Machine learning with mlr

HYPERPARAMETER TUNING IN R

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The mlr package

- `mlr` is another framework for **machine learning** in R.

Model training follows **three steps:**

1. Define the **task**
2. Define the **learner**
3. Fit the **model**

https://mlr-org.github.io/mlr

New dataset: User Knowledge Data

```r
library(tidyverse)
glimpse(knowledge_data)
```

```
Observations: 150
Variables: 6
$ STG <dbl> 0.080, 0.000, 0.180, 0.100, 0.120, 0.090, 0.080, 0.150, ...
$ SCG <dbl> 0.080, 0.000, 0.180, 0.100, 0.120, 0.300, 0.325, 0.275, ...
$ STR <dbl> 0.100, 0.500, 0.550, 0.700, 0.750, 0.680, 0.620, 0.800, ...
$ LPR <dbl> 0.24, 0.20, 0.30, 0.15, 0.35, 0.18, 0.94, 0.21, 0.19, ...
$ PEG <dbl> 0.90, 0.85, 0.81, 0.90, 0.80, 0.85, 0.56, 0.81, 0.82, ...
$ UNS <chr> "High", "High", "High", "High", "High", "High", ...
```

```r
knowledge_data %>%
    count(UNS)
```

```
# A tibble: 3 x 2
  UNS        n
  <chr>  <int>
1 High      50
2 Low       50
3 Middle    50
```

Tasks in mlr for supervised learning

- `RegrTask()` for regression
- `ClassifTask()` for binary and multi-class classification
- `MultilabelTask()` for multi-label classification problems
- `CostSensTask()` for general cost-sensitive classification

With our student knowledge dataset we can build a classifier:

```
task <- makeClassifTask(data = knowledge_train_data,
                        target = "UNS")
```

```
listLearners()
```

```
                 class              package
1          classif.ada            ada,rpart
2   classif.adaboostm1                RWeka
3  classif.bartMachine          bartMachine
4     classif.binomial                stats
5     classif.boosting         adabag,rpart
6          classif.bst            bst,rpart
7          classif.C50                  C50
8      classif.cforest                party
9   classif.clusterSVM  SwarmSVM,LiblineaR
10       classif.ctree                party
...
```

```
# Define learner
lrn <- makeLearner("classif.h2o.deeplearning",
                   fix.factors.prediction = TRUE,
                   predict.type = "prob")
```

Model fitting in mlr

```
tic()
# Define task
task <- makeClassifTask(data = knowledge_train_data,
                        target = "UNS")
# Define learner
lrn <- makeLearner("classif.h2o.deeplearning",
                   fix.factors.prediction = TRUE)
# Fit model
model <- train(lrn,
               task)
toc()
```

```
3.782 sec elapsed
```

Let's practice!

HYPERPARAMETER TUNING IN R

Grid and random search with mlr

HYPERPARAMETER TUNING IN R

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Hyperparameter tuning with mlr

In `mlr` you have to define

1. the **search space** for every hyperparameter
2. the **tuning method** (e.g. grid or random search)
3. the **resampling method**

Defining the search space

```r
makeParamSet(
  makeNumericParam(),
  makeIntegerParam(),
  makeDiscreteParam(),
  makeLogicalParam(),
  makeDiscreteVectorParam()
)
```

```
                                     Type  len              Def
autoencoder                       logical    -            FALSE
use_all_factor_level              logical    -             TRUE
activation                       discrete    -        Rectifier
hidden                      integervector <NA>          200,200
epochs                            numeric    -               10
train_samples_per_iteration       numeric    -               -2
seed                              integer    -                -
```

```r
getParamSet("classif.h2o.deeplearning")
```

```
adaptive_rate                      logical    -            TRUE
rho                                numeric    -            0.99
epsilon                            numeric    -           1e-08
rate                               numeric    -           0.005
```

```
                                    Type  len            Def
autoencoder                      logical    -          FALSE
use_all_factor_level             logical    -           TRUE
activation                      discrete    -      Rectifier
hidden                     integervector <NA>        200,200
epochs                           numeric    -             10
train_samples_per_iteration      numeric    -             -2
seed                             integer    -              -
adaptive_rate                    logical    -           TRUE
```

```
rho                              numeric    -           0.99
epsilon                          numeric    -          1e-08
rate                             numeric    -          0.005
```

```
param_set <- makeParamSet(
  makeDiscreteParam("hidden", values = list(one = 10, two = c(10, 5, 10))),
  makeDiscreteParam("activation", values = c("Rectifier", "Tanh")),
  makeNumericParam("l1", lower = 0.0001, upper = 1),
  makeNumericParam("l2", lower = 0.0001, upper = 1))
```

Defining the tuning method

- Grid search

```
ctrl_grid <- makeTuneControlGric
ctrl_grid
```

```
Tune control: TuneControlGrid
Same resampling instance: TRUE
Imputation value: <worst>
Start: <NULL>

Tune threshold: FALSE
Further arguments: resolution=10
```

Can only deal with **discrete** parameter sets!

