

# Package ‘mlr3viz’

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**Title** Visualizations for 'mlr3'

**Version** 0.6.2

**Description** Visualization package of the 'mlr3' ecosystem. It features plots for mlr3 objects such as tasks, learners, predictions, benchmark results, tuning instances and filters via the 'autoplot()' generic of 'ggplot2'. The package draws plots with the 'viridis' color palette and applies the minimal theme. Visualizations include barplots, boxplots, histograms, ROC curves, and Precision-Recall curves.

**License** LGPL-3

**URL** <https://mlr3viz.mlr-org.com>, <https://github.com/mlr-org/mlr3viz>

**BugReports** <https://github.com/mlr-org/mlr3viz/issues>

**Depends** R (>= 3.1.0)

**Imports** checkmate, data.table, ggplot2 (>= 3.3.0), mlr3misc (>= 0.7.0), scales, utils, viridis

**Suggests** bbotk (>= 0.7.3), cluster, GGally, ggdendro, ggfortify (>= 0.4.11), ggparty, glmnet, knitr, lgr, mlr3 (>= 0.6.0), mlr3cluster, mlr3filters, mlr3learners, mlr3tuning (>= 0.9.0), paradox, partykit, patchwork (>= 1.1.1), precrec, ranger, rpart, stats, testthat (>= 3.0.0), vdiffR (>= 1.0.2), xgboost

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'LearnerClassifGlmnet.R' 'LearnerClassifRpart.R'  
'LearnerClustHierarchical.R' 'LearnerRegrCVGlmnet.R'  
'LearnerRegrGlmnet.R' 'LearnerRegrRpart.R'  
'OptimInstanceSingleCrit.R' 'Prediction.R'  
'PredictionClassif.R' 'PredictionClust.R' 'PredictionRegr.R'  
'ResampleResult.R' 'Task.R' 'TaskClassif.R' 'TaskClust.R'

'TaskRegr.R' 'TuningInstanceSingleCrit.R' 'as\_precrec.R'  
 'bibentries.R' 'helper.R' 'plot\_learner\_prediction.R'  
 'reexports.R' 'zzz.R'

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mlr3viz-package

*mlr3viz: Visualizations for 'mlr3'*

---

## Description

Visualization package of the 'mlr3' ecosystem. It features plots for mlr3 objects such as tasks, learners, predictions, benchmark results, tuning instances and filters via the 'autoplot()' generic of 'ggplot2'. The package draws plots with the 'viridis' color palette and applies the minimal theme. Visualizations include barplots, boxplots, histograms, ROC curves, and Precision-Recall curves.

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**See Also**

Useful links:

- <https://mlr3viz.mlr-org.com>
- <https://github.com/mlr-org/mlr3viz>
- Report bugs at <https://github.com/mlr-org/mlr3viz/issues>

---

as\_precrec

*Convert to 'precrec' Format*

---

**Description**

Converts to a format which is understood by `precrec::evalmod()` of package **precrec**.

**Usage**

```
as_precrec(object)

## S3 method for class 'PredictionClassif'
as_precrec(object)

## S3 method for class 'ResampleResult'
as_precrec(object)

## S3 method for class 'BenchmarkResult'
as_precrec(object)
```

**Arguments**

object (any)  
Object to convert.

**Value**

Object as created by `precrec::mmdata()`.

**References**

Saito T, Rehmsmeier M (2017). "Precrec: fast and accurate precision-recall and ROC curve calculations in R." *Bioinformatics*, **33**(1), 145-147. doi:10.1093/bioinformatics/btw570.

---

autoplot.BenchmarkResult

*Plots for Benchmark Results*

---

**Description**

Visualizations for `mlr3::BenchmarkResult`. The argument type controls what kind of plot is drawn. Possible choices are:

- "boxplot" (default): Boxplots of performance measures, one box per `mlr3::Learner` and one facet per `mlr3::Task`.
- "roc": ROC curve (1 - specificity on x, sensitivity on y). The `mlr3::BenchmarkResult` may only have a single `mlr3::Task` and a single `mlr3::Resampling`. Note that you can subset any `mlr3::BenchmarkResult` with its `$filter()` method (see examples). Requires package **precrec**.
- "prc": Precision recall curve. See "roc".

