# Credit score approval prediction

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## Handling nominal variable with dummy variable

Use library 'fastDummies' to handle the nominal variable \$OCCUPATION TYPE.

```
library(fastDummies)
library(janitor)
dummy_var <- function(data){</pre>
  # Since the library 'fastDummies' tansforms all factor variable into dummy variables,
  # we will convert our target "y" (factor) into a character variable
  # to avoid it being transformed to dummy variable.
  data$y <- as.numeric(as.character(data$y))</pre>
  # transform all factor variables to dummy variables,
  # and removes the original variables that were used to generate the dummy variables.
  data_dummy <- fastDummies::dummy_cols(data, remove_selected_columns=TRUE)</pre>
  # column name convention fix (mlr3 name convention - space to underscore)
  data_dummy <- clean_names(data_dummy)</pre>
  data_dummy <- as.data.frame(sapply(data_dummy, as.numeric))</pre>
  data dummy$y <- as.factor(data dummy$y)</pre>
  dummy_var <- data_dummy</pre>
# ----- handle missing data
# ----- OCCUPATION_TYPE
dl_dummy_data <- read.csv2(".../credit_card_prediction/dl_na_data.csv", header = TRUE)</pre>
dl_dummy_data <- dummy_var(dl_dummy_data)</pre>
mf_dummy_data <- read.csv2(".../../credit_card_prediction/mf_na_data.csv", header = TRUE)</pre>
mf dummy data <- dummy var(mf dummy data)</pre>
mice_dummy_data <- read.csv2(".../..redit_card_prediction/mice_na_data.csv", header = TRUE)
mice_dummy_data <- dummy_var(mice_dummy_data)</pre>
# row, column, NA
cat("dl dummy data\t", dim(dl dummy data), any(is.na(dl dummy data)), "\n")
cat("mf_dummy_data\t", dim(mf_dummy_data), any(is.na(mf_dummy_data)), "\n")
cat("mice_dummy_data\t", dim(mice_dummy_data), any(is.na(mice_dummy_data)), "\n")
```

### Load all data for training (one-hot, dummy, IV)

```
library(mlr3)
# function to load data into task and define target
dataToTask <- function(path, id, sep=';', header=TRUE){</pre>
  dt <- read.csv2(path, sep = sep, header = header)</pre>
  dt <- as.data.frame(sapply(dt, as.numeric))</pre>
  dt$y <- as.factor(dt$y)</pre>
  dataToTask <- TaskClassif$new(id = id, backend = dt, target = "y")</pre>
}
dl dummy task <-
  dataToTask(".../credit card prediction/dummy data/dl dummy data.csv", "dl dummy")
dl oh task <-
  dataToTask("../../credit_card_prediction/oh_data/dl_oh_data.csv", "dl_oh", sep=',')
dl_iv_task <-
  dataToTask(".../credit_card_prediction/iv_data/dl_iv_data.csv", "dl_iv")
mf_dummy_task <-
  dataToTask(".../credit_card_prediction/dummy_data/mf_dummy_data.csv", "mf_dummy")
 dataToTask(".../credit_card_prediction/oh_data/mf_oh_data.csv", "mf_oh", sep=',')
mf_iv_task <-
  dataToTask(".../credit_card_prediction/iv_data/mf_iv_data.csv", "mf_iv")
mice_dummy_task <-
  dataToTask(".../credit card prediction/dummy data/mice dummy data.csv", "mice dummy")
mice_oh_task <-
 dataToTask("../../credit card prediction/oh data/mice oh data.csv", "mice oh", sep=',')
mice iv task <-
  dataToTask(".../credit_card_prediction/iv_data/mice_iv_data.csv", "mice_iv")
# combine all tasks into one list
dl <- list(dummy=dl_dummy_task, oh=dl_oh_task, iv=dl_iv_task)</pre>
mf <- list(dummy=mf_dummy_task, oh=mf_oh_task, iv=mf_iv_task)</pre>
mice <- list(dummy=mice_dummy_task, oh=mice_oh_task, iv=mice_iv_task)</pre>
# tasks[["<type>"]][["<code>"]], tasks$<type>$<code>
# ex. tasks[["dl"]][["dummy"]], tasks$dl$dummy
tasks <- list(dl=dl, mf=mf, mice=mice)</pre>
```

```
# remove unused variables (save memory)
rm(dl, mf, mice)
rm(dl_dummy_task, mf_dummy_task, mice_dummy_task)
rm(dl_oh_task, mf_oh_task, mice_oh_task)
rm(dl_iv_task, mf_iv_task, mice_iv_task)
\# print task ids and data size
for(t in tasks){
  for(c in t){
    cat(c$id, dim(c$data()), "\n")
}
## dl_dummy 25134 47
## dl_oh 25134 55
## dl_iv 25134 33
## mf_dummy 36457 47
## mf_oh 36457 55
## mf_iv 36457 33
## mice_dummy 36457 47
## mice_oh 36457 55
## mice_iv 36457 33
rm(t, c)
```

