

Package ‘ingredients’

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Title Effects and Importances of Model Ingredients

Version 2.3.0

Description Collection of tools for assessment of feature importance and feature effects.

Key functions are:

feature_importance() for assessment of global level feature importance,
ceteris_paribus() for calculation of the what-if plots,
partial_dependence() for partial dependence plots,
conditional_dependence() for conditional dependence plots,
accumulated_dependence() for accumulated local effects plots,
aggregate_profiles() and cluster_profiles() for aggregation of ceteris paribus profiles,
generic_print() and plot() for better usability of selected explainers,
generic_plotD3() for interactive, D3 based explanations, and
generic_describe() for explanations in natural language.

The package 'ingredients' is a part of the 'DrWhy.AI' universe (Biecek 2018) <[doi:10.48550/arXiv.1806.08915](https://doi.org/10.48550/arXiv.1806.08915)>.

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Suggests DALEX, gower, ranger, testthat, r2d3, jsonlite, knitr,
rmarkdown, covr

URL <https://ModelOriented.github.io/ingredients/>,
<https://github.com/ModelOriented/ingredients>

BugReports <https://github.com/ModelOriented/ingredients/issues>

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NeedsCompilation no

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`accumulated_dependence`*Accumulated Local Effects Profiles aka ALEPlots*

Description

Accumulated Local Effects Profiles accumulate local changes in Ceteris Paribus Profiles. Function `accumulated_dependence` calls `ceteris_paribus` and then `aggregate_profiles`.

Usage

```
accumulated_dependence(x, ...)
```

```
## S3 method for class 'explainer'
```

```
accumulated_dependence(  
  x,  
  variables = NULL,  
  N = 500,  
  variable_splits = NULL,  
  grid_points = 101,  
  ...,  
  variable_type = "numerical"  
)
```

```
## Default S3 method:
```

```
accumulated_dependence(  
  x,  
  data,  
  predict_function = predict,  
  label = class(x)[1],  
  variables = NULL,  
  N = 500,  
  variable_splits = NULL,  
  grid_points = 101,  
  ...,  
  variable_type = "numerical"  
)
```

```
## S3 method for class 'ceteris_paribus_explainer'
```

```
accumulated_dependence(x, ..., variables = NULL)
```

```
accumulated_dependency(x, ...)
```

Arguments

`x` an explainer created with function `DALEX::explain()`, an object of the class `ceteris_paribus_explainer` or a model to be explained.


```
head(adp_glm)
plot(adp_glm)

library("ranger")

model_titanic_rf <- ranger(survived ~., data = titanic_imputed, probability = TRUE)

explain_titanic_rf <- explain(model_titanic_rf,
                             data = titanic_imputed[,-8],
                             y = titanic_imputed[,8],
                             label = "ranger forest",
                             verbose = FALSE)

adp_rf <- accumulated_dependence(explain_titanic_rf, N = 200, variable_type = "numerical")
plot(adp_rf)

adp_rf <- accumulated_dependence(explain_titanic_rf, N = 200, variable_type = "categorical")
plotD3(adp_rf, label_margin = 80, scale_plot = TRUE)
```

aggregate_profiles *Aggregates Ceteris Paribus Profiles*

Description

The function `aggregate_profiles()` calculates an aggregate of ceteris paribus profiles. It can be: Partial Dependence Profile (average across Ceteris Paribus Profiles), Conditional Dependence Profile (local weighted average across Ceteris Paribus Profiles) or Accumulated Local Dependence Profile (cumulated average local changes in Ceteris Paribus Profiles).

Usage

```
aggregate_profiles(
  x,
  ...,
  variable_type = "numerical",
  groups = NULL,
  type = "partial",
  variables = NULL,
  span = 0.25,
  center = FALSE
)
```

Arguments

`x` a ceteris paribus explainer produced with function `ceteris_paribus()`
`...` other explainers that shall be calculated together

variable_type	a character. If numerical then only numerical variables will be calculated. If categorical then only categorical variables will be calculated.
groups	a variable name that will be used for grouping. By default NULL which means that no groups shall be calculated
type	either partial/conditional/accumulated for partial dependence, conditional profiles of accumulated local effects
variables	if not NULL then aggregate only for selected variables will be calculated
span	smoothing coefficient, by default 0.25. It's the sd for gaussian kernel
center	by default accumulated profiles start at 0. If center=TRUE, then they are centered around mean prediction, which is calculated on the observations used in ceteris_paribus.

Value

an object of the class aggregated_profiles_explainer

References

Explanatory Model Analysis. Explore, Explain, and Examine Predictive Models. <https://ema.drwhy.ai/>

Examples

```
library("DALEX")
library("ingredients")
library("ranger")
head(titanic_imputed)

model_titanic_rf <- ranger(survived ~., data = titanic_imputed, probability = TRUE)

explain_titanic_rf <- explain(model_titanic_rf,
                             data = titanic_imputed[, -8],
                             y = titanic_imputed[, 8],
                             label = "ranger forest",
                             verbose = FALSE)

selected_passangers <- select_sample(titanic_imputed, n = 100)
cp_rf <- ceteris_paribus(explain_titanic_rf, selected_passangers)
head(cp_rf)

# continuous variable
pdp_rf_p <- aggregate_profiles(cp_rf, variables = "age", type = "partial")
pdp_rf_p$`_label_` <- "RF_partial"
pdp_rf_c <- aggregate_profiles(cp_rf, variables = "age", type = "conditional")
pdp_rf_c$`_label_` <- "RF_conditional"
pdp_rf_a <- aggregate_profiles(cp_rf, variables = "age", type = "accumulated")
pdp_rf_a$`_label_` <- "RF_accumulated"

plot(pdp_rf_p, pdp_rf_c, pdp_rf_a, color = "_label_")
```

```

pdp_rf <- aggregate_profiles(cp_rf, variables = "age",
                             groups = "gender")

head(pdp_rf)
plot(cp_rf, variables = "age") +
  show_observations(cp_rf, variables = "age") +
  show_rugs(cp_rf, variables = "age", color = "red") +
  show_aggregated_profiles(pdp_rf, size = 3, color = "_label_")

# categorical variable
pdp_rf_p <- aggregate_profiles(cp_rf, variables = "class",
                              variable_type = "categorical", type = "partial")
pdp_rf_p$`_label_` <- "RF_partial"
pdp_rf_c <- aggregate_profiles(cp_rf, variables = "class",
                              variable_type = "categorical", type = "conditional")
pdp_rf_c$`_label_` <- "RF_conditional"
pdp_rf_a <- aggregate_profiles(cp_rf, variables = "class",
                              variable_type = "categorical", type = "accumulated")
pdp_rf_a$`_label_` <- "RF_accumulated"
plot(pdp_rf_p, pdp_rf_c, pdp_rf_a, color = "_label_")

# or maybe flipped?
library(ggplot2)
plot(pdp_rf_p, pdp_rf_c, pdp_rf_a, color = "_label_") + coord_flip()

pdp_rf <- aggregate_profiles(cp_rf, variables = "class", variable_type = "categorical",
                             groups = "gender")

head(pdp_rf)
plot(pdp_rf, variables = "class")
# or maybe flipped?
plot(pdp_rf, variables = "class") + coord_flip()

```

bind_plots

Bind Multiple ggplot Objects

Description

This is an aesthetically efficient implementation of the [grid.arrange](#)

Usage

```
bind_plots(..., byrow = FALSE)
```

Arguments

... (ggplot) ggplot objects to combine.

byrow (logical) if FALSE (the default) the plots are bind by columns, otherwise the plots are bind by rows.

Value

(gtable) A plottable object with plot().

Author(s)

<https://github.com/harell>

Examples

```
library("DALEX")
library("ingredients")

titanic_glm <- glm(survived ~ gender + age + fare,
                  data = titanic_imputed, family = "binomial")

explain_glm <- explain(titanic_glm,
                      data = titanic_imputed,
                      y = titanic_imputed$survived,
                      verbose = FALSE)

pdp_numerical <- partial_dependence(explain_glm, N = 50, variable_type = "numerical")
pdp_categorical <- partial_dependence(explain_glm, N = 50, variable_type = "categorical")

# Bind plots by rows
bind_plots(plot(pdp_numerical), plot(pdp_categorical), byrow = TRUE)

# Bind plots by columns
bind_plots(plot(pdp_numerical), plot(pdp_categorical), byrow = FALSE)
```

calculate_oscillations

Calculate Oscillations for Ceteris Paribus Explainer

Description

Oscillations are proxies for local feature importance at the instance level. Find more details in [Ceteris Paribus Oscillations Chapter](#).