**Usage**

```
## S3 method for class 'BenchmarkResult'
autoplot(
  object,
  type = "boxplot",
  measure = NULL,
  theme = theme_minimal(),
  ...
)
```

**Arguments**

object	( <code>mlr3::BenchmarkResult</code> ).
type	(character(1)): Type of the plot. See description.
measure	( <code>mlr3::Measure</code> ) Performance measure to use.
theme	( <code>ggplot2::theme()</code> ) The <code>ggplot2::theme_minimal()</code> is applied by default to all plots.
...	(ignored).

**Value**

`ggplot2::ggplot()`.

**References**

Saito T, Rehmsmeier M (2017). “Precrec: fast and accurate precision-recall and ROC curve calculations in R.” *Bioinformatics*, **33**(1), 145-147. doi:10.1093/bioinformatics/btw570.

**Examples**

```
if (requireNamespace("mlr3")) {
  library(mlr3)
  library(mlr3viz)

  tasks = tsks(c("pima", "sonar"))
  learner = lrns(c("classif.featureless", "classif.rpart"),
    predict_type = "prob")
  resampling = rsmpls("cv")
  object = benchmark(benchmark_grid(tasks, learner, resampling))

  head(fortify(object))
  autoplot(object)
  autoplot(object$clone(deep = TRUE)$filter(task_ids = "pima"), type = "roc")
}
```

---

 autoplot.Filter

*Plots for Filter Scores*


---

**Description**

Visualizations for `mlr3filters::Filter`. The argument `type` controls what kind of plot is drawn. Possible choices are:

- "barplot" (default): Bar plot of filter scores.

**Usage**

```
## S3 method for class 'Filter'
autoplot(object, type = "boxplot", n = Inf, theme = theme_minimal(), ...)
```

**Arguments**

<code>object</code>	( <code>mlr3filters::Filter</code> ).
<code>type</code>	( <code>character(1)</code> ): Type of the plot. See description.
<code>n</code>	( <code>integer(1)</code> ) Only include the first <code>n</code> features with the highest importance. Defaults to all features.

theme (ggplot2::theme())  
 The ggplot2::theme\_minimal() is applied by default to all plots.  
 ... (ignored).

**Value**

ggplot2::ggplot().

**Examples**

```
if (requireNamespace("mlr3")) {
  library(mlr3)
  library(mlr3viz)
  library(mlr3filters)

  task = tsk("mtcars")
  f = flt("correlation")
  f$calculate(task)

  head(fortify(f))
  autoplot(f, n = 5)
}
```

---

autoplot.LearnerClassifCVGlmnet  
*Plots for GLMNet Learners*

---

**Description**

Visualizations for GLMNet learners using the package **ggfortify**.

**Usage**

```
## S3 method for class 'LearnerClassifCVGlmnet'
autoplot(object, theme = theme_minimal(), ...)

## S3 method for class 'LearnerClassifGlmnet'
autoplot(object, theme = theme_minimal(), ...)

## S3 method for class 'LearnerRegrCVGlmnet'
autoplot(object, theme = theme_minimal(), ...)

## S3 method for class 'LearnerRegrGlmnet'
autoplot(object, theme = theme_minimal(), ...)
```

## Arguments

object (mlr3learners::LearnerClassifGlmnet | mlr3learners::LearnerRegrGlmnet | mlr3learners::LearnerRegrCVGlmnet | mlr3learners::LearnerRegrCVGlmnet).

theme (ggplot2::theme())  
The `ggplot2::theme_minimal()` is applied by default to all plots.

... (ignored).

## Value

`ggplot2::ggplot()`.

## References

Tang Y, Horikoshi M, Li W (2016). “ggfortify: Unified Interface to Visualize Statistical Result of Popular R Packages.” *The R Journal*, 8(2), 474–485. doi:10.32614/RJ2016060.

