# Package 'shapper'

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Title Wrapper of Python Library 'shap'

Version 0.1.3

**Description** Provides SHAP explanations of machine learning models. In applied machine learning, there is a strong belief that we need to strike a balance between interpretability and accuracy. However, in field of the Interpretable Machine Learn-

ing, there are more and more new ideas for explaining black-box mod-

els. One of the best known method for local explanations is SHapley Additive exPlanations (SHAP) introduced by Lund-

berg, S., et al., (2016) <arXiv:1705.07874> The SHAP method is used to calculate influences of variables on the particular observation. This method is based on Shapley values, a technique used in game theory. The R package 'shapper' is a port of the Python library 'shap'.

License GPL

**Encoding** UTF-8

LazyData true

URL https://github.com/ModelOriented/shapper

BugReports https://github.com/ModelOriented/shapper/issues

RoxygenNote 7.1.1

Imports reticulate, DALEX, ggplot2

Suggests covr, knitr, randomForest, rpart, testthat, markdown, qpdf

VignetteBuilder knitr

NeedsCompilation no

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```

individual\_variable\_effect

Individual Variable Effect

# **Description**

Individual Variable Effect

# **Usage**

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```
individual_variable_effect(x, ...)
## S3 method for class 'explainer'
individual_variable_effect(
 х,
 new_observation,
 method = "KernelSHAP",
 nsamples = "auto",
)
## Default S3 method:
individual_variable_effect(
  data,
 predict_function = predict,
 new_observation,
 label = tail(class(x), 1),
 method = "KernelSHAP",
 nsamples = "auto",
)
shap(x, ...)
```

#### **Arguments**

a model to be explained, or an explainer created with function explain.

other parameters.

new\_observation

an observation/observations to be explained. Required for local/instance level explainers. Columns in should correspond to columns in the data argument.

Data set should not contain any additional columns.

method an estimation method of SHAP values. Currently the only available is 'Ker-

nelSHAP'.

nsamples number of samples or "auto". Note that number must be as integer. Use 'as.integer()'.

validation dataset. Used to determine univariate distributions, calculation of data

quantiles, correlations and so on. It will be extracted from 'x' if it's an explainer.

predict\_function

predict function that operates on the model 'x'. Since the model is a black box, the 'predict function' is the only interface to access values from the model. It should be a function that takes at least a model 'x' and data and returns vector of predictions. If model response has more than a single number (like multiclass models) then this function should return a marix/data.frame of the size 'm' x 'd', where 'm' is the number of observations while 'd' is the dimensionality of

name of the model. By default it's extracted from the class attribute of the model

model response. It will be extracted from 'x' if it's an explainer.

Value

label

an object of class individual\_variable\_effect with shap values of each variable for each new observation. Columns:

- first d columns contains variable values.
- \_id\_ id of observation, number of row in 'new\_observation' data.
- \_ylevel\_ level of y
- · \_yhat\_ -predicted value for level of y
- \_yhat\_mean\_ expected value of prediction, mean of all predictions
- \_vname\_ variable name
- \_attribution\_ attribution of variable
- \_sign\_ a sign of attribution
- · \_label\_ a label

In order to use shapper with other python virtual environment following R command are required to execute reticulate::use\_virtualenv("path\_to\_your\_env") or for conda reticulate::use\_conda("name\_of\_conda\_env") before attaching shapper.

install\_shap

# **Examples**

```
have_shap <- reticulate::py_module_available("shap")

if(have_shap){
    library("shapper")
    library("DALEX")
    library("randomForest")
    Y_train <- HR$status
    x_train <- HR[ , -6]
    set.seed(123)
    model_rf <- randomForest(x = x_train, y = Y_train, ntree= 50)
    p_function <- function(model, data) predict(model, newdata = data, type = "prob")

ive_rf <- individual_variable_effect(model_rf, data = x_train, predict_function = p_function, new_observation = x_train[1:2,], nsamples = 50)

ive_rf
} else{
    print('Python testing environment is required.')
}</pre>
```

install\_shap

Install shap Python library

# Description

Install shap Python library

# Usage