Usage

```
calculate_oscillations(x, sort = TRUE, ...)
```

Arguments

x	a ceteris paribus explainer produced with the <code>ceteris_paribus()</code> function
sort	a logical value. If TRUE then rows are sorted along the oscillations
...	other arguments

Value

an object of the class `ceteris_paribus_oscillations`

References

Explanatory Model Analysis. Explore, Explain, and Examine Predictive Models. <https://ema.drwhy.ai/>

Examples

```
library("DALEX")
library("ingredients")

titanic_small <- select_sample(titanic_imputed, n = 500, seed = 1313)

# build a model
model_titanic_glm <- glm(survived ~ gender + age + fare,
                        data = titanic_small, family = "binomial")

explain_titanic_glm <- explain(model_titanic_glm,
                             data = titanic_small[,-8],
                             y = titanic_small[,8])

cp_rf <- ceteris_paribus(explain_titanic_glm, titanic_small[1,])

calculate_oscillations(cp_rf)

library("ranger")

apartments_rf_model <- ranger(m2.price ~ construction.year + surface + floor +
                             no.rooms + district, data = apartments)

explainer_rf <- explain(apartments_rf_model,
                       data = apartments_test[,-1],
                       y = apartments_test$m2.price,
                       label = "ranger forest",
                       verbose = FALSE)

apartment <- apartments_test[1,]

cp_rf <- ceteris_paribus(explainer_rf, apartment)

calculate_oscillations(cp_rf)
```

 calculate_variable_profile

Internal Function for Individual Variable Profiles

Description

This function calculates individual variable profiles (ceteris paribus profiles), i.e. series of predictions from a model calculated for observations with altered single coordinate.

Usage

```
calculate_variable_profile(
  data,
  variable_splits,
  model,
  predict_function = predict,
  ...
)
```

```
## Default S3 method:
calculate_variable_profile(
  data,
  variable_splits,
  model,
  predict_function = predict,
  ...
)
```

Arguments

data	set of observations. Profile will be calculated for every observation (every row)
variable_splits	named list of vectors. Elements of the list are vectors with points in which profiles should be calculated. See an example for more details.
model	a model that will be passed to the predict_function
predict_function	function that takes data and model and returns numeric predictions. Note that the ... arguments will be passed to this function.
...	other parameters that will be passed to the predict_function

Details

Note that [calculate_variable_profile](#) function is S3 generic. If you want to work on non standard data sources (like H2O ddf, external databases) you should overload it.

Value

a data frame with profiles for selected variables and selected observations

References

Explanatory Model Analysis. Explore, Explain, and Examine Predictive Models. <https://ema.drwhy.ai/>

calculate_variable_split

Internal Function for Split Points for Selected Variables

Description

This function calculate candidate splits for each selected variable. For numerical variables splits are calculated as percentiles (in general uniform quantiles of the length grid_points). For all other variables splits are calculated as unique values.

Usage

```
calculate_variable_split(  
  data,  
  variables = colnames(data),  
  grid_points = 101,  
  variable_splits_type = "quantiles",  
  new_observation = NA  
)
```

```
## Default S3 method:  
calculate_variable_split(  
  data,  
  variables = colnames(data),  
  grid_points = 101,  
  variable_splits_type = "quantiles",  
  new_observation = NA  
)
```

Arguments

data	validation dataset. Is used to determine distribution of observations.
variables	names of variables for which splits shall be calculated
grid_points	number of points used for response path
variable_splits_type	how variable grids shall be calculated? Use "quantiles" (default) for percentiles or "uniform" to get uniform grid of points
new_observation	if specified (not NA) then all values in new_observation will be included in variable_splits

Details

Note that `calculate_variable_split` function is S3 generic. If you want to work on non standard data sources (like H2O ddf, external databases) you should overload it.

Value

A named list with splits for selected variables

ceteris_paribus	<i>Ceteris Paribus Profiles aka Individual Variable Profiles</i>
-----------------	--

Description

This explainer works for individual observations. For each observation it calculates Ceteris Paribus Profiles for selected variables. Such profiles can be used to hypothesize about model results if selected variable is changed. For this reason it is also called 'What-If Profiles'.

Usage

```
ceteris_paribus(x, ...)

## S3 method for class 'explainer'
ceteris_paribus(
  x,
  new_observation,
  y = NULL,
  variables = NULL,
  variable_splits = NULL,
  grid_points = 101,
  variable_splits_type = "quantiles",
  ...
)

## Default S3 method:
ceteris_paribus(
  x,
  data,
  predict_function = predict,
  new_observation,
  y = NULL,
  variables = NULL,
  variable_splits = NULL,
  grid_points = 101,
  variable_splits_type = "quantiles",
  variable_splits_with_obs = FALSE,
  label = class(x)[1],
  ...
)
```

Arguments

x	an explainer created with the <code>DALEX::explain()</code> function, or a model to be explained.
...	other parameters
new_observation	a new observation with columns that corresponds to variables used in the model
y	true labels for new_observation. If specified then will be added to ceteris paribus plots. NOTE: It is best when target variable is not present in the new_observation
variables	names of variables for which profiles shall be calculated. Will be passed to calculate_variable_split . If NULL then all variables from the validation data will be used.
variable_splits	named list of splits for variables, in most cases created with calculate_variable_split . If NULL then it will be calculated based on validation data available in the explainer.
grid_points	maximum number of points for profile calculations. Note that the final number of points may be lower than grid_points, eg. if there is not enough unique values for a given variable. Will be passed to calculate_variable_split .
variable_splits_type	how variable grids shall be calculated? Use "quantiles" (default) for percentiles or "uniform" to get uniform grid of points
data	validation dataset. It will be extracted from x if it's an explainer NOTE: It is best when target variable is not present in the data
predict_function	predict function. It will be extracted from x if it's an explainer
variable_splits_with_obs	if TRUE then all values in new_observation will be included in variable_splits
label	name of the model. By default it's extracted from the class attribute of the model

Details

Find more details in [Ceteris Paribus Chapter](#).

Value

an object of the class `ceteris_paribus_explainer`.

References

Explanatory Model Analysis. Explore, Explain, and Examine Predictive Models. <https://ema.drwhy.ai/>

Examples

```

library("DALEX")
library("ingredients")
titanic_small <- select_sample(titanic_imputed, n = 500, seed = 1313)

# build a model
model_titanic_glm <- glm(survived ~ gender + age + fare,
                        data = titanic_small,
                        family = "binomial")

explain_titanic_glm <- explain(model_titanic_glm,
                              data = titanic_small[,-8],
                              y = titanic_small[,8])

cp_rf <- ceteris_paribus(explain_titanic_glm, titanic_small[1,])
cp_rf

plot(cp_rf, variables = "age")

library("ranger")
model_titanic_rf <- ranger(survived ~., data = titanic_imputed, probability = TRUE)

explain_titanic_rf <- explain(model_titanic_rf,
                              data = titanic_imputed[,-8],
                              y = titanic_imputed[,8],
                              label = "ranger forest",
                              verbose = FALSE)

# select few passengers
selected_passangers <- select_sample(titanic_imputed, n = 20)
cp_rf <- ceteris_paribus(explain_titanic_rf, selected_passangers)
cp_rf

plot(cp_rf, variables = "age") +
  show_observations(cp_rf, variables = "age") +
  show_rugs(cp_rf, variables = "age", color = "red")

```

ceteris_paribus_2d *Ceteris Paribus 2D Plot*

Description

This function calculates ceteris paribus profiles for grid of values spanned by two variables. It may be useful to identify or present interactions between two variables.

Usage

```
ceteris_paribus_2d(explainer, observation, grid_points = 101, variables = NULL)
```

Arguments

explainer	a model to be explained, preprocessed by the DALEX::explain() function
observation	a new observation for which predictions need to be explained
grid_points	number of points used for response path. Will be used for both variables
variables	if specified, then only these variables will be explained

Value

an object of the class ceteris_paribus_2d_explainer.

References

Explanatory Model Analysis. Explore, Explain, and Examine Predictive Models. <https://ema.drwhy.ai/>

Examples

```
library("DALEX")
library("ingredients")

model_titanic_glm <- glm(survived ~ age + fare,
                        data = titanic_imputed, family = "binomial")

explain_titanic_glm <- explain(model_titanic_glm,
                              data = titanic_imputed[,-8],
                              y = titanic_imputed[,8])

cp_rf <- ceteris_paribus_2d(explain_titanic_glm, titanic_imputed[1,],
                          variables = c("age", "fare", "sibsp"))

head(cp_rf)

plot(cp_rf)

library("ranger")
set.seed(59)

apartments_rf_model <- ranger(m2.price ~., data = apartments)

explainer_rf <- explain(apartments_rf_model,
                      data = apartments_test[,-1],
                      y = apartments_test[,1],
                      label = "ranger forest",
                      verbose = FALSE)

new_apartment <- apartments_test[1,]
```

```

new_apartment

wi_rf_2d <- ceteris_paribus_2d(explainer_rf, observation = new_apartment,
                             variables = c("surface", "floor", "no.rooms"))

head(wi_rf_2d)
plot(wi_rf_2d)

```

cluster_profiles *Cluster Ceteris Paribus Profiles*

Description

This function calculates aggregates of ceteris paribus profiles based on hierarchical clustering.

Usage

```

cluster_profiles(
  x,
  ...,
  aggregate_function = mean,
  variable_type = "numerical",
  center = FALSE,
  k = 3,
  variables = NULL
)

```

Arguments

x	a ceteris paribus explainer produced with function <code>ceteris_paribus()</code>
...	other explainers that shall be plotted together
aggregate_function	a function for profile aggregation. By default it's mean
variable_type	a character. If <code>numerical</code> then only numerical variables will be computed. If <code>categorical</code> then only categorical variables will be computed.
center	shall profiles be centered before clustering
k	number of clusters for the <code>hclust</code> function
variables	if not <code>NULL</code> then only variables will be presented

Details

Find more details in the [Clustering Profiles Chapter](#).