## Examples

```
## Not run:
library(mlr3)
library(mlr3viz)
library(mlr3learners)

# classification
task = tsk("sonar")
learner = lrn("classif.glmnet")
learner$train(task)
autoplot(learner)

# regression
task = tsk("mtcars")
learner = lrn("regr.glmnet")
learner$train(task)
autoplot(learner)

## End(Not run)
```

---

autoplot.LearnerClassifRpart

*Plots for Rpart Learners*

---

## Description

Visualizations rpart trees using the package **ggparty**.

**Usage**

```
## S3 method for class 'LearnerClassifRpart'
autoplot(object, theme = theme_minimal(), ...)

## S3 method for class 'LearnerRegrRpart'
autoplot(object, theme = theme_minimal(), ...)
```

**Arguments**

```
object      (mlr3::LearnerClassifRpart | mlr3::LearnerRegrRpart).
theme      (ggplot2::theme())
            The ggplot2::theme_minimal() is applied by default to all plots.
...        (ignored).
```

**Value**

```
ggplot2::ggplot().
```

**Examples**

```
if (requireNamespace("mlr3")) {
  library(mlr3)
  library(mlr3viz)

  # classification
  task = tsk("iris")
  learner = lrn("classif.rpart", keep_model = TRUE)
  learner$train(task)
  autoplot(learner)

  # regression
  task = tsk("mtcars")
  learner = lrn("regr.rpart", keep_model = TRUE)
  learner$train(task)
  autoplot(learner)
}
```

---

autoplot.LearnerClustHierarchical

*Plots for Hierarchical Clustering Learners*

---

**Description**

Visualizations for hierarchical clusters. The argument type controls what kind of plot is drawn. Possible choices are:

- "dend" (default): Dendrograms using **ggdendro** package.
- "scree": Scree plot that shows the number of possible clusters on the x-axis and the height on the y-axis.



**Usage**

```
## S3 method for class 'LearnerClustHierarchical'
autoplot(
  object,
  type = "dend",
  task = NULL,
  theme = theme_minimal(),
  theme_dendro = TRUE,
  ...
)
```

**Arguments**

object	(mlr3cluster::LearnerClustAgnes   mlr3cluster::LearnerClustDiana   mlr3cluster::LearnerClustHclust).
type	(character(1)): Type of the plot. See description.
task	(mlr3::Task) Optionally, pass the task to add labels of observations to a hclust dendrogram. Labels are set via the row names of the task.
theme	(ggplot2::theme()) The <code>ggplot2::theme_minimal()</code> is applied by default to all plots.
theme_dendro	(logical(1)) If TRUE (default), the special dendrogram theme from <b>ggdendro</b> package is used in plot "dend". Set to FALSE to use the theme passed in theme.
...	(ignored).

**Value**

`ggplot2::ggplot()`.

**Examples**

```
if (requireNamespace("mlr3")) {
  library(mlr3)
  library(mlr3cluster)
  library(mlr3viz)

  task = tsk("usarrests")

  # agnes clustering
  learner = lrn("clust.agnes")
  learner$train(task)
  autoplot(learner)

  # diana clustering
  learner = lrn("clust.diana")
  learner$train(task)
  autoplot(learner)
}
```

```

# hclust clustering
learner = lrn("clust.hclust")
learner$train(task)
autoplot(learner, type = "scree")
}

```

---

```

autoplot.OptimInstanceSingleCrit
Plots for Optimization Instances

```

---

## Description

Visualizations for `bbotk::OptimInstanceSingleCrit`. The argument `type` controls what kind of plot is drawn. Possible choices are:

- "marginal" (default): Scatter plots of x versus y. The color of the points shows the batch number.
- "performance": Scatter plots of batch number versus y
- "parameter": Scatter plots of batch number versus input. The color of the points shows the y values.
- "parallel": Parallel coordinates plot. x values are rescaled by  $(x - \text{mean}(x)) / \text{sd}(x)$ .
- "points": Scatter plot of two x dimensions versus. The color of the points shows the y values.
- "surface": Surface plot of two x dimensions versus y values. The y values are interpolated with the supplied `mlr3::Learner`.
- "pairs": Plots all x and y values against each other.
- "incumbent": Plots the incumbent versus the number of configurations.

