Machine learning with mlr3::CHEAT SHEET



Class Overview

The package provides a set of R6 classes which allow to (a) define general feature selection instances and (b) run algorithms which optimize on these. (a) is called a FSelectInstanceSingleCrit or FSelectInstaneMultiCrit, which define a blackbox optimization function that maps feature subsets to resampled performance values for arbitrary performance measures.

mlr3 Dictionaries

Key-value store for sets of mlr objects. These are provided by mlr3:

- mlr_tasks-ML example tasks.
- mlr_task_generators Example generators.
- mlr_learners-ML algorithms.
- mlr_measures Performance measures.
- mlr resamplings-Resampling strategies.

These dictionaries can be extended by loading extension packages. For example, by loading the **mlr3learners** package, the mlr_learners dictionary is extended with more learners.

Syntactic sugar functions retrieve objects from dictionaries, set hyperparameters and assign fields in one go e.g.lrn("classif.rpart", cp = 0.1).

Dictionary\$keys(pattern = NULL)

Returns all keys which match pattern. If NULL, all keys are returned.

Dictionary\$get(key, ...)

Retrieves object by key and passes arguments "..." to the construction of the objects.

Dictionary\$mget(keys, ...)

Retrieves objects by keys and passes named arguments "..." to the construction of the objects.

as.data.table(Dictionary)

Lists objects with metadata.

Class: Task

Stores data and metadata. backend can be a data.table, target points to y-column by name.

```
task = TaskRegr$new(backend, target)
```

Create task for regression or classification.

```
task = tsk(.key)
```

Sugar to get example task from mlr_tasks:

- Twoclass: german_credit, pima, sonar, spam
- Multiclass: iris. wine. zoo
- Regression: boston housing, mtcars

Print the mlr tasks dictionary for more.

```
task$positive = "<positive_class>"
```

Set positive class for binary classification.

Column Roles

Column roles affect the behavior of the task for different operations. Set with

task\$col_roles\$<role> = "<column_name>":

- · feature Regular features.
- target Target variable.
- name Labels for plots.
- · group Groups for block resampling.
- · stratum Stratification variables.
- weight Observation weights.

Data Operations

task\$select(cols)

Subsets the task based on feature names.

task\$filter(rows)

Subsets the task based on row ids.

task\$cbind(data) / task\$rbind(data)

Adds additional columns / rows.

task\$rename(from, to)

Rename columns.

Class: Learner

Wraps learners from R with a unified interface.

```
learner = lrn(.key, ...)
```

Get learner by .key (from mlr_learners) and construct the learner with specific hyperparameters and settings "..." in one go. github.com/mlr-org/mlr3learners (R package) and github.com/mlr3learners (GitHub organization) hold all available learners.

learner\$param_set

Returns description of hyperparameters.

```
learner$param_set$values = list(id = value)
```

Change the current hyperparameter values by assigning a named list(id = value) to the \$values field. This overwrites all previously set parameters.

learner\$param_set\$values\$<id> = <value>

Update a single hyperparameter.

```
learner$predict_type = "<type>"
```

Changes/sets the output type of the prediction. For classification, "response" means class labels, "prob" means posterior probabilities. For regression, "response" means numeric response, "se" extracts the standard error.

Example

```
task = tsk("sonar")
learner = lrn("classif.rpart")

train_set = sample(taskSnrow, 8.8 * taskSnrow)
test_set = setdiff(seq_len(taskSnrow), train_set)

learnerStrain(task, row_ids = train_set)

prediction = learnerSpredict(task, row_ids = test_set)
predictionSacore()
## > classif.ce
## > 8.2619848
```

Train & Predict

learner\$train(task, row_ids)

Train on (selected) observations.

learner\$model

The resulting model is stored in the \$model slot of the learner.

```
prediction = learner$predict(task, row_ids)
```

Predict on (selected) observations.

Measures & Scoring

```
measure = msr(.key)
```

Get measure by . key from `mlr_measures:

- · classif.ce-Classification error.
- classif.auc-AUROC.
- · regr.rmse-Root mean square error.

Print mlr measures for all measures.

prediction\$score(measures)

Calculate performance with one or more measures.

Class: Resampling

Define partitioning of task into train and test sets. Creation: resampling = rsmp(.key, ...)

- · holdout (ratio) Holdout-validation.
- cv (folds) k-fold cross-validation.
- repeated_cv (folds, repeats) Repeated k-fold cross-validation
- subsampling (repeats, ratio) Repeated holdouts.
- · bootstrap (repeats, ratio) Out-of-bag bootstrap.
- Custom splits

```
resampling = rsmp("custom")
resampling$instantiate(task,
    train = list(c(1:10, 51:60, 101:110)),
    test = list(c(11:20, 61:70, 111:120)))
```

resampling\$param_set

Returns a description of parameter settings.

```
resampling$param_set$values = list(folds = 10)
```

Sets folds to 10.

```
task$col_roles$stratum = "<column_names>"
```

Sets stratification variables.

```
task$col_roles$group = "<column_name>"
```

Sets group variable.

```
resampling$instantiate(task)
```

Perform splitting and define index sets.