Value

an object of the class `aggregated_profiles_explainer`

References

Explanatory Model Analysis. Explore, Explain, and Examine Predictive Models. <https://ema.drwhy.ai/>

Examples

```
library("DALEX")
library("ingredients")

selected_passangers <- select_sample(titanic_imputed, n = 100)
model_titanic_glm <- glm(survived ~ gender + age + fare,
                        data = titanic_imputed, family = "binomial")

explain_titanic_glm <- explain(model_titanic_glm,
                              data = titanic_imputed[,-8],
                              y = titanic_imputed[,8])

cp_rf <- ceteris_paribus(explain_titanic_glm, selected_passangers)
clust_rf <- cluster_profiles(cp_rf, k = 3, variables = "age")
plot(clust_rf)

library("ranger")
model_titanic_rf <- ranger(survived ~., data = titanic_imputed, probability = TRUE)

explain_titanic_rf <- explain(model_titanic_rf,
                              data = titanic_imputed[,-8],
                              y = titanic_imputed[,8],
                              label = "ranger forest",
                              verbose = FALSE)

cp_rf <- ceteris_paribus(explain_titanic_rf, selected_passangers)
cp_rf

pdp_rf <- aggregate_profiles(cp_rf, variables = "age")
head(pdp_rf)
clust_rf <- cluster_profiles(cp_rf, k = 3, variables = "age")
head(clust_rf)

plot(clust_rf, color = "_label_") +
  show_aggregated_profiles(pdp_rf, color = "black", size = 3)

plot(cp_rf, color = "grey", variables = "age") +
  show_aggregated_profiles(clust_rf, color = "_label_", size = 2)

clust_rf <- cluster_profiles(cp_rf, k = 3, center = TRUE, variables = "age")
head(clust_rf)
```

 conditional_dependence

Conditional Dependence Profiles

Description

Conditional Dependence Profiles (aka Local Profiles) average locally Ceteris Paribus Profiles. Function 'conditional_dependence' calls 'ceteris_paribus' and then 'aggregate_profiles'.

Usage

```
conditional_dependence(x, ...)
```

```
## S3 method for class 'explainer'
```

```
conditional_dependence(
  x,
  variables = NULL,
  N = 500,
  variable_splits = NULL,
  grid_points = 101,
  ...,
  variable_type = "numerical"
)
```

```
## Default S3 method:
```

```
conditional_dependence(
  x,
  data,
  predict_function = predict,
  label = class(x)[1],
  variables = NULL,
  N = 500,
  variable_splits = NULL,
  grid_points = 101,
  ...,
  variable_type = "numerical"
)
```

```
## S3 method for class 'ceteris_paribus_explainer'
```

```
conditional_dependence(x, ..., variables = NULL)
```

```
local_dependency(x, ...)
```

```
conditional_dependency(x, ...)
```

Arguments

x	an explainer created with function <code>DALEX::explain()</code> , an object of the class <code>ceteris_paribus_explainer</code> or a model to be explained.
...	other parameters
variables	names of variables for which profiles shall be calculated. Will be passed to <code>calculate_variable_split</code> . If <code>NULL</code> then all variables from the validation data will be used.
N	number of observations used for calculation of partial dependence profiles. By default 500.
variable_splits	named list of splits for variables, in most cases created with <code>calculate_variable_split</code> . If <code>NULL</code> then it will be calculated based on validation data available in the explainer.
grid_points	number of points for profile. Will be passed to <code>calculate_variable_split</code> .
variable_type	a character. If "numerical" then only numerical variables will be calculated. If "categorical" then only categorical variables will be calculated.
data	validation dataset, will be extracted from x if it's an explainer NOTE: It is best when target variable is not present in the data
predict_function	predict function, 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

Details

Find more details in the [Accumulated Local Dependence Chapter](#).

Value

an object of the class `aggregated_profile_explainer`

References

Explanatory Model Analysis. Explore, Explain, and Examine Predictive Models. <https://ema.drwhy.ai/>

Examples

```
library("DALEX")
library("ingredients")

model_titanic_glm <- glm(survived ~ gender + age + fare,
                        data = titanic_imputed, family = "binomial")

explain_titanic_glm <- explain(model_titanic_glm,
                              data = titanic_imputed[,-8],
                              y = titanic_imputed[,8],
                              verbose = FALSE)
```

```

cdp_glm <- conditional_dependence(explain_titanic_glm,
                                  N = 150, variables = c("age", "fare"))
head(cdp_glm)
plot(cdp_glm)

library("ranger")

model_titanic_rf <- ranger(survived ~., data = titanic_imputed, probability = TRUE)

explain_titanic_rf <- explain(model_titanic_rf,
                              data = titanic_imputed[,-8],
                              y = titanic_imputed[,8],
                              label = "ranger forest",
                              verbose = FALSE)

cdp_rf <- conditional_dependence(explain_titanic_rf, N = 200, variable_type = "numerical")
plot(cdp_rf)

cdp_rf <- conditional_dependence(explain_titanic_rf, N = 200, variable_type = "categorical")
plotD3(cdp_rf, label_margin = 100, scale_plot = TRUE)

```

```
describe.partial_dependence_explainer
```

Natural language description of feature importance explainer

Description

Generic function `describe` generates a natural language description of `ceteris_paribus()`, `aggregated_profiles()` and `feature_importance()` explanations what enhances their interpretability.

Usage

```

## S3 method for class 'partial_dependence_explainer'
describe(
  x,
  nonsignificance_treshold = 0.15,
  ...,
  display_values = FALSE,
  display_numbers = FALSE,
  variables = NULL,
  label = "prediction"
)

describe(x, ...)

```

```

## S3 method for class 'ceteris_paribus_explainer'
describe(
  x,
  nonsignificance_treshold = 0.15,
  ...,
  display_values = FALSE,
  display_numbers = FALSE,
  variables = NULL,
  label = "prediction"
)

## S3 method for class 'feature_importance_explainer'
describe(x, nonsignificance_treshold = 0.15, ...)

```

Arguments

x a ceteris paribus explanation produced with function `ceteris_paribus()`
nonsignificance_treshold a parameter specifying a treshold for variable importance
... other arguments
display_values allows for displaying variable values
display_numbers allows for displaying numerical values
variables a character of a single variable name to be described
label label for model's prediction

Details

Function `describe.ceteris_paribus()` generates a natural language description of ceteris paribus profile. The description summarizes variable values, that would change model's prediction at most. If a ceteris paribus profile for multiple variables is passed, `variables` must specify a single variable to be described. Works only for a ceteris paribus profile for one observation. In current version only categorical values are discribed. For `display_numbers = TRUE` three most important variable values are displayed, while `display_numbers = FALSE` displays all the important variables, however without further details.

Function `describe.ceteris_paribus()` generates a natural language description of ceteris paribus profile. The description summarizes variable values, that would change model's prediction at most. If a ceteris paribus profile for multiple variables is passed, `variables` must specify a single variable to be described. Works only for a ceteris paribus profile for one observation. For `display_numbers = TRUE` three most important variable values are displayed, while `display_numbers = FALSE` displays all the important variables, however without further details.

Function `describe.feature_importance_explainer()` generates a natural language description of feature importance explanation. It prints the number of important variables, that have significant dropout difference from the full model, depending on `nonsignificance_treshold`. The description prints the three most important variables for the model's prediction. The current design of DALEX explainer does not allow for displaying variables values.

References

Explanatory Model Analysis. Explore, Explain, and Examine Predictive Models. <https://ema.drwhy.ai/>

Examples

```
library("DALEX")
library("ingredients")
library("ranger")

model_titanic_rf <- ranger(survived ~., data = titanic_imputed, probability = TRUE)

explain_titanic_rf <- explain(model_titanic_rf,
                             data = titanic_imputed[,-8],
                             y = titanic_imputed[,8],
                             label = "ranger forest",
                             verbose = FALSE)

selected_passangers <- select_sample(titanic_imputed, n = 10)
cp_rf <- ceteris_paribus(explain_titanic_rf, selected_passangers)
pdp <- aggregate_profiles(cp_rf, type = "partial", variable_type = "categorical")
describe(pdp, variables = "gender")

library("DALEX")
library("ingredients")
library("ranger")

model_titanic_rf <- ranger(survived ~., data = titanic_imputed, probability = TRUE)

explain_titanic_rf <- explain(model_titanic_rf,
                             data = titanic_imputed[,-8],
                             y = titanic_imputed[,8],
                             label = "ranger forest",
                             verbose = FALSE)

selected_passanger <- select_sample(titanic_imputed, n = 1, seed = 123)
cp_rf <- ceteris_paribus(explain_titanic_rf, selected_passanger)

plot(cp_rf, variable_type = "categorical")
describe(cp_rf, variables = "class", label = "the predicted probability")

library("DALEX")
library("ingredients")

lm_model <- lm(m2.price~., data = apartments)
explainer_lm <- explain(lm_model, data = apartments[,-1], y = apartments[,1])

fi_lm <- feature_importance(explainer_lm, loss_function = DALEX::loss_root_mean_square)
```

```
plot(fi_lm)
describe(fi_lm)
```

feature_importance	<i>Feature Importance</i>
--------------------	---------------------------

Description

This function calculates permutation based feature importance. For this reason it is also called the Variable Dropout Plot.

