Introduction to Machine Learning

(NPFL054)

Homework 2

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Contents

Set up the project

```r
rm(list = ls())
library(ISLR) # for the data
library(tidyverse) # convenient
library(rpart) # for decision trees
library(randomForest) # for ensemble learning
library(glmnet) # for regularized logistic regression
library(ROCR) # for ROC curves
```

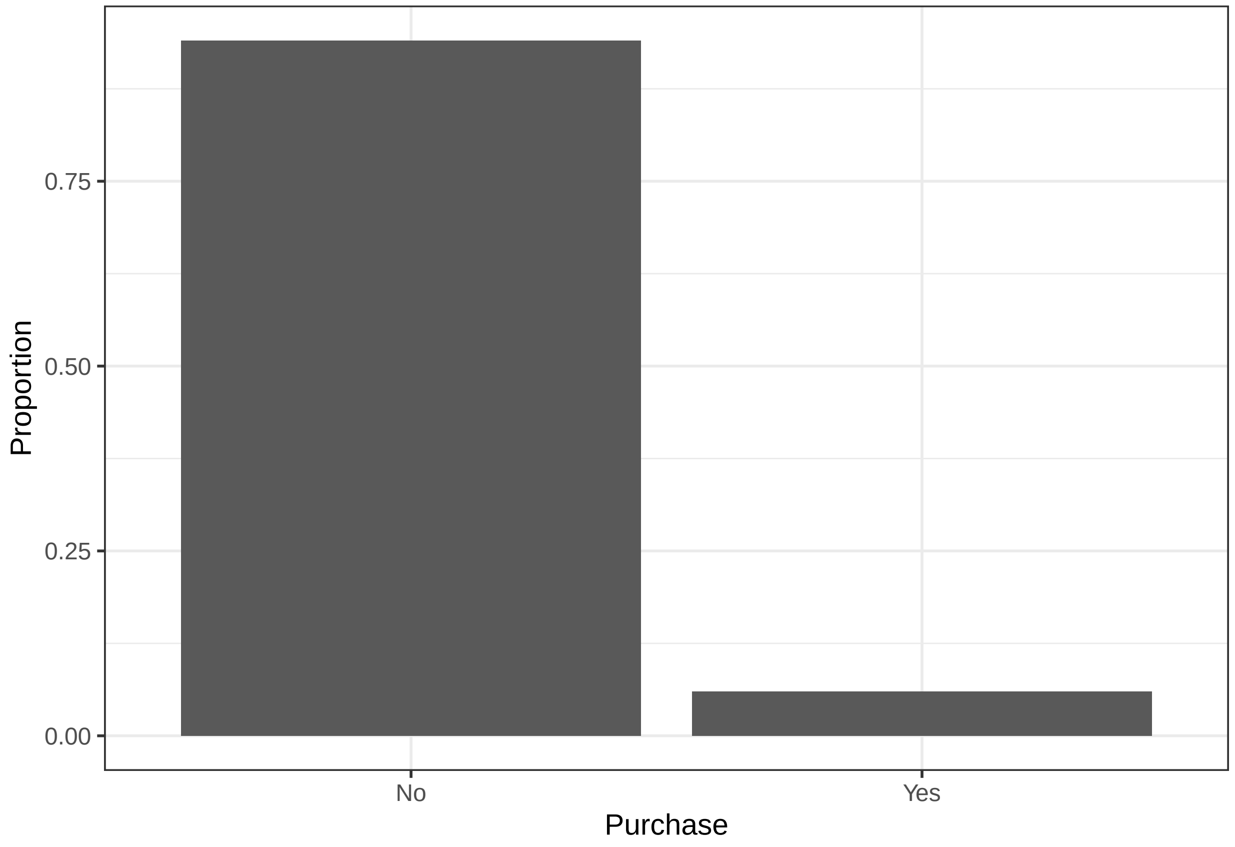
```r
## Reproduce the result
set.seed(123)
## Create the splitting vector
split <- sample(nrow(Caravan), 1000)
## Create the test dataset
d_test <- Caravan[split,]
## Create the training dataset
d_train <- Caravan[-split,]
```