## Usage

```

## S3 method for class 'OptimInstanceSingleCrit'
autoplot(
  object,
  type = "marginal",
  cols_x = NULL,
  trafo = FALSE,
  learner = mlr3::lrn("regr.ranger"),
  grid_resolution = 100,
  batch = NULL,
  theme = theme_minimal(),
  ...
)

```

**Arguments**

object	( <a href="#">bbotk::OptimInstanceSingleCrit</a> ).
type	(character(1)): Type of the plot. See description.
cols_x	(character()) Column names of x values. By default, all untransformed x values from the search space are plotted. Transformed hyperparameters are prefixed with <code>x_domain_</code> .
trafo	(logical(1)) If FALSE (default), the untransformed x values are plotted. If TRUE, the transformed x values are plotted.
learner	( <a href="#">mlr3::Learner</a> ) Regression learner used to interpolate the data of the surface plot.
grid_resolution	(numeric()) Resolution of the surface plot.
batch	(integer()) The batch number(s) to limit the plot to. The default is all batches.
theme	( <a href="#">ggplot2::theme()</a> ) The <a href="#">ggplot2::theme_minimal()</a> is applied by default to all plots.
...	(ignored).

**Value**

[ggplot2::ggplot\(\)](#).

**Examples**

```
if (requireNamespace("mlr3") && requireNamespace("bbotk") && requireNamespace("patchwork")) {
  library(bbotk)
  library(paradox)

  fun = function(xs) {
    c(y = -(xs[[1]] - 2)^2 - (xs[[2]] + 3)^2 + 10)
  }
  domain = ps(
    x1 = p_dbl(-10, 10),
    x2 = p_dbl(-5, 5)
  )
  codomain = ps(
    y = p_dbl(tags = "maximize")
  )
  obfun = ObjectiveRFun$new(
    fun = fun,
    domain = domain,
    codomain = codomain
  )

  instance = OptimInstanceSingleCrit$new(objective = obfun, terminator = trm("evals", n_evals = 20))
}
```

```

optimizer = opt("random_search", batch_size = 2)
optimizer$optimize(instance)

# plot y versus batch number
print(autoplot(instance, type = "performance"))

# plot x1 values versus performance
print(autoplot(instance, type = "marginal", cols_x = "x1"))

# plot parallel coordinates plot
print(autoplot(instance, type = "parallel"))

# plot pairs
print(autoplot(instance, type = "pairs"))

# plot incumbent
print(autoplot(instance, type = "incumbent"))
}

```

---

autoplot.PredictionClassif

*Plots for Classification Predictions*

---

## Description

Visualizations for [mlr3::PredictionClassif](#). The argument `type` controls what kind of plot is drawn. Possible choices are:

- "stacked" (default): Stacked barplot of true and estimated class labels.
- "roc": ROC curve (1 - specificity on x, sensitivity on y). Requires package **precrec**.
- "prc": Precision recall curve. Requires package **precrec**.
- "threshold": Systematically varies the threshold of the [mlr3::PredictionClassif](#) object and plots the resulting performance as returned by `measure`.

## Usage

```

## S3 method for class 'PredictionClassif'
autoplot(
  object,
  type = "stacked",
  measure = NULL,
  theme = theme_minimal(),
  ...
)

```

**Arguments**

object	(mlr3::PredictionClassif).
type	(character(1)): Type of the plot. See description.
measure	(mlr3::Measure) Performance measure to use.
theme	(ggplot2::theme()) The <code>ggplot2::theme_minimal()</code> is applied by default to all plots.
...	(ignored).

**Value**

`ggplot2::ggplot()`.

**References**

Saito T, Rehmsmeier M (2017). "Precrec: fast and accurate precision-recall and ROC curve calculations in R." *Bioinformatics*, **33**(1), 145-147. doi:10.1093/bioinformatics/btw570.