Usage

```
feature_importance(x, ...)
```

```
## S3 method for class 'explainer'
feature_importance(
  x,
  loss_function = DALEX::loss_root_mean_square,
  ...,
  type = c("raw", "ratio", "difference"),
  n_sample = NULL,
  B = 10,
  variables = NULL,
  variable_groups = NULL,
  N = n_sample,
  label = NULL
)
```

```
## Default S3 method:
feature_importance(
  x,
  data,
  y,
  predict_function = predict,
  loss_function = DALEX::loss_root_mean_square,
  ...,
  label = class(x)[1],
  type = c("raw", "ratio", "difference"),
  n_sample = NULL,
  B = 10,
  variables = NULL,
  N = n_sample,
  variable_groups = NULL
)
```

Arguments

x	an explainer created with function DALEX::explain(), or a model to be explained.
...	other parameters
loss_function	a function that will be used to assess variable importance
type	character, type of transformation that should be applied for dropout loss. "raw" results raw drop losses, "ratio" returns drop_loss/drop_loss_full_model while "difference" returns drop_loss - drop_loss_full_model
n_sample	alias for N held for backwards compatibility. number of observations that should be sampled for calculation of variable importance.
B	integer, number of permutation rounds to perform on each variable. By default it's 10.
variables	vector of variables. If NULL then variable importance will be tested for each variable from the data separately. By default NULL
variable_groups	list of variables names vectors. This is for testing joint variable importance. If NULL then variable importance will be tested separately for variables. By default NULL. If specified then it will override variables
N	number of observations that should be sampled for calculation of variable importance. If NULL then variable importance will be calculated on whole dataset (no sampling).
label	name of the model. By default it's extracted from the class attribute of the model
data	validation dataset, will be extracted from x if it's an explainer NOTE: It is best when target variable is not present in the data
y	true labels for data, will be extracted from x if it's an explainer
predict_function	predict function, will be extracted from x if it's an explainer

Details

Find more details in the [Feature Importance Chapter](#).

Value

an object of the class feature_importance

References

Explanatory Model Analysis. Explore, Explain, and Examine Predictive Models. <https://ema.drwhy.ai/>


```

        label = "rf 4 groups")

plot(fi_rf_group, fi_rf)

HR_rf_model <- ranger(status ~., data = HR, probability = TRUE)

explainer_rf <- explain(HR_rf_model, data = HR, y = HR$status,
                        model_info = list(type = 'multiclass'))

fi_rf <- feature_importance(explainer_rf, type = "raw",
                           loss_function = DALEX::loss_cross_entropy)

head(fi_rf)
plot(fi_rf)

HR_glm_model <- glm(status == "fired"~., data = HR, family = "binomial")
explainer_glm <- explain(HR_glm_model, data = HR, y = as.numeric(HR$status == "fired"))
fi_glm <- feature_importance(explainer_glm, type = "raw",
                             loss_function = DALEX::loss_root_mean_square)

head(fi_glm)
plot(fi_glm)

```

partial_dependence *Partial Dependence Profiles*

Description

Partial Dependence Profiles are averages from Ceteris Paribus Profiles. Function `partial_dependence` calls `ceteris_paribus` and then `aggregate_profiles`.

Usage

```

partial_dependence(x, ...)

## S3 method for class 'explainer'
partial_dependence(
  x,
  variables = NULL,
  N = 500,
  variable_splits = NULL,
  grid_points = 101,
  ...,
  variable_type = "numerical"
)

## Default S3 method:
partial_dependence(
  x,

```

```

    data,
    predict_function = predict,
    label = class(x)[1],
    variables = NULL,
    grid_points = 101,
    variable_splits = NULL,
    N = 500,
    ...,
    variable_type = "numerical"
)

## S3 method for class 'ceteris_paribus_explainer'
partial_dependence(x, ..., variables = NULL)

partial_dependency(x, ...)

```

Arguments

x	an explainer created with function <code>DALEX::explain()</code> , an object of the class <code>ceteris_paribus_explainer</code> or a model to be explained.
...	other parameters
variables	names of variables for which profiles shall be calculated. Will be passed to calculate_variable_split . If <code>NULL</code> then all variables from the validation data will be used.
N	number of observations used for calculation of partial dependence profiles. By default 500.
variable_splits	named list of splits for variables, in most cases created with calculate_variable_split . If <code>NULL</code> then it will be calculated based on validation data available in the explainer.
grid_points	number of points for profile. Will be passed to calculate_variable_split .
variable_type	a character. If <code>"numerical"</code> then only numerical variables will be calculated. If <code>"categorical"</code> then only categorical variables will be calculated.
data	validation dataset, will be extracted from x if it's an explainer NOTE: It is best when target variable is not present in the data
predict_function	predict function, 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

Details

Find more details in the [Partial Dependence Profiles Chapter](#).

Value

an object of the class `aggregated_profiles_explainer`

References

Explanatory Model Analysis. Explore, Explain, and Examine Predictive Models. <https://ema.drwhy.ai/>

Examples

```
library("DALEX")

model_titanic_glm <- glm(survived ~ gender + age + fare,
                        data = titanic_imputed, family = "binomial")

explain_titanic_glm <- explain(model_titanic_glm,
                              data = titanic_imputed[,-8],
                              y = titanic_imputed[,8],
                              verbose = FALSE)

pdp_glm <- partial_dependence(explain_titanic_glm,
                              N = 25, variables = c("age", "fare"))

head(pdp_glm)
plot(pdp_glm)

library("ranger")

model_titanic_rf <- ranger(survived ~., data = titanic_imputed, probability = TRUE)

explain_titanic_rf <- explain(model_titanic_rf,
                              data = titanic_imputed[,-8],
                              y = titanic_imputed[,8],
                              label = "ranger forest",
                              verbose = FALSE)

pdp_rf <- partial_dependence(explain_titanic_rf, variable_type = "numerical")
plot(pdp_rf)

pdp_rf <- partial_dependence(explain_titanic_rf, variable_type = "categorical")
plotD3(pdp_rf, label_margin = 80, scale_plot = TRUE)
```

plot.aggregated_profiles_explainer

Plots Aggregated Profiles

Description

Function `plot.aggregated_profiles_explainer` plots partial dependence plot or accumulated effect plot. It works in a similar way to `plot.ceteris_paribus`, but instead of individual profiles show average profiles for each variable listed in the `variables` vector.

Usage

```
## S3 method for class 'aggregated_profiles_explainer'
plot(
  x,
  ...,
  size = 1,
  alpha = 1,
  color = "_label_",
  facet_ncol = NULL,
  facet_scales = "free_x",
  variables = NULL,
  title = NULL,
  subtitle = NULL
)
```

Arguments

x	a ceteris paribus explainer produced with function <code>aggregate_profiles()</code>
...	other explainers that shall be plotted together
size	a numeric. Size of lines to be plotted
alpha	a numeric between 0 and 1. Opacity of lines
color	a character. Either name of a color, or hex code for a color, or <code>_label_</code> if models shall be colored, or <code>_ids_</code> if instances shall be colored
facet_ncol	number of columns for the <code>facet_wrap</code>
facet_scales	a character value for the <code>facet_wrap</code> . Default is <code>"free_x"</code> .
variables	if not NULL then only variables will be presented
title	a character. Partial and accumulated dependence explainers have default value.
subtitle	a character. If NULL value will be dependent on model usage.

Value

a ggplot2 object

References

Explanatory Model Analysis. Explore, Explain, and Examine Predictive Models. <https://ema.drwhy.ai/>

Examples

```
library("DALEX")
library("ingredients")

model_titanic_glm <- glm(survived ~ gender + age + fare,
                        data = titanic_imputed, family = "binomial")

explain_titanic_glm <- explain(model_titanic_glm,
```

```

      data = titanic_imputed[,-8],
      y = titanic_imputed[,8],
      verbose = FALSE)

pdp_rf_p <- partial_dependence(explain_titanic_glm, N = 50)
pdp_rf_p$`_label_` <- "RF_partial"
pdp_rf_l <- conditional_dependence(explain_titanic_glm, N = 50)
pdp_rf_l$`_label_` <- "RF_local"
pdp_rf_a <- accumulated_dependence(explain_titanic_glm, N = 50)
pdp_rf_a$`_label_` <- "RF_accumulated"
head(pdp_rf_p)
plot(pdp_rf_p, pdp_rf_l, pdp_rf_a, color = "_label_")

library("ranger")

model_titanic_rf <- ranger(survived ~., data = titanic_imputed, probability = TRUE)

explain_titanic_rf <- explain(model_titanic_rf,
                             data = titanic_imputed[,-8],
                             y = titanic_imputed[,8],
                             label = "ranger forest",
                             verbose = FALSE)

selected_passangers <- select_sample(titanic_imputed, n = 100)
cp_rf <- ceteris_paribus(explain_titanic_rf, selected_passangers)
cp_rf

pdp_rf_p <- aggregate_profiles(cp_rf, variables = "age", type = "partial")
pdp_rf_p$`_label_` <- "RF_partial"
pdp_rf_c <- aggregate_profiles(cp_rf, variables = "age", type = "conditional")
pdp_rf_c$`_label_` <- "RF_conditional"
pdp_rf_a <- aggregate_profiles(cp_rf, variables = "age", type = "accumulated")
pdp_rf_a$`_label_` <- "RF_accumulated"

head(pdp_rf_p)
plot(pdp_rf_p)
plot(pdp_rf_p, pdp_rf_c, pdp_rf_a)

plot(cp_rf, variables = "age") +
  show_observations(cp_rf, variables = "age") +
  show_rugs(cp_rf, variables = "age", color = "red") +
  show_aggregated_profiles(pdp_rf_p, size = 2)

```

Description

This function plots What-If Plots for a single prediction / observation.