1. Task 1 - Data analysis

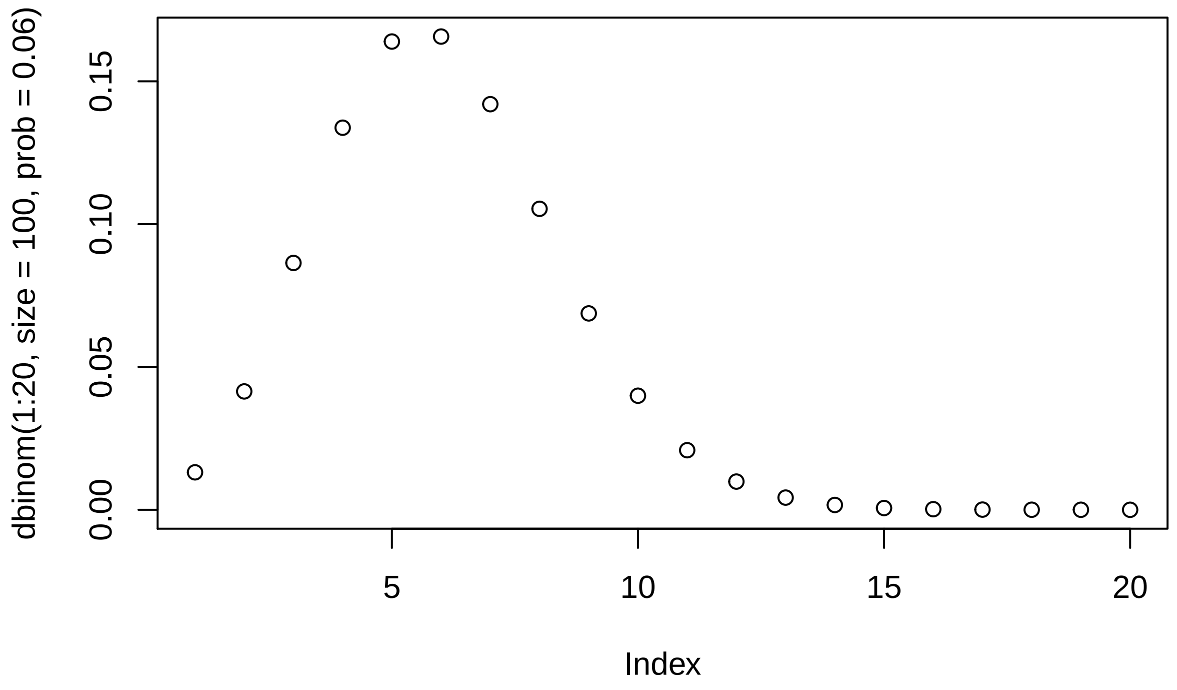
- **First, check the distribution of the target attribute. What would be your precision if you select 100 examples by chance?**

```
round(table(Caravan$Purchase), 2)
```

```
##
##   No  Yes
## 5474  348
```



```
plot(dbinom(1:20, size = 100, prob = .06))
```



We can see that there is 94% of customers who didn't purchase the insurance and that 6% who did. As the precision is the number of examples classified as *Yes* when the value is actually *Yes*, by chance, the precision should be 0.06.