- Random search

```
ctrl_random <- makeTuneControlRa
ctrl_random
```

```
Tune control: TuneControlRandom
Same resampling instance: TRUE
Imputation value: <worst>
Start: <NULL>
Budget: 100
Tune threshold: FALSE
Further arguments: maxit=100
```

Define resampling strategy

```
cross_val <- makeResampleDesc("RepCV",
                              predict = "both",
                              folds = 5 * 3)
param_set <- makeParamSet(...)
ctrl_grid <- makeTuneControlGrid()
task <- makeClassifTask(data = knowledge_train_data,
                        target = "UNS")
lrn <- makeLearner("classif.h2o.deeplearning",
                   predict.type = "prob",
                   fix.factors.prediction = TRUE)
lrn_tune <- tuneParams(lrn,
                       task,
                       resampling = cross_val,
                       control = ctrl_grid,
                       par.set = param_set)
```

Tuning hyperparameters

```
lrn_tune <- tuneParams(lrn, task, resampling = cross_val, control = ctrl_grid,
```

```
[Tune-y] 27: mmce.test.mean=0.6200000; time: 0.0 min
[Tune-x] 28: hidden=two; activation=Rectifier; l1=0.578; l2=1
[Tune-y] 28: mmce.test.mean=0.6800000; time: 0.0 min
[Tune-x] 29: hidden=one; activation=Rectifier; l1=0.156; l2=0.68
[Tune-y] 29: mmce.test.mean=0.4400000; time: 0.0 min
[Tune-x] 30: hidden=one; activation=Rectifier; l1=0.717; l2=0.427
[Tune-y] 30: mmce.test.mean=0.6600000; time: 0.0 min

[Tune] Result: hidden=two; activation=Tanh; l1=0.113;
l2=0.0973 : mmce.test.mean=0.2000000

# tictoc
26.13 sec elapsed
```

Let's practice!

HYPERPARAMETER TUNING IN R

Evaluating hyperparameters with mlr

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Evaluation of our results can tell us:

- How different hyperparameters **affect the performance** of our model.
- Which hyperparameters have a particularly strong or weak **impact** on our model performance.
- Whether our hyperparameter search **converged**, i.e. whether we can be reasonably confident that we found the most **optimal hyperparameter combination** (or close to it).

Recap

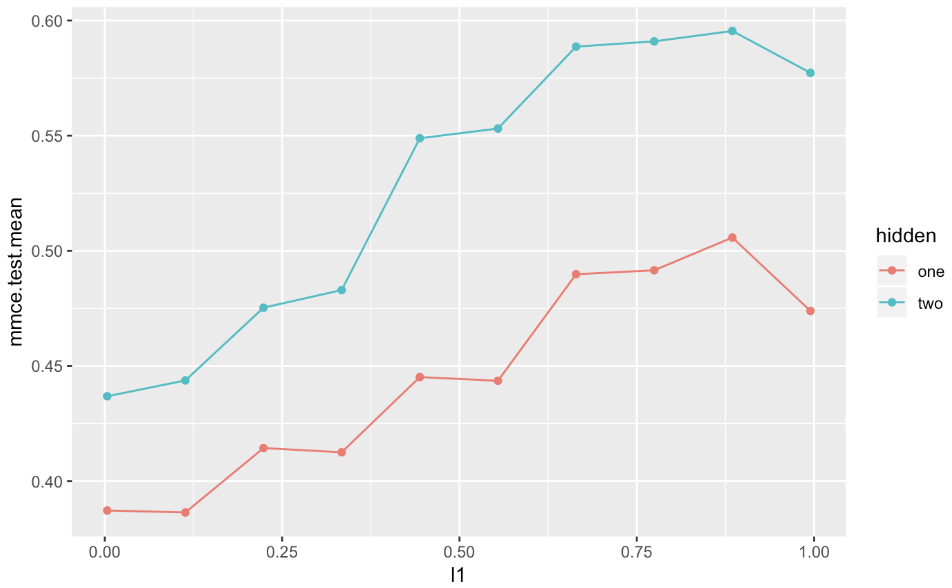
```
getParamSet("classif.h2o.deeplearning")
param_set <- makeParamSet(
  makeDiscreteParam("hidden", values = list(one = 10, two = c(10, 5, 10))),
  makeDiscreteParam("activation", values = c("Rectifier", "Tanh")),
  makeNumericParam("l1", lower = 0.0001, upper = 1),
  makeNumericParam("l2", lower = 0.0001, upper = 1)  )
ctrl_random <- makeTuneControlRandom(maxit = 50)
holdout <- makeResampleDesc("Holdout")
task <- makeClassifTask(data = knowledge_train_data, target = "UNS")
lrn <- makeLearner("classif.h2o.deeplearning", predict.type = "prob",
                   fix.factors.prediction = TRUE)
lrn_tune <- tuneParams(lrn, task,
                       resampling = holdout,
                       control = ctrl_random,
                       par.set = param_set)
```

```r
lrn_tune
generateHyperParsEffectData(lrn_tune, partial.dep = TRUE)
```

```
Tune result:
Op. pars: hidden=one; activation=Rectifier; l1=0.541; l2=0.229
mmce.test.mean=0.160000
HyperParsEffectData:
Hyperparameters: hidden,activation,l1,l2
Measures: mmce.test.mean
Optimizer: TuneControlRandom
Nested CV Used: FALSE
[1] "Partial dependence requested"
Snapshot of data:
  hidden activation         l1        l2 mmce.test.mean iteration exec.time
1    one  Rectifier 0.75940339 0.9956819           0.40         1     0.883
2    one  Rectifier 0.16701526 0.2948697           0.40         2     0.836
3    one  Rectifier 0.88458832 0.9228281           0.70         3     0.830
4    two  Rectifier 0.48840740 0.7276899           0.70         4     0.820
5    one       Tanh 0.87114452 0.9971268           0.40         5     0.835
6    two       Tanh 0.07412213 0.3841913           0.44         6     0.830
```