#### **KNN**

```
#warnings()
library(mlr3)
library(mlr3learners)
library(mlr3viz)
library(ggplot2)
library(gridExtra)
# turn info log off, only show warnings
lgr::get_logger("mlr3")$set_threshold("warn")
# train one model with fixed seed
train_model <- function(task, learner, resampling){</pre>
  set.seed(2020)
  print(task$id)
  start_time <- Sys.time()</pre>
  model <- resample(task, learner, resampling, store_models = TRUE)</pre>
  end_time <- Sys.time()</pre>
  duration <- (end_time-start_time)[[1]]</pre>
  print(model)
  print(paste0("training time (5 fold CV): ", duration))
  train_model <- model</pre>
# train all task with one learner
```

```
train_all <- function(tasks, learner, resampling){</pre>
  models <- list()
  miss_name <- c('dl', 'mf', 'mice')</pre>
  code_name <- c('dummy', 'oh', 'iv')</pre>
  for(missing in miss_name){
    for(coding in code name){
      name <- pasteO(missing, "_", coding)</pre>
      task <- tasks[[missing]][[coding]]</pre>
      models[[name]] <- train_model(task, learner, resampling)</pre>
    }
  }
  train_all <- models
# evaluate multiple models with AUC
evaluate_models <- function(models){</pre>
  for(m in models){
    name <- m$task$id
    auc <- m$aggregate(msr("classif.auc"))[[1]]</pre>
    max_auc <- max(m$score(msr("classif.auc"))[,9])</pre>
    print(sprintf("%10s: %.4f (max: %.4f)", name, auc, max_auc))
    \#cat(pasteO(name, ": ", auc, "\t(max: ", max\_auc, ")\n"))
  }
}
multiplot_roc <- function(models){</pre>
  plots <- list()</pre>
  k <- 1
  for(m in models){
    name <- m$task$id
    plots[[k]] <- autoplot(m, type = "roc") + xlab("") + ylab("") + ggtitle(name)</pre>
  }
  do.call("grid.arrange", plots)
  # grid.arrange(plots[[1]], plots[[2]], plots[[3]],
                  plots[[4]], plots[[5]], plots[[6]],
                  plots[[7]], plots[[8]], plots[[9]])
  #
}
resampling = rsmp("cv", folds = 5)
learner <- lrn("classif.kknn", id = "knn", predict_type = "prob", k=15, distance=2, scale=FALSE)</pre>
models <- train_all(tasks, learner, resampling)</pre>
## [1] "dl dummy"
## <ResampleResult> of 5 iterations
## * Task: dl_dummy
## * Learner: knn
## * Warnings: 0 in 0 iterations
## * Errors: 0 in 0 iterations
## [1] "training time (5 fold CV): 7.27843403816223"
## [1] "dl_oh"
## <ResampleResult> of 5 iterations
```

```
## * Task: dl_oh
## * Learner: knn
## * Warnings: 0 in 0 iterations
## * Errors: 0 in 0 iterations
## [1] "training time (5 fold CV): 6.14534783363342"
## [1] "dl iv"
## <ResampleResult> of 5 iterations
## * Task: dl iv
## * Learner: knn
## * Warnings: 0 in 0 iterations
## * Errors: 0 in 0 iterations
## [1] "training time (5 fold CV): 5.05030107498169"
## [1] "mf_dummy"
## <ResampleResult> of 5 iterations
## * Task: mf_dummy
## * Learner: knn
## * Warnings: 0 in 0 iterations
## * Errors: 0 in 0 iterations
## [1] "training time (5 fold CV): 13.8096261024475"
## [1] "mf oh"
## <ResampleResult> of 5 iterations
## * Task: mf oh
## * Learner: knn
## * Warnings: 0 in 0 iterations
## * Errors: 0 in 0 iterations
## [1] "training time (5 fold CV): 11.7247531414032"
## [1] "mf_iv"
## <ResampleResult> of 5 iterations
## * Task: mf_iv
## * Learner: knn
## * Warnings: 0 in 0 iterations
## * Errors: 0 in 0 iterations
## [1] "training time (5 fold CV): 12.2844760417938"
## [1] "mice_dummy"
## <ResampleResult> of 5 iterations
## * Task: mice_dummy
## * Learner: knn
## * Warnings: 0 in 0 iterations
## * Errors: 0 in 0 iterations
## [1] "training time (5 fold CV): 13.4485490322113"
## [1] "mice oh"
## <ResampleResult> of 5 iterations
## * Task: mice oh
## * Learner: knn
## * Warnings: 0 in 0 iterations
## * Errors: 0 in 0 iterations
## [1] "training time (5 fold CV): 11.7488088607788"
## [1] "mice_iv"
## <ResampleResult> of 5 iterations
## * Task: mice_iv
## * Learner: knn
## * Warnings: 0 in 0 iterations
## * Errors: 0 in 0 iterations
## [1] "training time (5 fold CV): 12.7940769195557"
```

#### evaluate\_models(models)

```
## [1] "
         dl_dummy: 0.7445 (max: 0.7839)"
## [1] "
             dl_oh: 0.7568 (max: 0.7838)"
## [1] "
             dl_iv: 0.7445 (max: 0.7841)"
## [1] "
         mf_dummy: 0.7520 (max: 0.7884)"
## [1] "
             mf_oh: 0.7506 (max: 0.7744)"
## [1] "
             mf_iv: 0.7520 (max: 0.7885)"
## [1] "mice_dummy: 0.7519 (max: 0.7884)"
           mice_oh: 0.7506 (max: 0.7745)"
## [1] "
## [1] "
           mice_iv: 0.7520 (max: 0.7886)"
```

#### multiplot\_roc(models)

