```
install_shap(method = "auto", conda = "auto", envname = NULL)
```

#### **Arguments**

| method | Installation method. By | y default, | "auto". It is 1 | passed to the py | _install function |
|--------|-------------------------|------------|-----------------|------------------|-------------------|
|--------|-------------------------|------------|-----------------|------------------|-------------------|

from package 'reticulate'.

conda Path to conda executable. It is passed to the py\_install function from package

'reticulate'.

envname Name of environment to install shapp package into. If NULL it will install into

default It is passed to the py\_install function from package 'reticulate'.

To use conda installation execute install\_shap(method = "conda", envname = nameofenv) Please keep in mind that winodws accepts only conda installations

# **Examples**

```
## Not run:
 install_shap((method = "auto", conda = "auto")
## End(Not run)
```

plot.individual\_variable\_effect

Plots Attributions for Variables of Individual Prediction

# **Description**

Function 'plot.individual\_variable\_effect' plots variables effects plots.

#### Usage

```
## S3 method for class 'individual_variable_effect'
plot(
  х,
  ...,
  id = 1,
  digits = 2,
  rounding_function = round,
  show_predicted = TRUE,
  show_attributions = TRUE,
  cols = c("label", "id"),
  rows = "ylevel",
  selected = NULL,
  bar_width = 8,
 vcolors = c('-' = "#f05a71", '0' = "#371ea3", '+' = "#8bdcbe", X = "#371ea3", pred =
    "#371ea3")
)
```

# **Arguments**

```
an individual variable effect explainer produced with function 'individual_variable_effect()'
Х
                   other explainers that shall be plotted together
id
                   of observation. By default first observation is taken.
```

digits number of decimal places (round) or significant digits (signif) to be used. See the rounding\_function argument.

rounding\_function

function that is to used for rounding numbers. It may be signif() which keeps a specified number of significant digits. Or the default round() to have the same precision for all components

show\_predicted show arrows for predicted values.

show\_attributions

show attributions values.

cols A vector of characters defining faceting groups on columns dimension. Possible

values: 'label', 'id', 'ylevel'.

rows A vector of characters defining faceting groups on rows dimension. Possible

values: 'label', 'id', 'ylevel'.

selected A vector of characters. If specified, then only selected classes are presented

bar\_width width of bars. By default 8
vcolors named vector with colors

#### Value

a ggplot2 object

# **Examples**

```
have_shap <- reticulate::py_module_available("shap")</pre>
if(have_shap){
 library("shapper")
 library("DALEX")
 library("randomForest")
 Y_train <- HR$status
 x_{train} \leftarrow HR[, -6]
 set.seed(123)
 model_rf <- randomForest(x = x_train, y = Y_train, ntree = 50)</pre>
 p_function <- function(model, data) predict(model, newdata = data, type = "prob")
 ive_rf <- individual_variable_effect(model_rf, data = x_train, predict_function = p_function,</pre>
                                       new_observation = x_train[1:2,], nsamples = 50)
 pl1 <- plot(ive_rf, bar_width = 4)</pre>
 pl2 <- plot(ive_rf, bar_width = 4, show_predicted = FALSE)</pre>
 pl3 <- plot(ive_rf, bar_width = 4, show_predicted = FALSE,
               cols = c("id","ylevel"), rows = "label")
 print(pl1)
 print(pl2)
 print(pl3)
} else {
    print('Python testing environment is required.')
```

```
\verb|print.individual_variable_effect|\\
```

Print Individual Variable Effects

# **Description**

Print Individual Variable Effects

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# Usage

```
## S3 method for class 'individual_variable_effect' print(x, \ldots)
```

# **Arguments**

x an individual variable importance explainer created with the individual\_variable\_effect function.

... further arguments passed to or from other methods.

# **Examples**

```
have_shap <- reticulate::py_module_available("shap")</pre>
if(have_shap){
  library("shapper")
  library("DALEX")
  library("randomForest")
  Y_train <- HR$status
  x_{train} \leftarrow HR[, -6]
  set.seed(123)
  model_rf \leftarrow randomForest(x = x_train, y = Y_train, ntree= 50)
  p_function <- function(model, data) predict(model, newdata = data, type = "prob")</pre>
 ive_rf <- individual_variable_effect(model_rf, data = x_train, predict_function = p_function,</pre>
                                        new_observation = x_train[1:2,], nsamples = 50)
  print(ive_rf)
}else{
    print('Python testing environment is required.')
}
```

theme\_drwhy\_colors

DrWhy Theme for ggplot objects

# **Description**

DrWhy Theme for ggplot objects

# Usage

```
theme_drwhy_colors(n = 2)
```

# **Arguments**

n number of colors for color palette

#### Value

theme for ggplot2 objects

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