Plotting hyperparameter tuning results

```
hyperpar_effects <- generateHyperParsEffectData(lrn_tune, partial.d
plotHyperParsEffect(hyperpar_effects, partial.dep.learn = "regr.ran
                    x = "l1", y = "mmce.test.mean", z = "hidden",
                    plot.type = "line")
```



Now it's your turn!

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Advanced tuning with mlr

HYPERPARAMETER TUNING IN R

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Advanced tuning controls

- `makeTuneControlCMAES` : CMA Evolution Strategy
- `makeTuneControlDesign` : Predefined data frame of hyperparameters
- `makeTuneControlGenSA` : Generalized simulated annealing
- `makeTuneControlIrace` : Tuning with iterated F-Racing
- `makeTuneControlMBO` : Model-based / Bayesian optimization

```r
# Generalized simulated annealing
ctrl_gensa <- makeTuneControlGenSA()
# Create holdout sampling
bootstrap <- makeResampleDesc("Bootstrap", predict = "both")
# Perform tuning
lrn_tune <- tuneParams(learner = lrn, task = task,
                       resampling = bootstrap,
                       control = ctrl_gensa,
                       par.set = param_set,
                       measures = list(acc, mmce))
```

```
[Tune-x] 2170: eta=0.0771; max_depth=4
[Tune-y] 2170: acc.test.mean=0.9317275,mmce.test.mean=0.0682725; time: 0.0 m
[Tune-x] 2171: eta=0.822; max_depth=8
[Tune-y] 2171: acc.test.mean=0.9276912,mmce.test.mean=0.0723088; time: 0.0 m
[Tune-x] 2172: eta=0.498; max_depth=4
[Tune-y] 2172: acc.test.mean=0.9311626,mmce.test.mean=0.0688374; time: 0.0 m
[Tune-x] 2173: eta=0.365; max_depth=4
[Tune-y] 2173: acc.test.mean=0.9288406,mmce.test.mean=0.0711594; time: 0.0 m
```

```r
# Create holdout sampling
bootstrap <- makeResampleDesc("Bootstrap", predict = "both")
# Perform tuning
lrn_tune <- tuneParams(learner = lrn,
                       task = task,
                       resampling = bootstrap,
                       control = ctrl_gensa,
                       par.set = param_set,
                       measures = list(acc, setAggregation(acc, tra
                                       mmce, setAggregation(mmce, t
```

```
[Tune-x] 3920: eta=0.294; max_depth=8
[Tune-y] 3920: acc.test.mean=0.9250118,
               acc.train.mean=0.9740000,
               mmce.test.mean=0.0749882,
               mmce.train.mean=0.0260000;
               time: 0.0 min
```

Nested cross-validation & nested resampling

```
lrn_wrapper <- makeTuneWrapper(learner = lrn,
                               resampling = bootstrap,
                               control = ctrl_gensa,
                               par.set = param_set,
                               measures = list(acc, mmce))
```

- Either train **directly**

```
model_nested <-  train(lrn_wrapper, task)
getTuneResult(model_nested)
```

- Or add 2x **nested** cross-validation

```
cv2 <- makeResampleDesc("CV", iters = 2)
res <- resample(lrn_wrapper, task,
                resampling = cv2,
                extract = getTuneResult)
generateHyperParsEffectData(res)
```

Choose hyperparameters from a tuning set

```
lrn_best <- setHyperPars(lrn, par.vals = list(minsplit = 4,
                                              minbucket = 3,
                                              maxdepth = 6))
model_best <- train(lrn_best, task)
predict(model_best, newdata = knowledge_test_data)
```

```
Prediction: 30 observations
predict.type: response
threshold:
time: 0.00
  truth response
1  High     High
2  High     High
3  High     High
4  High     High
5  High     High
6  High     High
... (#rows: 30, #cols: 2)
```

It's your turn!

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