

mlr3book

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Preamble

```
1 set.seed(0)
```

Welcome to the Machine Learning in R 3 universe (mlr3verse), let us show you some of its magic. Before we begin, make sure you have installed [mlr3](#) if you want to follow along, we recommend installing the full universe at once:

```
1 install.packages("mlr3verse")
```

You can also just install the base package:

```
1 install.packages("mlr3")
```

In this first example we'll show you the most basic use-case, train and predict.

```
1 library("mlr3")
2 task = tsk("penguins")
3 split = partition(task)
4 learner = lrn("classif.rpart", predict_type = "prob")
5
6 learner$train(task, row_ids = split$train)
7 learner$model
```

```
n= 231
```

```
node), split, n, loss, yval, (yprob)
  * denotes terminal node
```

```
1) root 231 129 Adelie (0.441558442 0.199134199 0.359307359)
  2) flipper_length< 207.5 145 44 Adelie (0.696551724 0.296551724 0.006896552)
    4) bill_length< 44.65 100 2 Adelie (0.980000000 0.020000000 0.000000000) *
    5) bill_length>=44.65 45 4 Chinstrap (0.066666667 0.911111111 0.022222222) *
  3) flipper_length>=207.5 86 4 Gentoo (0.011627907 0.034883721 0.953488372) *
```

```
1 predictions = learner$predict(task, row_ids = split$test)
2 predictions
```

```
<PredictionClassif> for 113 observations:
```

row_ids	truth	response	prob.Adelie	prob.Chinstrap	prob.Gentoo
3	Adelie	Adelie	0.98000000	0.02000000	0.00000000
4	Adelie	Adelie	0.98000000	0.02000000	0.00000000
5	Adelie	Adelie	0.98000000	0.02000000	0.00000000

341	Chinstrap	Adelie	0.98000000	0.02000000	0.00000000
343	Chinstrap	Gentoo	0.01162791	0.03488372	0.95348837
344	Chinstrap	Chinstrap	0.06666667	0.91111111	0.02222222

```
1 predictions$score(msr("classif.acc"))
```

```
classif.acc
0.9380531
```

Here we have picked the ‘penguins’ task (which is [mlr3](#) language for dataset), randomly split the task into 67% training data and 33% testing data, trained a random forest on the training data to learn the probability of an observation falling into one of the outcome classes, showed the fitted model, and then made prediction on the test data, showed these predictions and evaluated the model using the accuracy measure.

Whilst [mlr3](#) makes training and predicting easy, it also uses a unified interface to perform some very complex operations in just a few lines of code:

```
1 library(mlr3verse)
2 library(mlr3pipelines)
3 library(mlr3benchmark)
4
5 tasks = tsks(c("breast_cancer", "sonar"))
6 tuned_rf = auto_tuner(
7   tnr("grid_search", resolution = 5),
8   lrn("classif.ranger", num.trees = to_tune(200, 500)),
9   rsmp("holdout")
10 )
11 tuned_rf = pipeline_robustify(NULL, tuned_rf, TRUE) %>%
12   po("learner", tuned_rf)
13 stack_lrn = ppl(
14   "stacking",
15   base_learners = lrns(c("classif.rpart", "classif.kknn")),
16   lrn("classif.log_reg"))
17 stack_lrn = pipeline_robustify(NULL, stack_lrn, TRUE) %>%
18   po("learner", stack_lrn)
19
20 learners = c(tuned_rf, stack_lrn)
21 bm = benchmark(benchmark_grid(tasks, learners, rsmp("holdout")))

1 bma = bm$aggregate(msr("classif.acc"))[, c("task_id", "learner_id", "classif.acc")]
2 bma$learner_id = rep(c("RF", "Stack"), 2)
3 bma

      task_id learner_id classif.acc
1: breast_cancer      RF    0.9605263
2: breast_cancer    Stack    0.9122807
```