- **1.a. Focus on the customer type MOSHOOFD: create a table with the number of customers that belong to each of 10 L2 groups and the percentage of customers that purchased a caravan insurance policy in each group. Comment the figures in the table. Then do the same for the customer subtype MOSTYPE (41 subgroups defined in L1).**

MOSHOOFD type:

```r
Caravan %>%
  count(MOSHOOFD, Purchase) %>%
  group_by(MOSHOOFD) %>%
  summarise(size = sum(n),
            purchase_prop = round(n[Purchase == "Yes"]/sum(n), 2)) %>%
  rename(group = MOSHOOFD) %>%
  kableExtra::kable()
```

group	size	purchase_prop
1	552	0.09
2	502	0.13
3	886	0.07
5	569	0.03
6	205	0.02
7	550	0.04
8	1563	0.06
9	667	0.06
10	276	0.02

From this first table, we can see that the customers that are more prone to purchase an insurance (13% of them) are the one belonging to the group 2, *i.e.* the *driven growers*. On the other hand, the customers belonging to the class 6 and 10, respectively the *cruising seniors* and the *farmers*, are less likely to subscribe to the insurance (only 2% in each group).

MOSHOOFD type:

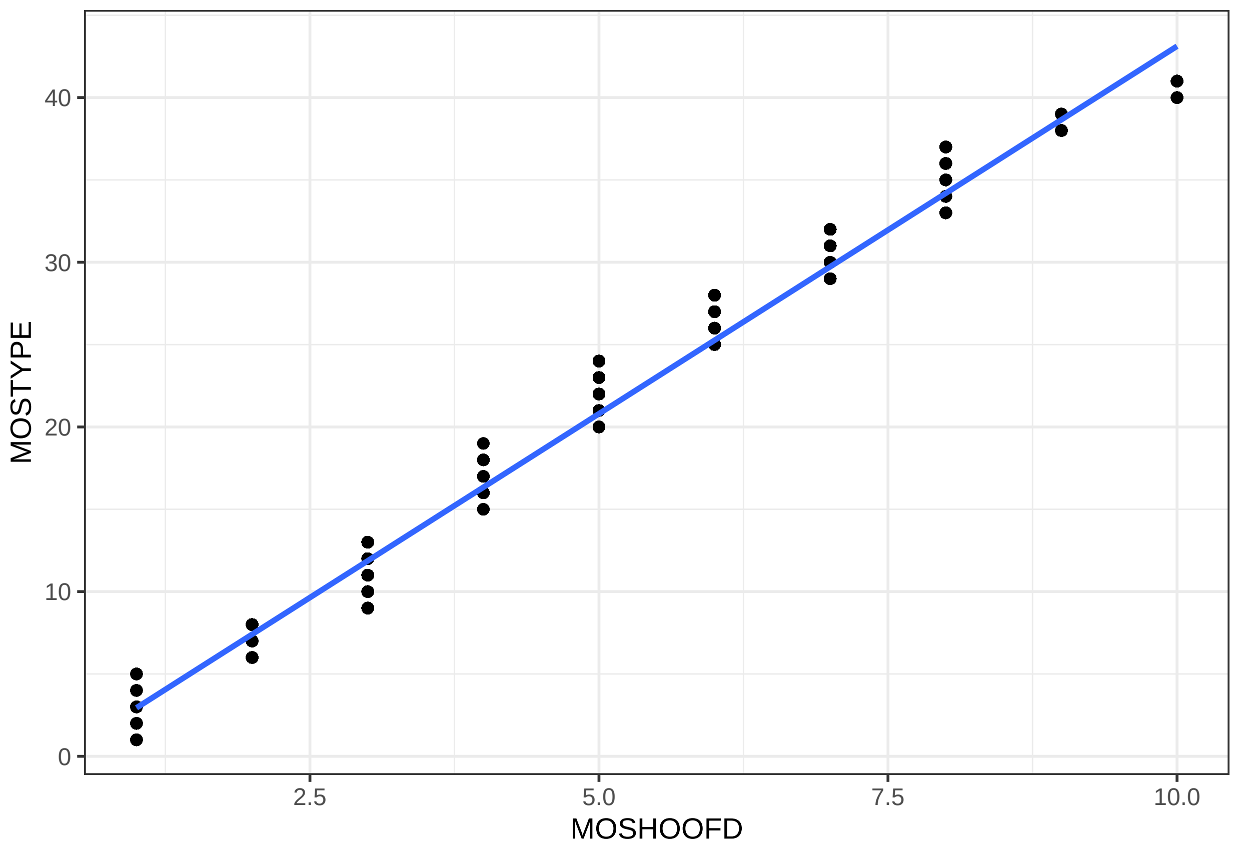
```
table <-
Caravan %>%
  count(MOSTYPE, Purchase) %>%
  group_by(MOSTYPE) %>%
  summarise(size = sum(n),
            purchase_prop = round(n[Purchase == "Yes"]/sum(n), 2)) %>%
  rename(group = MOSTYPE) %>%
  arrange(desc(purchase_prop))
## Display in 2 columns
kableExtra::kable(list(table[1:(nrow(table)/2),],
                       table[((nrow(table)/2)+1):nrow(table),])) %>%
  kableExtra::kable_styling(latex_options = "HOLD_position")
```