**Examples**

```
if (requireNamespace("mlr3")) {
  library(mlr3)
  library(mlr3viz)

  task = tsk("spam")
  learner = lrn("classif.rpart", predict_type = "prob")
  object = learner$train(task)$predict(task)

  head(fortify(object))
  autoplot(object)
  autoplot(object, type = "roc")
  autoplot(object, type = "prc")
}
```

---

autoplot.PredictionClust

*Plots for Cluster Predictions*

---

**Description**

Visualizations for `mlr3cluster::PredictionClust`. The argument `type` controls what kind of plot is drawn. Possible choices are:

- "scatter" (default): scatterplot with correlation values and colored cluster assignments.

- "sil": Silhouette plot with mean silhouette value as the reference line. Requires package **ggfortify**.
- "pca": Perform PCA on data and color code cluster assignments. Inspired by and uses `ggfortify::autoplot.kmeans`.

### Usage

```
## S3 method for class 'PredictionClust'
autoplot(
  object,
  task,
  row_ids = NULL,
  type = "scatter",
  theme = theme_minimal(),
  ...
)
```

### Arguments

object	( <code>mlr3cluster::PredictionClust</code> ).
task	( <code>mlr3cluster::TaskClust</code> ).
row_ids	( <code>integer()</code> ) Row ids to subset task data to ensure that only the data used to make predictions are shown in plots.
type	( <code>character(1)</code> ): Type of the plot. See description.
theme	( <code>ggplot2::theme()</code> ) The <code>ggplot2::theme_minimal()</code> is applied by default to all plots.
...	(ignored).

### Value

`ggplot2::ggplot()`.

### References

Tang Y, Horikoshi M, Li W (2016). "ggfortify: Unified Interface to Visualize Statistical Result of Popular R Packages." *The R Journal*, 8(2), 474–485. doi:10.32614/RJ2016060.

### Examples

```
if (requireNamespace("mlr3")) {
  library(mlr3)
  library(mlr3cluster)
  library(mlr3viz)

  task = tsk("usarrests")
  learner = lrn("clust.kmeans", centers = 3)
  object = learner$train(task)$predict(task)
```

```

  head(fortify(object))
  autoplot(object, task)
}

```

---

 autoplot.PredictionRegr

*Plots for Regression Predictions*


---

## Description

Visualizations for [mlr3::PredictionRegr](#). The argument `type` controls what kind of plot is drawn. Possible choices are:

- "xy" (default): Scatterplot of "true" response vs. "predicted" response. By default a linear model is fitted via `geom_smooth(method = "lm")` to visualize the trend between x and y (by default colored blue). In addition `geom_abline()` with `slope = 1` is added to the plot. Note that `geom_smooth()` and `geom_abline()` may overlap, depending on the given data.
- "histogram": Histogram of residuals:  $r = y - \hat{y}$ .
- "residual": Plot of the residuals, with the response  $\hat{y}$  on the "x" and the residuals on the "y" axis. By default a linear model is fitted via `geom_smooth(method = "lm")` to visualize the trend between x and y (by default colored blue).
- "confidence": Scatterplot of "true" response vs. "predicted" response with confidence intervals. Error bars calculated as `object$reponse +/- quantile * object$se` and so only possible with `predict_type = "se"`. `geom_abline()` with `slope = 1` is added to the plot.

## Usage

```

## S3 method for class 'PredictionRegr'
autoplot(
  object,
  type = "xy",
  binwidth = NULL,
  theme = theme_minimal(),
  quantile = 1.96,
  ...
)

```

## Arguments

<code>object</code>	( <a href="#">mlr3::PredictionRegr</a> ).
<code>type</code>	(character(1)): Type of the plot. See description.
<code>binwidth</code>	(integer(1)) Width of the bins for the histogram.

theme (ggplot2::theme())  
The `ggplot2::theme_minimal()` is applied by default to all plots.

quantile (numeric(1))  
Quantile multiplier for standard errors for `type="confidence"`. Default 1.96.

... (ignored).

**Value**

`ggplot2::ggplot()`.