Usage

```
## S3 method for class 'ceteris_paribus_2d_explainer'
plot(
  x,
  ...,
  facet_ncol = NULL,
  add_raster = TRUE,
  add_contour = TRUE,
  bins = 3,
  add_observation = TRUE,
  pch = "+",
  size = 6
)
```

Arguments

x	a ceteris paribus explainer produced with the ceteris_paribus_2d() function
...	currently will be ignored
facet_ncol	number of columns for the facet_wrap
add_raster	if TRUE then geom_raster will be added to present levels with diverging colors
add_contour	if TRUE then geom_contour will be added to present contours
bins	number of contours to be added
add_observation	if TRUE then geom_point will be added to present observation that is explained
pch	character, symbol used to plot observations
size	numeric, size of individual datapoints

Value

a ggplot2 object

References

Explanatory Model Analysis. Explore, Explain, and Examine Predictive Models. <https://ema.drwhy.ai/>

Examples

```
library("DALEX")
library("ingredients")
library("ranger")
```

```

apartments_rf_model <- ranger(m2.price ~., data = apartments)

explainer_rf <- explain(apartments_rf_model,
                        data = apartments_test[,-1],
                        y = apartments_test[,1],
                        verbose = FALSE)

new_apartment <- apartments_test[1,]
new_apartment

wi_rf_2d <- ceteris_paribus_2d(explainer_rf, observation = new_apartment)
head(wi_rf_2d)

plot(wi_rf_2d)
plot(wi_rf_2d, add_contour = FALSE)
plot(wi_rf_2d, add_observation = FALSE)
plot(wi_rf_2d, add_raster = FALSE)

# HR data
model <- ranger(status ~ gender + age + hours + evaluation + salary, data = HR,
                probability = TRUE)

pred1 <- function(m, x)  predict(m, x)$predictions[,1]

explainer_rf_fired <- explain(model,
                              data = HR[,1:5],
                              y = as.numeric(HR$status == "fired"),
                              predict_function = pred1,
                              label = "fired")

new_emp <- HR[1,]
new_emp

wi_rf_2d <- ceteris_paribus_2d(explainer_rf_fired, observation = new_emp)
head(wi_rf_2d)

plot(wi_rf_2d)

```

```
plot.ceteris_paribus_explainer
```

Plots Ceteris Paribus Profiles

Description

Function `plot.ceteris_paribus_explainer` plots Individual Variable Profiles for selected observations. Various parameters help to decide what should be plotted, profiles, aggregated profiles, points or rugs.

Find more details in [Ceteris Paribus Chapter](#).

Usage

```
## S3 method for class 'ceteris_paribus_explainer'
plot(
  x,
  ...,
  size = 1,
  alpha = 1,
  color = "#46bac2",
  variable_type = "numerical",
  facet_ncol = NULL,
  facet_scales = NULL,
  variables = NULL,
  title = "Ceteris Paribus profile",
  subtitle = NULL,
  categorical_type = "profiles"
)
```

Arguments

x	a ceteris paribus explainer produced with function <code>ceteris_paribus()</code>
...	other explainers that shall be plotted together
size	a numeric. Size of lines to be plotted
alpha	a numeric between 0 and 1. Opacity of lines
color	a character. Either name of a color or name of a variable that should be used for coloring
variable_type	a character. If numerical then only numerical variables will be plotted. If categorical then only categorical variables will be plotted.
facet_ncol	number of columns for the <code>facet_wrap</code>
facet_scales	a character value for the <code>facet_wrap</code> . Default is "free_x", but "free_y" if <code>categorical_type="bars"</code> .
variables	if not NULL then only variables will be presented
title	a character. Plot title. By default "Ceteris Paribus profile".
subtitle	a character. Plot subtitle. By default NULL - then subtitle is set to "created for the XXX, YYY model", where XXX, YYY are labels of given explainers.
categorical_type	a character. How categorical variables shall be plotted? Either "profiles" (default) or "bars" or "lines".

Value

a ggplot2 object

References

Explanatory Model Analysis. Explore, Explain, and Examine Predictive Models. <https://ema.drwhy.ai/>

Examples

```

library("DALEX")

model_titanic_glm <- glm(survived ~ gender + age + fare,
                        data = titanic_imputed, family = "binomial")

explain_titanic_glm <- explain(model_titanic_glm,
                              data = titanic_imputed[,-8],
                              y = titanic_imputed[,8],
                              verbose = FALSE)

cp_glm <- ceteris_paribus(explain_titanic_glm, titanic_imputed[1,])
cp_glm

plot(cp_glm, variables = "age")

library("ranger")
model_titanic_rf <- ranger(survived ~., data = titanic_imputed, probability = TRUE)

explain_titanic_rf <- explain(model_titanic_rf,
                              data = titanic_imputed[,-8],
                              y = titanic_imputed[,8],
                              label = "ranger forest",
                              verbose = FALSE)

selected_passangers <- select_sample(titanic_imputed, n = 100)

cp_rf <- ceteris_paribus(explain_titanic_rf, selected_passangers)
cp_rf

plot(cp_rf, variables = "age") +
  show_observations(cp_rf, variables = "age") +
  show_rugs(cp_rf, variables = "age", color = "red")

selected_passangers <- select_sample(titanic_imputed, n = 1)
selected_passangers

cp_rf <- ceteris_paribus(explain_titanic_rf, selected_passangers)

plot(cp_rf) +
  show_observations(cp_rf)

plot(cp_rf, variables = "age") +
  show_observations(cp_rf, variables = "age")

plot(cp_rf, variables = "class")
plot(cp_rf, variables = c("class", "embarked"), facet_ncol = 1)
plot(cp_rf, variables = c("class", "embarked"), facet_ncol = 1, categorical_type = "bars")
plotD3(cp_rf, variables = c("class", "embarked", "gender"),
       variable_type = "categorical", scale_plot = TRUE,
       label_margin = 70)

```

```
plot.ceteris_paribus_oscillations
```

Plot Ceteris Paribus Oscillations

Description

This function plots local variable importance plots calculated as oscillations in the Ceteris Paribus Profiles.

Usage

```
## S3 method for class 'ceteris_paribus_oscillations'  
plot(x, ..., bar_width = 10)
```

Arguments

x	a ceteris paribus oscillation explainer produced with function <code>calculate_oscillations()</code>
...	other explainers that shall be plotted together
bar_width	width of bars. By default 10.

Value

a ggplot2 object

References

Explanatory Model Analysis. Explore, Explain, and Examine Predictive Models. <https://ema.drwhy.ai/>

Examples

```
library("DALEX")  
library("ranger")  
  
apartments_rf_model <- ranger(m2.price ~., data = apartments)  
  
explainer_rf <- explain(apartments_rf_model,  
  data = apartments_test[,-1],  
  y = apartments_test[,1],  
  label = "ranger forest",  
  verbose = FALSE)  
  
apartment <- apartments_test[1:2,]  
  
cp_rf <- ceteris_paribus(explainer_rf, apartment)  
plot(cp_rf, color = "_ids_")
```

```
vips <- calculate_oscillations(cp_rf)
vips

plot(vips)
```

```
plot.feature_importance_explainer
Plots Feature Importance
```

Description

This function plots variable importance calculated as changes in the loss function after variable drops. It uses output from `feature_importance` function that corresponds to permutation based measure of variable importance. Variables are sorted in the same order in all panels. The order depends on the average drop out loss. In different panels variable contributions may not look like sorted if variable importance is different in different in different models.

Usage

```
## S3 method for class 'feature_importance_explainer'
plot(
  x,
  ...,
  max_vars = NULL,
  show_boxplots = TRUE,
  bar_width = 10,
  desc_sorting = TRUE,
  title = "Feature Importance",
  subtitle = NULL
)
```

Arguments

<code>x</code>	a feature importance explainer produced with the <code>feature_importance()</code> function
<code>...</code>	other explainers that shall be plotted together
<code>max_vars</code>	maximum number of variables that shall be presented for for each model. By default NULL what means all variables
<code>show_boxplots</code>	logical if TRUE (default) boxplot will be plotted to show permutation data.
<code>bar_width</code>	width of bars. By default 10
<code>desc_sorting</code>	logical. Should the bars be sorted descending? By default TRUE
<code>title</code>	the plot's title, by default 'Feature Importance'
<code>subtitle</code>	the plot's subtitle. By default - NULL, which means the subtitle will be 'created for the XXX model', where XXX is the label of explainer(s)

Details

Find more details in the [Feature Importance Chapter](#).