group	size	purchase_prop	group	size	purchase_prop
8	339	0.15	10	165	0.05
12	111	0.14	34	182	0.05
1	124	0.10	4	52	0.04
3	249	0.10	5	45	0.04
6	119	0.10	9	278	0.04
20	25	0.08	22	98	0.04
37	132	0.08	35	214	0.04
2	82	0.07	24	180	0.03
7	44	0.07	30	118	0.03
13	179	0.07	31	205	0.03
36	225	0.07	23	251	0.02
38	339	0.07	25	82	0.02
11	153	0.06	26	48	0.02
32	141	0.06	27	50	0.02
33	810	0.06	29	86	0.02
39	328	0.06	41	205	0.02

The two groups more prone to buy an insurance are the group 8 and 12, which correspond respectively to *middle class families* and *affluent young families*. Thus, we can say that families are potential good targets to sell insurances. We can see that the class 25, 26, 27 and 29 all have a low proportion of individuals buying a insurance. They are all related to old people (*i.e.*, *Young seniors in the city*, *Own home elderly*, *Seniors in apartments*, *Porchless seniors: no front yard*). Thus, old people are not a good target to sell insurances.

1.b. Analyze the relationship between features MOSHOOFD and MOSTYPE.

```
Caravan %>%
  ggplot(aes(y = MOSTYPE, x = MOSHOOFD))+
  geom_point()+
  geom_smooth(method = "lm")+
  theme_bw()
```

