It wraps the pytorch library.

Usage

```
varae_encode_decode(
  input_size,
  encoding_size,
  batch_size = 32,
  num_epochs = 1000,
  learning_rate = 0.001
)
```

Arguments

input_size	input size
encoding_size	encoding size
batch_size	size for batch learning
num_epochs	number of epochs for training
learning_rate	learning rate

Value

returns a varae_encode_decode object.

Examples

```
#See an example of using `varae_encode_decode` at this
#[link](https://github.com/cefet-rj-dal/daltoolbox/blob/main/transf/varae_enc_decode.ipynb)
```

---

zscore *Z-score normalization*

Description

Scale data using z-score normalization.

$zscore = (x - mean(x))/sd(x)$

Usage

```
zscore(nmean = 0, nsd = 1)
```

Arguments

nmean	new mean for normalized data
nsd	new standard deviation for normalized data

Value

returns the z-score transformation object

Examples

```
data(iris)
head(iris)

trans <- zscore()
trans <- fit(trans, iris)
tiris <- transform(trans, iris)
head(tiris)

itiris <- inverse_transform(trans, tiris)
head(itiris)
```

[.ts_data *Subset Extraction for Time Series Data*

Description

Extracts a subset of a time series object based on specified rows and columns. The function allows for flexible indexing and subsetting of time series data.

Usage

```
## S3 method for class 'ts_data'
x[i, j, ...]
```

Arguments

x	ts_data object
i	row i
j	column j
...	optional arguments

Value

returns a new ts_data object

Examples

```
data(sin_data)
data10 <- ts_data(sin_data$y, 10)
ts_head(data10)
#single line
data10[12,]

#range of lines
data10[12:13,]

#single column
```

```
data10[,1]

#range of columns
data10[,1:2]

#range of rows and columns
data10[12:13,1:2]

#single line and a range of columns
#'data10[12,1:2]

#range of lines and a single column
data10[12:13,1]

#single observation
data10[12,1]
```

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