Value

a ggplot2 object

References

Explanatory Model Analysis. Explore, Explain, and Examine Predictive Models. <https://ema.drwhy.ai/>

Examples

```
library("DALEX")
library("ingredients")

model_titanic_glm <- glm(survived ~ gender + age + fare,
                        data = titanic_imputed, family = "binomial")

explain_titanic_glm <- explain(model_titanic_glm,
                              data = titanic_imputed[, -8],
                              y = titanic_imputed[, 8])

fi_rf <- feature_importance(explain_titanic_glm, B = 1)
plot(fi_rf)

library("ranger")
model_titanic_rf <- ranger(survived ~., data = titanic_imputed, probability = TRUE)

explain_titanic_rf <- explain(model_titanic_rf,
                              data = titanic_imputed[, -8],
                              y = titanic_imputed[, 8],
                              label = "ranger forest",
                              verbose = FALSE)

fi_rf <- feature_importance(explain_titanic_rf)
plot(fi_rf)

HR_rf_model <- ranger(status~., data = HR, probability = TRUE)

explainer_rf <- explain(HR_rf_model, data = HR, y = HR$status,
                       verbose = FALSE, precalculate = FALSE)

fi_rf <- feature_importance(explainer_rf, type = "raw", max_vars = 3,
                           loss_function = DALEX::loss_cross_entropy)

head(fi_rf)
plot(fi_rf)

HR_glm_model <- glm(status == "fired"~., data = HR, family = "binomial")
explainer_glm <- explain(HR_glm_model, data = HR, y = as.numeric(HR$status == "fired"))
```

```

fi_glm <- feature_importance(explainer_glm, type = "raw",
                             loss_function = DALEX::loss_root_mean_square)
head(fi_glm)
plot(fi_glm)

```

plotD3

Plots Ceteris Paribus Profiles in D3 with r2d3 Package.

Description

Function `plotD3.ceteris_paribus_explainer` plots Individual Variable Profiles for selected observations. It uses output from `ceteris_paribus` function. Various parameters help to decide what should be plotted, profiles, aggregated profiles, points or rugs.

Find more details in [Ceteris Paribus Chapter](#).

Usage

```
plotD3(x, ...)
```

```

## S3 method for class 'ceteris_paribus_explainer'
plotD3(
  x,
  ...,
  size = 2,
  alpha = 1,
  color = "#46bac2",
  variable_type = "numerical",
  facet_ncol = 2,
  scale_plot = FALSE,
  variables = NULL,
  chart_title = "Ceteris Paribus Profiles",
  label_margin = 60,
  show_observations = TRUE,
  show_rugs = TRUE
)

```

Arguments

<code>x</code>	a ceteris paribus explainer produced with function <code>ceteris_paribus()</code>
<code>...</code>	other explainers that shall be plotted together
<code>size</code>	a numeric. Set width of lines
<code>alpha</code>	a numeric between 0 and 1. Opacity of lines
<code>color</code>	a character. Set line color

variable_type	a character. If "numerical" then only numerical variables will be plotted. If "categorical" then only categorical variables will be plotted.
facet_ncol	number of columns for the <code>facet_wrap</code>
scale_plot	a logical. If TRUE, the height of plot scales with window size. By default it's FALSE
variables	if not NULL then only variables will be presented
chart_title	a character. Set custom title
label_margin	a numeric. Set width of label margins in categorical type
show_observations	a logical. Adds observations layer to a plot. By default it's TRUE
show_rugs	a logical. Adds rugs layer to a plot. By default it's TRUE

Value

a r2d3 object.

References

Explanatory Model Analysis. Explore, Explain, and Examine Predictive Models. <https://ema.drwhy.ai/>

Examples

```
library("DALEX")
library("ingredients")
library("ranger")

model_titanic_rf <- ranger(survived ~., data = titanic_imputed, probability = TRUE)

explain_titanic_rf <- explain(model_titanic_rf,
                             data = titanic_imputed[,-8],
                             y = titanic_imputed[,8],
                             label = "ranger forest",
                             verbose = FALSE)

selected_passangers <- select_sample(titanic_imputed, n = 10)
cp_rf <- ceteris_paribus(explain_titanic_rf, selected_passangers)

plotD3(cp_rf, variables = c("age", "parch", "fare", "sibsp"),
       facet_ncol = 2, scale_plot = TRUE)

selected_passanger <- select_sample(titanic_imputed, n = 1)
cp_rf <- ceteris_paribus(explain_titanic_rf, selected_passanger)

plotD3(cp_rf, variables = c("class", "embarked", "gender", "sibsp"),
       facet_ncol = 2, variable_type = "categorical", label_margin = 100, scale_plot = TRUE)
```

plotD3.aggreated_profiles_explainer

Plots Aggregated Ceteris Paribus Profiles in D3 with r2d3 Package.

Description

Function `plotD3.aggreated_profiles_explainer` plots an aggregate of ceteris paribus profiles. It works in a similar way to `plotD3.ceteris_paribus_explainer` but, instead of individual profiles, show average profiles for each variable listed in the `variables` vector.

Find more details in [Ceteris Paribus Chapter](#).

Usage

```
## S3 method for class 'aggreated_profiles_explainer'
plotD3(
  x,
  ...,
  size = 2,
  alpha = 1,
  color = "#46bac2",
  facet_ncol = 2,
  scale_plot = FALSE,
  variables = NULL,
  chart_title = "Aggregated Profiles",
  label_margin = 60
)
```

Arguments

<code>x</code>	a aggregated profiles explainer produced with function <code>aggregate_profiles()</code>
<code>...</code>	other explainers that shall be plotted together
<code>size</code>	a numeric. Set width of lines
<code>alpha</code>	a numeric between 0 and 1. Opacity of lines
<code>color</code>	a character. Set line/bar color
<code>facet_ncol</code>	number of columns for the facet_wrap
<code>scale_plot</code>	a logical. If TRUE, the height of plot scales with window size. By default it's FALSE
<code>variables</code>	if not NULL then only variables will be presented
<code>chart_title</code>	a character. Set custom title
<code>label_margin</code>	a numeric. Set width of label margins in categorical type

Value

a `r2d3` object.

References

Explanatory Model Analysis. Explore, Explain, and Examine Predictive Models. <https://ema.drwhy.ai/>

Examples

```
library("DALEX")
library("ingredients")
library("ranger")

# smaller data, quicker example
titanic_small <- select_sample(titanic_imputed, n = 500, seed = 1313)

# build a model
model_titanic_rf <- ranger(survived ~., data = titanic_small, probability = TRUE)

explain_titanic_rf <- explain(model_titanic_rf,
                             data = titanic_small[,-8],
                             y = titanic_small[,8],
                             label = "ranger forest",
                             verbose = FALSE)

selected_passangers <- select_sample(titanic_small, n = 100)
cp_rf <- ceteris_paribus(explain_titanic_rf, selected_passangers)

pdp_rf_p <- aggregate_profiles(cp_rf, type = "partial", variable_type = "numerical")
pdp_rf_p$`_label_` <- "RF_partial"
pdp_rf_c <- aggregate_profiles(cp_rf, type = "conditional", variable_type = "numerical")
pdp_rf_c$`_label_` <- "RF_conditional"
pdp_rf_a <- aggregate_profiles(cp_rf, type = "accumulated", variable_type = "numerical")
pdp_rf_a$`_label_` <- "RF_accumulated"

plotD3(pdp_rf_p, pdp_rf_c, pdp_rf_a, scale_plot = TRUE)

pdp <- aggregate_profiles(cp_rf, type = "partial", variable_type = "categorical")
pdp$`_label_` <- "RF_partial"

plotD3(pdp, variables = c("gender","class"), label_margin = 70)
```

plotD3.feature_importance_explainer

Plot Feature Importance Objects in D3 with r2d3 Package.

Description

Function `plotD3.feature_importance_explainer` plots dropouts for variables used in the model. It uses output from `feature_importance` function that corresponds to permutation based measure

of feature importance. Variables are sorted in the same order in all panels. The order depends on the average drop out loss. In different panels variable contributions may not look like sorted if variable importance is different in different models.

Usage

```
## S3 method for class 'feature_importance_explainer'
plotD3(
  x,
  ...,
  max_vars = NULL,
  show_boxplots = TRUE,
  bar_width = 12,
  split = "model",
  scale_height = FALSE,
  margin = 0.15,
  chart_title = "Feature importance"
)
```

Arguments

<code>x</code>	a feature importance explainer produced with the <code>feature_importance()</code> function
<code>...</code>	other explainers that shall be plotted together
<code>max_vars</code>	maximum number of variables that shall be presented for for each model. By default NULL which means all variables
<code>show_boxplots</code>	logical if TRUE (default) boxplot will be plotted to show permutation data.
<code>bar_width</code>	width of bars in px. By default 12px
<code>split</code>	either "model" or "feature" determines the plot layout
<code>scale_height</code>	a logical. If TRUE, the height of plot scales with window size. By default it's FALSE
<code>margin</code>	extend x axis domain range to adjust the plot. Usually value between 0.1 and 0.3, by default it's 0.15
<code>chart_title</code>	a character. Set custom title

Value

a `r2d3` object.