**Examples**

```
if (requireNamespace("mlr3")) {
  library(mlr3)
  library(mlr3viz)

  task = tsk("boston_housing")
  learner = lrn("regr.rpart")
  object = learner$train(task)$predict(task)

  head(fortify(object))
  autoplot(object)
  autoplot(object, type = "histogram", binwidth = 1)
  autoplot(object, type = "residual")

  if (requireNamespace("mlr3learners")) {
    library(mlr3learners)
    learner = lrn("regr.ranger", predict_type = "se")
    object = learner$train(task)$predict(task)
    autoplot(object, type = "confidence")
  }
}
```

---

autoplot.ResampleResult

*Plots for Resample Results*

---

**Description**

Visualizations for `mlr3::ResampleResult`. The argument `type` controls what kind of plot is drawn. Possible choices are:

- `"boxplot"` (default): Boxplot of performance measures.
- `"histogram"`: Histogram of performance measures.
- `"roc"`: ROC curve (1 - specificity on x, sensitivity on y). The predictions of the individual `mlr3::Resamplings` are merged prior to calculating the ROC curve (micro averaged). Requires package **precrec**.
- `"prc"`: Precision recall curve. See `"roc"`.



- "prediction": Plots the learner prediction for a grid of points. Needs models to be stored. Set `store_models = TRUE` for `[mlr3::resample]`. For classification, we support tasks with exactly two features and learners with `predict_type=` set to "response" or "prob". For regression, we support tasks with one or two features. For tasks with one feature we can print confidence bounds if the predict type of the learner was set to "se". For tasks with two features the predict type will be ignored.

## Usage

```
## S3 method for class 'ResampleResult'
autoplot(
  object,
  type = "boxplot",
  measure = NULL,
  predict_sets = "test",
  binwidth = NULL,
  theme = theme_minimal(),
  ...
)
```

## Arguments

<code>object</code>	( <a href="#">mlr3::ResampleResult</a> ).
<code>type</code>	( <code>character(1)</code> ): Type of the plot. See description.
<code>measure</code>	( <a href="#">mlr3::Measure</a> ) Performance measure to use.
<code>predict_sets</code>	( <code>character()</code> ) Only for type set to "prediction". Which points should be shown in the plot? Can be a subset of ("train", "test") or empty.
<code>binwidth</code>	( <code>integer(1)</code> ) Width of the bins for the histogram.
<code>theme</code>	( <a href="#">ggplot2::theme()</a> ) The <a href="#">ggplot2::theme_minimal()</a> is applied by default to all plots.
<code>...</code>	(ignored).

## Value

[ggplot2::ggplot\(\)](#).

## References

Saito T, Rehmsmeier M (2017). "Precrec: fast and accurate precision-recall and ROC curve calculations in R." *Bioinformatics*, **33**(1), 145-147. doi:10.1093/bioinformatics/btw570.

## Examples

```

if (requireNamespace("mlr3")) {
  library(mlr3)
  library(mlr3viz)

  task = tsk("sonar")
  learner = lrn("classif.rpart", predict_type = "prob")
  resampling = rsmpl("cv", folds = 3)
  object = resample(task, learner, resampling)

  head(fortify(object))

  # Default: boxplot
  autoplot(object)

  # Histogram
  autoplot(object, type = "histogram", bins = 30)

  # ROC curve, averaged over resampling folds:
  autoplot(object, type = "roc")

  # ROC curve of joint prediction object:
  autoplot(object$prediction(), type = "roc")

  # Precision Recall Curve
  autoplot(object, type = "prc")

  # Prediction Plot
  task = tsk("iris")$select(c("Sepal.Length", "Sepal.Width"))
  resampling = rsmpl("cv", folds = 3)
  object = resample(task, learner, resampling, store_models = TRUE)
  autoplot(object, type = "prediction")
}

```

---

autoplot.TaskClassif *Plots for Classification Tasks*

---

## Description

Visualizations for `mlr3::TaskClassif`. The argument `type` controls what kind of plot is drawn. Possible choices are:

- "target" (default): Bar plot of the target variable (default).
- "duo": Passes data to `GGally::ggduo()`. `columnsX` is the target and `columnsY` are the features.
- "pairs": Passes data to `GGally::ggpairs()`. Color is set to target column.

