

Exercise 1:

Shortly answer the following questions:

- (a) What is the difference between inner and outer loss?
- (b) Which model is more likely to overfit the training data:
 - k-NN with 1 or with 10 neighbours?
 - Logistic regression with 10 or 20 features?
 - LDA or QDA?
- (c) Which of the following methods yield an unbiased generalization error estimate?
Performance estimation ...
 - on training data
 - on test data
 - on training and test data combined
 - using cross validation
 - using subsampling
- (d) Which problem does resampling of training and test data solve?
- (e) Which problem does nested resampling solve?

Exercise 2:

The Satellite dataset consists of pixels in 3x3 neighbourhoods in a satellite image, where each pixel is described by 4 spectral values, and the classification label of the central pixel. (for further information see [?Satellite](#)) We fit a k-NN model to predict the class of the middle pixel. The performance is evaluated with the mmce.

Look at the following R code and output: The performance is estimated in different ways: using training data, test data and then with cross validation. How do the estimates differ and why? Which one should be used?

```
library(mlr3)
library(mlr3learners)
library(mlbench)

data(Satellite)
satellite_task <-
  TaskClassif$new(id = "satellite_task",
                  backend = Satellite,
                  target = "classes")
knn_learner <- lrn("classif.kknn", k = 3)

# Train and test subsets:
set.seed(42)
train_indices <-
  sample.int(nrow(Satellite), size = 0.8 * nrow(Satellite))
test_indices <- setdiff(1:nrow(Satellite), train_indices)
```

```

# Training data performance estimate
knn_learner$train(task = satellite_task, row_ids = train_indices)
pred <-
  knn_learner$predict(task = satellite_task, row_ids = train_indices)
pred$score()

## classif.ce
##          0

# Test data performance estimate
pred <-
  knn_learner$predict(task = satellite_task, row_ids = test_indices)
pred$score()

## classif.ce
## 0.09246309

# CV performance estimate
rdesc <- rsmp("cv", folds = 10)
res <- resample(satellite_task, knn_learner, rdesc)

## INFO [21:03:14.162] [mlr3] Applying learner 'classif.kknn' on task 'satellite_task' (iter 1/10)
## INFO [21:03:14.345] [mlr3] Applying learner 'classif.kknn' on task 'satellite_task' (iter 4/10)
## INFO [21:03:14.479] [mlr3] Applying learner 'classif.kknn' on task 'satellite_task' (iter 7/10)
## INFO [21:03:14.605] [mlr3] Applying learner 'classif.kknn' on task 'satellite_task' (iter 5/10)
## INFO [21:03:14.740] [mlr3] Applying learner 'classif.kknn' on task 'satellite_task' (iter 3/10)
## INFO [21:03:14.866] [mlr3] Applying learner 'classif.kknn' on task 'satellite_task' (iter 9/10)
## INFO [21:03:15.095] [mlr3] Applying learner 'classif.kknn' on task 'satellite_task' (iter 6/10)
## INFO [21:03:15.217] [mlr3] Applying learner 'classif.kknn' on task 'satellite_task' (iter 10/10)
## INFO [21:03:15.340] [mlr3] Applying learner 'classif.kknn' on task 'satellite_task' (iter 2/10)
## INFO [21:03:15.466] [mlr3] Applying learner 'classif.kknn' on task 'satellite_task' (iter 8/10)

res$score()

##          task          task_id          learner  learner_id
## 1: <TaskClassif[46]> satellite_task <LearnerClassifKKNN[32]> classif.kknn
## 2: <TaskClassif[46]> satellite_task <LearnerClassifKKNN[32]> classif.kknn
## 3: <TaskClassif[46]> satellite_task <LearnerClassifKKNN[32]> classif.kknn
## 4: <TaskClassif[46]> satellite_task <LearnerClassifKKNN[32]> classif.kknn
## 5: <TaskClassif[46]> satellite_task <LearnerClassifKKNN[32]> classif.kknn
## 6: <TaskClassif[46]> satellite_task <LearnerClassifKKNN[32]> classif.kknn
## 7: <TaskClassif[46]> satellite_task <LearnerClassifKKNN[32]> classif.kknn
## 8: <TaskClassif[46]> satellite_task <LearnerClassifKKNN[32]> classif.kknn
## 9: <TaskClassif[46]> satellite_task <LearnerClassifKKNN[32]> classif.kknn
## 10: <TaskClassif[46]> satellite_task <LearnerClassifKKNN[32]> classif.kknn
##          resampling resampling_id iteration          prediction
## 1: <ResamplingCV[19]>          cv          1 <PredictionClassif[19]>
## 2: <ResamplingCV[19]>          cv          2 <PredictionClassif[19]>
## 3: <ResamplingCV[19]>          cv          3 <PredictionClassif[19]>
## 4: <ResamplingCV[19]>          cv          4 <PredictionClassif[19]>
## 5: <ResamplingCV[19]>          cv          5 <PredictionClassif[19]>
## 6: <ResamplingCV[19]>          cv          6 <PredictionClassif[19]>
## 7: <ResamplingCV[19]>          cv          7 <PredictionClassif[19]>
## 8: <ResamplingCV[19]>          cv          8 <PredictionClassif[19]>
## 9: <ResamplingCV[19]>          cv          9 <PredictionClassif[19]>
## 10: <ResamplingCV[19]>          cv         10 <PredictionClassif[19]>
##          classif.ce

```

```
## 1: 0.09627329
## 2: 0.07919255
## 3: 0.08540373
## 4: 0.09472050
## 5: 0.10559006
## 6: 0.08553655
## 7: 0.08864697
## 8: 0.10108865
## 9: 0.08864697
## 10: 0.10419907

res$aggregate()

## classif.ce
## 0.09292983
```

Exercise 3:

In preparing this course you already learned about `mlr3`. If you need to refresh your knowledge you can find help at <https://mlr3book.mlr-org.com/> under 'Basics'.

- a) How many performance measures do you already know? Try to explain some of them. How can you see which of them are available in `mlr3`?
- b) Use the `boston_housing` regression task from `mlr3` and split the data into 50 % training data and 50 % test data while training and predicting (i. e., use the `row_ids` argument of the `train` and `predict` function). Fit a prediction model (e. g. k-NN) to the training set and make predictions for the test set.
- c) Compare the performance on training and test data. Use the `score` function.
- d) Now use different observations (but still 50 % of them) for the training set. How does this affect the predictions and the error estimates of the test data?
- e) Use 10 fold cross-validation to estimate the performance. Hint: Use the `mlr` functions `rsmp` and `resample`.