References

Explanatory Model Analysis. Explore, Explain, and Examine Predictive Models. <https://ema.drwhy.ai/>

Examples

```
library("DALEX")
library("ingredients")

lm_model <- lm(m2.price ~., data = apartments)
explainer_lm <- explain(lm_model,
  data = apartments[,-1],
  y = apartments[,1],
  verbose = FALSE)

fi_lm <- feature_importance(explainer_lm,
  loss_function = DALEX::loss_root_mean_square, B = 1)

head(fi_lm)
plotD3(fi_lm)

library("ranger")

rf_model <- ranger(m2.price~., data = apartments)

explainer_rf <- explain(rf_model,
  data = apartments[,-1],
  y = apartments[,1],
  label = "ranger forest",
  verbose = FALSE)

fi_rf <- feature_importance(explainer_rf, loss_function = DALEX::loss_root_mean_square)

head(fi_rf)
plotD3(fi_lm, fi_rf)

plotD3(fi_lm, fi_rf, split = "feature")

plotD3(fi_lm, fi_rf, max_vars = 3, bar_width = 16, scale_height = TRUE)
plotD3(fi_lm, fi_rf, max_vars = 3, bar_width = 16, split = "feature", scale_height = TRUE)
plotD3(fi_lm, margin = 0.2)
```

```
print.aggregated_profiles_explainer
```

Prints Aggregated Profiles

Description

Prints Aggregated Profiles

Usage

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

Arguments

```
x          an individual variable profile explainer produced with the aggregate_profiles()  
           function  
...       other arguments that will be passed to head()
```

Examples

```
library("DALEX")  
library("ingredients")  
  
model_titanic_glm <- glm(survived ~ gender + age + fare,  
                        data = titanic_imputed, family = "binomial")  
  
explain_titanic_glm <- explain(model_titanic_glm,  
                              data = titanic_imputed[,-8],  
                              y = titanic_imputed[,8])  
  
selected_passangers <- select_sample(titanic_imputed, n = 100)  
cp_rf <- ceteris_paribus(explain_titanic_glm, selected_passangers)  
  
head(cp_rf)  
  
pdp_rf <- aggregate_profiles(cp_rf, variables = "age")  
head(pdp_rf)  
  
library("ranger")  
  
model_titanic_rf <- ranger(survived ~., data = titanic_imputed,  
                          probability = TRUE)  
  
explain_titanic_rf <- explain(model_titanic_rf,  
                             data = titanic_imputed[,-8],  
                             y = titanic_imputed[,8],  
                             label = "ranger forest",  
                             verbose = FALSE)  
  
cp_rf <- ceteris_paribus(explain_titanic_rf, selected_passangers)  
cp_rf  
  
pdp_rf <- aggregate_profiles(cp_rf, variables = "age")  
head(pdp_rf)
```

```
print.ceteris_paribus_explainer
  Prints Individual Variable Explainer Summary
```

Description

Prints Individual Variable Explainer Summary

Usage

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

Arguments

x	an individual variable profile explainer produced with the ceteris_paribus() function
...	other arguments that will be passed to head()

Examples

```
library("DALEX")
library("ingredients")
titanic_small <- select_sample(titanic_imputed, n = 500, seed = 1313)

# build a model
model_titanic_glm <- glm(survived ~ gender + age + fare,
  data = titanic_small,
  family = "binomial")

explain_titanic_glm <- explain(model_titanic_glm,
  data = titanic_small[,-8],
  y = titanic_small[,8])

cp_glm <- ceteris_paribus(explain_titanic_glm, titanic_small[,])
cp_glm

library("ranger")

apartments_rf_model <- ranger(m2.price ~., data = apartments)

explainer_rf <- explain(apartments_rf_model,
  data = apartments_test[,-1],
  y = apartments_test[,1],
  label = "ranger forest",
  verbose = FALSE)

apartments_small <- select_sample(apartments_test, 10)
```

```
cp_rf <- ceteris_paribus(explainer_rf, apartments_small)
cp_rf
```

```
print.feature_importance_explainer
```

Print Generic for Feature Importance Object

Description

Print Generic for Feature Importance Object

Usage

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

Arguments

x an explanation created with `feature_importance`
... other parameters.

Value

a data frame.

References

Explanatory Model Analysis. Explore, Explain, and Examine Predictive Models. <https://ema.drwhy.ai/>

Examples

```
library("DALEX")
library("ingredients")

model_titanic_glm <- glm(survived ~ gender + age + fare,
                        data = titanic_imputed, family = "binomial")

explain_titanic_glm <- explain(model_titanic_glm,
                              data = titanic_imputed[,-8],
                              y = titanic_imputed[,8],
                              verbose = FALSE)

fi_glm <- feature_importance(explain_titanic_glm)

fi_glm
```

select_neighbours	<i>Select Subset of Rows Closest to a Specified Observation</i>
-------------------	---

Description

Function `select_neighbours` selects subset of rows from data set. This is useful if data is large and we need just a sample to calculate profiles.

Usage

```
select_neighbours(  
  observation,  
  data,  
  variables = NULL,  
  distance = gower::gower_dist,  
  n = 20,  
  frac = NULL  
)
```

Arguments

observation	single observation
data	set of observations
variables	names of variables that shall be used for calculation of distance. By default these are all variables present in data and observation
distance	the distance function, by default the <code>gower_dist()</code> function.
n	number of neighbors to select
frac	if n is not specified (NULL), then will be calculated as $\text{frac} * \text{number of rows in data}$. Either n or frac need to be specified.

Details

Note that `select_neighbours()` function is S3 generic. If you want to work on non standard data sources (like H2O ddf, external databases) you should overload it.

Value

a data frame with selected rows

Examples

```
library("ingredients")  
  
new_apartment <- DALEX::apartments[1,]  
small_apartments <- select_neighbours(new_apartment, DALEX::apartments_test, n = 10)
```

```
new_apartment  
small_apartments
```

select_sample	<i>Select Subset of Rows</i>
---------------	------------------------------

Description

Function `select_sample` selects subset of rows from data set. This is useful if data is large and we need just a sample to calculate profiles.

Usage

```
select_sample(data, n = 100, seed = 1313)
```

Arguments

data	set of observations. Profile will be calculated for every observation (every row)
n	number of observations to select.
seed	seed for random number generator.

Details

Note that `select_subsample()` function is S3 generic. If you want to work on non standard data sources (like H2O ddf, external databases) you should overload it.

Value

a data frame with selected rows

Examples

```
library("ingredients")  
  
small_apartments <- select_sample(DALEX::apartments_test)  
head(small_apartments)
```

`show_aggregated_profiles`*Adds a Layer with Aggregated Profiles*

Description

Function `show_aggregated_profiles` adds a layer to a plot created with `plot.ceteris_paribus_explainer`.

Usage

```
show_aggregated_profiles(  
  x,  
  ...,  
  size = 0.5,  
  alpha = 1,  
  color = "#371ea3",  
  variables = NULL  
)
```

Arguments

<code>x</code>	a ceteris paribus explainer produced with function <code>ceteris_paribus()</code>
<code>...</code>	other explainers that shall be plotted together
<code>size</code>	a numeric. Size of lines to be plotted
<code>alpha</code>	a numeric between 0 and 1. Opacity of lines
<code>color</code>	a character. Either name of a color or name of a variable that should be used for coloring
<code>variables</code>	if not NULL then only variables will be presented

Value

a `ggplot2` layer

References

Explanatory Model Analysis. Explore, Explain, and Examine Predictive Models. <https://ema.drwhy.ai/>

Examples

```
library("DALEX")  
library("ingredients")  
  
selected_passangers <- select_sample(titanic_imputed, n = 100)  
  
model_titanic_glm <- glm(survived ~ gender + age + fare,
```

```

data = titanic_imputed, family = "binomial")

explain_titanic_glm <- explain(model_titanic_glm,
                             data = titanic_imputed[,-8],
                             y = titanic_imputed[,8])

cp_rf <- ceteris_paribus(explain_titanic_glm, selected_passangers)

pdp_rf <- aggregate_profiles(cp_rf, type = "partial", variables = "age")

plot(cp_rf, variables = "age") +
  show_observations(cp_rf, variables = "age") +
  show_aggregated_profiles(pdp_rf, size = 3)

library("ranger")

model_titanic_rf <- ranger(survived ~., data = titanic_imputed, probability = TRUE)

explain_titanic_rf <- explain(model_titanic_rf,
                             data = titanic_imputed[,-8],
                             y = titanic_imputed[,8],
                             label = "ranger forest",
                             verbose = FALSE)

cp_rf <- ceteris_paribus(explain_titanic_rf, selected_passangers)
cp_rf

pdp_rf <- aggregate_profiles(cp_rf, type = "partial", variables = "age")
head(pdp_rf)

plot(cp_rf, variables = "age") +
  show_observations(cp_rf, variables = "age") +
  show_rugs(cp_rf, variables = "age", color = "red") +
  show_aggregated_profiles(pdp_rf, size = 3)

```

show_observations *Adds a Layer with Observations to a Profile Plot*

Description

Function `show_observations` adds a layer to a plot created with `plot.ceteris_paribus_explainer` for selected observations. Various parameters help to decide what should be plotted, profiles, aggregated profiles, points or rugs.