**Usage**

```
## S3 method for class 'TaskClassif'
autoplot(object, type = "target", theme = theme_minimal(), ...)
```

**Arguments**

```
object      (mlr3::TaskClassif).
type        (character(1)):
            Type of the plot. See description.
theme       (ggplot2::theme())
            The ggplot2::theme_minimal() is applied by default to all plots.
...         (ignored).
```

**Value**

```
ggplot2::ggplot().
```

**Examples**

```
if (requireNamespace("mlr3")) {
  library(mlr3)
  library(mlr3viz)

  task = tsk("iris")

  head(fortify(task))
  autoplot(task)
  autoplot(task$clone())$select(c("Sepal.Length", "Sepal.Width")),
  type = "pairs")
  autoplot(task, type = "duo")
}
```

---

autoplot.TaskClust      *Plots for Clustering Tasks*

---

**Description**

Visualizations for `mlr3cluster::TaskClust`. The argument `type` controls what kind of plot is drawn. Possible choices are:

- "pairs" (default): Passes data `GGally::ggpairs()`.

**Usage**

```
## S3 method for class 'TaskClust'
autoplot(object, type = "pairs", theme = theme_minimal(), ...)
```

**Arguments**

object	(mlr3cluster::TaskClust).
type	(character(1)): Type of the plot. See description.
theme	(ggplot2::theme()) The <code>ggplot2::theme_minimal()</code> is applied by default to all plots.
...	(ignored).

**Value**

`ggplot2::ggplot()`.

**Examples**

```
if (requireNamespace("mlr3")) {
  library(mlr3)
  library(mlr3cluster)
  library(mlr3viz)

  task = mlr_tasks$get("usarrests")

  head(fortify(task))
  autoplot(task)
}
```

---

autoplot.TaskRegr      *Plots for Regression Tasks*

---

**Description**

Visualizations for `mlr3::TaskRegr`. The argument type controls what kind of plot is drawn. Possible choices are:

- "target" (default): Box plot of the target variable.
- "pairs": Passes data to `GGally::ggpairs()`. Color is set to target column.

**Usage**

```
## S3 method for class 'TaskRegr'
autoplot(object, type = "target", theme = theme_minimal(), ...)
```

**Arguments**

object	(mlr3::TaskRegr).
type	(character(1)): Type of the plot. See description.
theme	(ggplot2::theme()) The <code>ggplot2::theme_minimal()</code> is applied by default to all plots.
...	(ignored).

**Value**

`ggplot2::ggplot()`.

**Examples**

```
if (requireNamespace("mlr3")) {
  library(mlr3)
  library(mlr3viz)

  task = tsk("mtcars")
  task$select(c("am", "carb"))

  head(fortify(task))
  autoplot(task)
  autoplot(task, type = "pairs")
}
```

---

autoplot.TuningInstanceSingleCrit

*Plots for Tuning Instances*

---

**Description**

Visualizations for `mlr3tuning::TuningInstanceSingleCrit`. The argument `type` controls what kind of plot is drawn. Possible choices are:

- "marginal" (default): Scatter plots of  $x$  versus  $y$ . The color of the points shows the batch number.
- "performance": Scatter plots of batch number versus  $y$
- "parameter": Scatter plots of batch number versus input. The color of the points shows the  $y$  values.
- "parallel": Parallel coordinates plot. hyperparameters are rescaled by  $(x - \text{mean}(x)) / \text{sd}(x)$ .
- "points": Scatter plot of two  $x$  dimensions versus  $y$ . The color of the points shows the  $y$  values.
- "surface": Surface plot of two  $x$  dimensions versus  $y$  values. The  $y$  values are interpolated with the supplied `mlr3::Learner`.
- "pairs": Plots all  $x$  and  $y$  values against each other.
- "incumbent": Plots the incumbent versus the number of configurations.

