

# Package: shapper (via r-universe)

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**Title** Wrapper of Python Library 'shap'

**Version** 0.1.4

**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 Learning, there are more and more new ideas for explaining black-box models. One of the best known method for local explanations is SHapley Additive exPlanations (SHAP) introduced by Lundberg, 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** 7.2.3

**Imports** reticulate, DALEX, ggplot2

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

**VignetteBuilder** knitr

**Repository** <https://modeloriented.r-universe.dev>

**RemoteUrl** <https://github.com/modeloriented/shapper>

**RemoteRef** HEAD

**RemoteSha** 3b54449553210c53cde323ef9a0ddbf91f8bea5

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individual\_variable\_effect  
*Individual Variable Effect*

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### Description

Individual Variable Effect

### Usage

```
individual_variable_effect(x, ...)

## S3 method for class 'explainer'
individual_variable_effect(
  x,
  new_observation,
  method = "KernelSHAP",
  nsamples = "auto",
  ...
)

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

shap(x, ...)
```

**Arguments**

x	a model to be explained, or an explainer created with function <code>explain</code> .
...	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 'KernelSHAP'.
nsamples	number of samples or "auto". Note that number must be as integer. Use 'as.integer()'.
data	validation dataset. Used to determine univariate distributions, calculation of 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 matrix/data.frame of the size 'm' x 'd', where 'm' is the number of observations while 'd' is the dimensionality of model response. It will be extracted from 'x' if it's an explainer.
label	name of the model. By default it's extracted from the class attribute of the model

**Value**

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.

**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.')
}

```

---

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 default, "auto". It is passed to the <a href="#">py_install</a> function from package 'reticulate'.
conda	Path to conda executable. It is passed to the <a href="#">py_install</a> 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 <a href="#">py_install</a> function from package 'reticulate'. To use conda installation execute <code>install_shap(method = "conda", envname = nameofenv)</code> Please keep in mind that winodws accepts only conda instalations

**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(
  x,
  ...,
  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**

x	an individual variable effect explainer produced with function 'individual_variable_effect'
...	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.

<code>show_attributions</code>	show attributions values.
<code>cols</code>	A vector of characters defining faceting groups on columns dimension. Possible values: 'label', 'id', 'ylevel'.
<code>rows</code>	A vector of characters defining faceting groups on rows dimension. Possible values: 'label', 'id', 'ylevel'.
<code>selected</code>	A vector of characters. If specified, then only selected classes are presented
<code>bar_width</code>	width of bars. By default 8
<code>vcolors</code>	named vector with colors

**Value**

a ggplot2 object

**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)

  p1 <- plot(ive_rf, bar_width = 4)
  p2 <- plot(ive_rf, bar_width = 4, show_predicted = FALSE)
  p3 <- plot(ive_rf, bar_width = 4, show_predicted = FALSE,
            cols = c("id", "ylevel"), rows = "label")

  print(p1)
  print(p2)
  print(p3)
} else {
  print('Python testing environment is required.')
}

```

---

```
print.individual_variable_effect
```

*Print Individual Variable Effects*

---

**Description**

Print Individual Variable Effects

**Usage**

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

**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")

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)

  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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