Usage

```
show_observations(
```

```

  x,
  ...,
  size = 2,
  alpha = 1,
  color = "#371ea3",
  variable_type = "numerical",
  variables = NULL
)

```

Arguments

x	a ceteris paribus explainer produced with function <code>ceteris_paribus()</code>
...	other explainers that shall be plotted together
size	a numeric. Size of lines to be plotted
alpha	a numeric between 0 and 1. Opacity of lines
color	a character. Either name of a color or name of a variable that should be used for coloring
variable_type	a character. If <code>numerical</code> then only numerical variables will be plotted. If <code>categorical</code> then only categorical variables will be plotted.
variables	if not <code>NULL</code> then only variables will be presented

Value

a `ggplot2` layer

References

Explanatory Model Analysis. Explore, Explain, and Examine Predictive Models. <https://ema.drwhy.ai/>

Examples

```

library("DALEX")
library("ingredients")

library("ranger")

rf_model <- ranger(survived ~., data = titanic_imputed, probability = TRUE)

explainer_rf <- explain(rf_model,
  data = titanic_imputed[,-8],
  y = titanic_imputed[,8],
  label = "ranger forest",
  verbose = FALSE)

selected_passangers <- select_sample(titanic_imputed, n = 100)
cp_rf <- ceteris_paribus(explainer_rf, selected_passangers)
cp_rf

```

```
plot(cp_rf, variables = "age", color = "grey") +  
show_observations(cp_rf, variables = "age", color = "black") +  
  show_rugs(cp_rf, variables = "age", color = "red")
```

show_profiles	<i>Adds a Layer with Profiles</i>
---------------	-----------------------------------

Description

Function `show_profiles` adds a layer to a plot created with `plot.ceteris_paribus_explainer`.

Usage

```
show_profiles(  
  x,  
  ...,  
  size = 0.5,  
  alpha = 1,  
  color = "#371ea3",  
  variables = NULL  
)
```

Arguments

<code>x</code>	a ceteris paribus explainer produced with function <code>ceteris_paribus()</code>
<code>...</code>	other explainers that shall be plotted together
<code>size</code>	a numeric. Size of lines to be plotted
<code>alpha</code>	a numeric between 0 and 1. Opacity of lines
<code>color</code>	a character. Either name of a color or name of a variable that should be used for coloring
<code>variables</code>	if not NULL then only variables will be presented

Value

a ggplot2 layer

References

Explanatory Model Analysis. Explore, Explain, and Examine Predictive Models. <https://ema.drwhy.ai/>

Examples

```

library("DALEX")
library("ingredients")

selected_passangers <- select_sample(titanic_imputed, n = 100)
selected_john <- titanic_imputed[1,]

model_titanic_glm <- glm(survived ~ gender + age + fare,
                        data = titanic_imputed, family = "binomial")

explain_titanic_glm <- explain(model_titanic_glm,
                             data = titanic_imputed[,-8],
                             y = titanic_imputed[,8],
                             label = "glm", verbose = FALSE)

cp_rf <- ceteris_paribus(explain_titanic_glm, selected_passangers)
cp_rf_john <- ceteris_paribus(explain_titanic_glm, selected_john)
plot(cp_rf, variables = "age") +
  show_profiles(cp_rf_john, variables = "age", size = 2)

library("ranger")

model_titanic_rf <- ranger(survived ~., data = titanic_imputed, probability = TRUE)

explain_titanic_rf <- explain(model_titanic_rf,
                             data = titanic_imputed[,-8],
                             y = titanic_imputed[,8],
                             label = "ranger forest",
                             verbose = FALSE)

cp_rf <- ceteris_paribus(explain_titanic_rf, selected_passangers)
cp_rf_john <- ceteris_paribus(explain_titanic_rf, selected_john)

cp_rf

pdp_rf <- aggregate_profiles(cp_rf, variables = "age")
head(pdp_rf)

plot(cp_rf, variables = "age") +
  show_observations(cp_rf, variables = "age") +
  show_rugs(cp_rf, variables = "age", color = "red") +
  show_profiles(cp_rf_john, variables = "age", color = "red", size = 2)

```

Description

Function `show_residuals` adds a layer to a plot created with `plot.ceteris_paribus_explainer` for selected observations. Note that the `y` argument has to be specified in the `ceteris_paribus` function.

Usage

```
show_residuals(
  x,
  ...,
  size = 0.75,
  alpha = 1,
  color = c(`TRUE` = "#8bdcbe", `FALSE` = "#f05a71"),
  variables = NULL
)
```

Arguments

<code>x</code>	a ceteris paribus explainer produced with function <code>ceteris_paribus()</code> . Note that <code>y</code> parameter shall be supplied in this function.
<code>...</code>	other explainers that shall be plotted together
<code>size</code>	a numeric. Size of lines to be plotted
<code>alpha</code>	a numeric between 0 and 1. Opacity of lines
<code>color</code>	a character. Either name of a color or name of a variable that should be used for coloring
<code>variables</code>	if not NULL then only variables will be presented

Value

a `ggplot2` layer

References

Explanatory Model Analysis. Explore, Explain, and Examine Predictive Models. <https://ema.drwhy.ai/>

Examples

```
library("DALEX")
library("ingredients")
library("ranger")

johnny_d <- data.frame(
  class = factor("1st", levels = c("1st", "2nd", "3rd", "deck crew", "engineering crew",
                                   "restaurant staff", "victualling crew")),
  gender = factor("male", levels = c("female", "male")),
  age = 8,
  sibsp = 0,
```

```

  parch = 0,
  fare = 72,
  embarked = factor("Southampton", levels = c("Belfast", "Cherbourg", "Queenstown", "Southampton"))
)

model_titanic_rf <- ranger(survived ~., data = titanic_imputed, probability = TRUE)

explain_titanic_rf <- explain(model_titanic_rf,
  data = titanic_imputed[,-8],
  y = titanic_imputed[,8],
  label = "ranger forest",
  verbose = FALSE)

johny_neighbours <- select_neighbours(data = titanic_imputed,
  observation = johny_d,
  variables = c("age", "gender", "class",
    "fare", "sibsp", "parch"),
  n = 10)

cp_neighbours <- ceteris_paribus(explain_titanic_rf,
  johny_neighbours,
  y = johny_neighbours$survived == "yes",
  variable_splits = list(age = seq(0,70, length.out = 1000)))

plot(cp_neighbours, variables = "age") +
  show_observations(cp_neighbours, variables = "age")

cp_johny <- ceteris_paribus(explain_titanic_rf, johny_d,
  variable_splits = list(age = seq(0,70, length.out = 1000)))

plot(cp_johny, variables = "age", size = 1.5, color = "#8bdcbf") +
  show_profiles(cp_neighbours, variables = "age", color = "#ceced9") +
  show_observations(cp_johny, variables = "age", size = 5, color = "#371ea3") +
  show_residuals(cp_neighbours, variables = "age")

```

show_rugs

Adds a Layer with Rugs to a Profile Plot

Description

Function `show_rugs` adds a layer to a plot created with `plot.ceteris_paribus_explainer` for selected observations. Various parameters help to decide what should be plotted, profiles, aggregated profiles, points or rugs.

Usage

```
show_rugs(
  x,
  ...,
  size = 0.5,
  alpha = 1,
  color = "#371ea3",
  variable_type = "numerical",
  sides = "b",
  variables = NULL
)
```

Arguments

x	a ceteris paribus explainer produced with function <code>ceteris_paribus()</code>
...	other explainers that shall be plotted together
size	a numeric. Size of lines to be plotted
alpha	a numeric between 0 and 1. Opacity of lines
color	a character. Either name of a color or name of a variable that should be used for coloring
variable_type	a character. If numerical then only numerical variables will be plotted. If categorical then only categorical variables will be plotted.
sides	a string containing any of "trbl", for top, right, bottom, and left. Passed to <code>geom_rug</code> .
variables	if not NULL then only variables will be presented

Value

a `ggplot2` layer

References

Explanatory Model Analysis. Explore, Explain, and Examine Predictive Models. <https://ema.drwhy.ai/>

Examples

```
library("DALEX")
library("ingredients")
titanic_small <- select_sample(titanic_imputed, n = 500, seed = 1313)

# build a model
model_titanic_glm <- glm(survived ~ gender + age + fare,
  data = titanic_small,
  family = "binomial")

explain_titanic_glm <- explain(model_titanic_glm,
  data = titanic_small[,-8],
```

```
      y = titanic_small[,8])

cp_glm <- ceteris_paribus(explain_titanic_glm, titanic_small[,1,])
cp_glm

library("ranger")

rf_model <- ranger(survived ~., data = titanic_imputed, probability = TRUE)

explainer_rf <- explain(rf_model,
  data = titanic_imputed[,-8],
  y = titanic_imputed[,8],
  label = "ranger forest",
  verbose = FALSE)

selected_passangers <- select_sample(titanic_imputed, n = 100)
cp_rf <- ceteris_paribus(explainer_rf, selected_passangers)
cp_rf

plot(cp_rf, variables = "age", color = "grey") +
show_observations(cp_rf, variables = "age", color = "black") +
  show_rugs(cp_rf, variables = "age", color = "red")
```

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