**Usage**

```
## S3 method for class 'TuningInstanceSingleCrit'
autoplot(
  object,
  type = "marginal",
  cols_x = NULL,
```

```

trafo = FALSE,
learner = mlr3::lrn("regr.ranger"),
grid_resolution = 100,
theme = theme_minimal(),
...
)

```

## Arguments

object	( <a href="#">mlr3tuning::TuningInstanceSingleCrit</a> .
type	(character(1)): Type of the plot. See description.
cols_x	(character()) Column names of hyperparameters. By default, all untransformed hyperparameters are plotted. Transformed hyperparameters are prefixed with <code>x_domain_</code> .
trafo	(logical(1)) If FALSE (default), the untransformed hyperparameters are plotted. If TRUE, the transformed hyperparameters are plotted.
learner	( <a href="#">mlr3::Learner</a> ) Regression learner used to interpolate the data of the surface plot.
grid_resolution	(numeric()) Resolution of the surface plot.
theme	( <a href="#">ggplot2::theme()</a> ) The <a href="#">ggplot2::theme_minimal()</a> is applied by default to all plots.
...	(ignored).

## Value

[ggplot2::ggplot\(\)](#).

## Examples

```

if (requireNamespace("mlr3tuning") && requireNamespace("patchwork")) {
  library(mlr3tuning)

  learner = lrn("classif.rpart")
  learner$param_set$values$cp = to_tune(0.001, 0.1)
  learner$param_set$values$minsplit = to_tune(1, 10)

  instance = TuningInstanceSingleCrit$new(
    task = tsk("iris"),
    learner = learner,
    resampling = rsmpl("holdout"),
    measure = msr("classif.ce"),
    terminator = trm("evals", n_evals = 10))

  tuner = tnr("random_search")
}

```

```

tuner$optimize(instance)

# plot performance versus batch number
autoplot(instance, type = "performance")

# plot cp values versus performance
autoplot(instance, type = "marginal", cols_x = "cp")

# plot transformed parameter values versus batch number
autoplot(instance, type = "parameter", trafo = TRUE)

# plot parallel coordinates plot
autoplot(instance, type = "parallel")

# plot pairs
autoplot(instance, type = "pairs")
}

```

---

plot\_learner\_prediction

*Plots for Learner Predictions*


---

## Description

Visualizations for the [mlr3::Prediction](#) of a single [mlr3::Learner](#) on a single [mlr3::Task](#).

- For classification we support tasks with exactly two features and learners with `predict_type` set to "response" or "prob".
- For regression we support tasks with one or two features. For tasks with one feature we print confidence bounds if the predict type of the learner was set to "se". For tasks with two features the predict type will be ignored.

Note that this function is a wrapper around `autoplot.ResampleResult()` for a temporary [mlr3::ResampleResult](#) using [mlr3::mlr\\_resamplings\\_holdout](#) with ratio 1 (all observations in the training set).

## Usage

```
plot_learner_prediction(learner, task, grid_points = 100L, expand_range = 0)
```

## Arguments

learner	( <a href="#">mlr3::Learner</a> ).
task	( <a href="#">mlr3::Task</a> ).
grid_points	( <code>integer(1)</code> ) Resolution of the grid. For factors, ordered and logicals this value is ignored.
expand_range	( <code>numeric(1)</code> ) Expand the prediction range for numerical features.

**Value**

ggplot2::ggplot().

**Examples**

```
if (requireNamespace("mlr3")) {  
  library(mlr3)  
  library(mlr3viz)  
  
  task = mlr3::tsk("pima")$select(c("age", "glucose"))  
  learner = lrn("classif.rpart", predict_type = "prob")  
  p = plot_learner_prediction(learner, task)  
  print(p)  
}
```

---

predict\_grid

*Generates a data.table of evenly distributed points.*

---

**Description**

For each point we have the predicted class / regression value in column response. If the learner predicts probabilities, a column ".prob.response" is added that contains the probability of the predicted class

**Usage**

```
predict_grid(learners, task, grid_points, expand_range)
```

**Arguments**

learners	list of trained learners, each learner belongs to one resampling iteration
task	the task all learners are trained on
grid_points	(int): see sequenize
expand_range	see sequenize



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