Resample

Train-Predict-Score a learner on each train/test set.

```
rr = resample(task, learner, resampling)
```

Returns a ResampleResult container object.

```
rr$score(measures)
```

Returns a data.table of scores on test sets.

```
rr$aggregate(measures)
```

Gets aggregated performance scores as vector.

```
rr$filter(iters)
```

Filters to specific iterations.

Example

```
library(mlr3learners)
task = tsk("pima")
learner = lrn("classif.rpart", predict_type = "prob")
measure = msr("classif.ce")
resampling = rsmp("cv", folds = 3L)
resamplingSinstantiate(task)
rr = resample(task, learner, resampling)
as.data.table(rr)[, list(resampling, iteration, prediction)]
## > resampling iteration prediction
## > 1: <ResamplingCV[19]> 1 <PredictionClassif[19]>
## > 2: <ResamplingCV[19]> 2 <PredictionClassif[19]>
rr$aggregate(measure)
## > classif co
## > 0.2239583
learners = lrns(c("classif.rpart", "classif.ranger"))
tasks = tsks(c("sonar", "spam"))
resampling = rsmp("cv", folds = 3L)
design = benchmark_grid(tasks, learners,resampling)
bmr = benchmark(design)
                                      resampling iteration
## > 1: <LearnerClassifRpart[33]> <ResamplingCV[19]>
## > 2: <LearnerClassifRpart[33]> <ResamplingCV[19]>
## > 3: <LearnerClassifRoart[33]> <ResamplingCV[19]>
## > 4: <LearnerClassifRanger[33]> <ResamplingCV[19]>
bmr$aggregate()[, list(nr, resample_result, task_id, learner_id, classif.ce)]
## > nr resample_result task_id learner_id classif.ce
## > 1: 1 <ResampleResult[21]> sonar classif.rpart \theta.30276052
## > 2: 2 <ResampleResult[21]> sonar classif.ranger 0.17308489
## > 3: 3 <ResampleResult[21]> spam classif.rpart 0.09997865
## > 4: 4 <ResampleResult[21]> spam classif.ranger 0.04868526
```

Results are stored as a data.table. BenchmarkResult contains a ResampleResult object for each task-learner-resampling combination which in turn contain a Prediction object for each resampling iteration.

Benchmark

Compare learner(s) on task(s) with resampling(s).

```
design = benchmark_grid(
  tasks, learners, resamplings)
```

Creates a cross-join datatable with list-columns. Can also be set up manually for full control.

```
bmr = benchmark(design)
```

Returns a BenckmarkResult container.

```
bmr$aggregate(measures)
```

data.table of ResampleResult with scores.

```
bmr$score(measures)
```

Data data.table of resampling iterations with scores.

```
bmr$filter(task_ids, learner_ids, resampling_ids)
```

Filter by task, learner and resampling.

```
bmr$combine(bmr)
c(bmr, bmr1) # alternative S3 method
```

Merge other BenchmarkResult.

Parallelization

The future framework is used for parallelization

```
future::plan(backend)
```

Selects the parallelization backend for the current session. Parallelization is automatically applied to all levels (resampling, tuning and FeatSel).

Logging

1gr is used for logging and progress output.

```
getOption("lgr.log_levels")
## > fatal error warn info debug trace
## > 100 200 300 400 500 600
```

Gets threshold levels. The default is 400.

```
lgr::get_logger("mlr3")$set_threshold("<level>")
```

Changes the log-level on a per-package basis.

mlr3viz

Provides visualization for mlr3} objects. Creation:mlr3viz::autoplot(object, type)}

- BenchmarkResult (boxplot of performance measures, roc, prc)
- Filter (barplot of filter scores)
- PredictionClassif (Stacked barplot of true and estimated class labels, roc, prc)
- PredictionRegr (xy scatterplot, histogram of residuals)
- ResampleResult (boxplot or histogram of performance measures, roc, prc)
- TaskClassif (barplot of target, duo target-features plot matrix, pairs feature plot matrix with color set to target)
- TaskRegr (target, pairs)
- TaskSurv (target, duo, pairs)

Error Handling and Encapsulation

Packages evaluate and callr can be used to encapsulate execution of \$train() and \$predict() to prevent stops in case of errors - useful for larger experiments. callr isolates the execution in a separate R sessions, guarding against segfaults.

```
learner$encapsulate = c(
train = "evaluate",
predict = "callr")
```

learner\$errors

Returns the log of recorded errors.

```
learner$fallback = lrn(.key)
```

If learner fails, a fallback learner is used to generate predictions. Use a robust fallback, e.g. a "featureless" learner.

Resources

- mlr3book
- (https://mlr3book.mlr-org.com)
- · mlr-org on GitHub
- (https://github.com/mlr-org)
- mlr3learners R package
- (https://github.com/mlr-org/mlr3learners)
- mir3learners organization
- (https://github.com/mlr3learners)
- mlr3gallery use cases
- (https://mlr3gallery.mlr-org.com/)