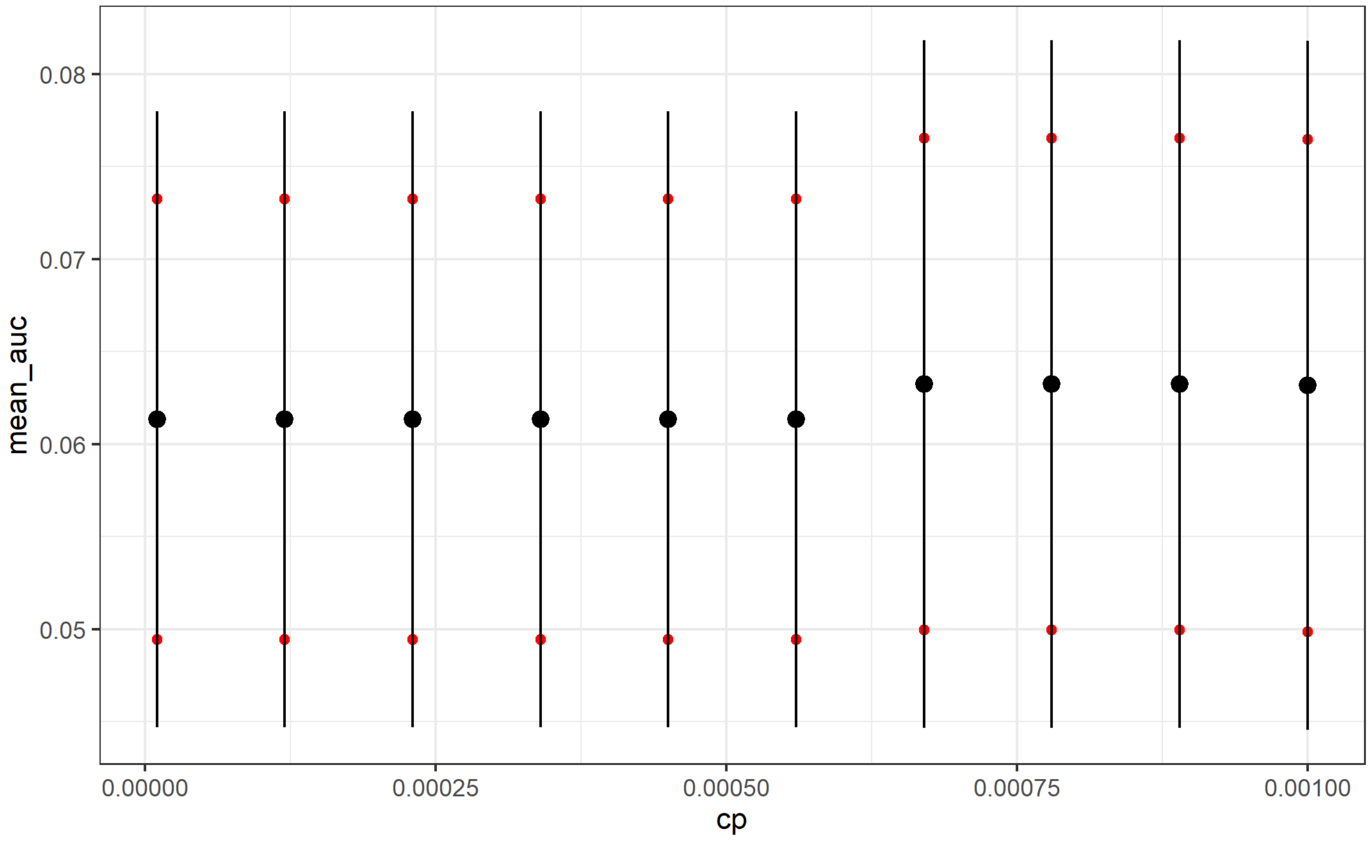


We can clearly see a relationship between these two features which are MOSHOOFD = *Customer main type* and MOSTYPE = *Customer Subtype*. This is expected because MOSTYPE is just a more precise social position. For instance, we can see that when $MOSHOOFD = 10$, $MOSTYPE = 40|41$. We can see that $MOSHOOFD = 10$ correspond to *Farmers* and that $MOSTYPE = 40|41$ are two subclasses of farmers: *Large family farms* and *Mixed rurals*, respectively.

2. Task 2 - Model fitting, optimization, and selection

```r
## Function to randomly extract the test dataset in d_train
## using always the same number of positive and negative
## values of Purchase
prepare_cv_folds <-  function(k){
  # Create the subsets data containing Purchase == Yes
  # in one hand and Purchase == No in an other hand
  pos_data <- d_train[d_train$Purchase == "Yes",]
  neg_data <- d_train[d_train$Purchase == "No",]
  ## Compute the size of each fold
  fold.size.pos <- nrow(pos_data)%/%k
  fold.size.neg <- nrow(neg_data)%/%k
  ## Randomly rearrange the indexes
  set.seed(12); s_pos <- sample(nrow(pos_data))
  set.seed(12); s_neg <- sample(nrow(neg_data))
  ## create the list that will contain the test folds
  f.idx <-  list()
  ## For each fold, extract the dataset that will be used as test
  for(i in 1:k){
      f.idx[[i]] <-
        rbind(pos_data[s_pos[(1 + (i-1)*fold.size.pos):(i*fold.size.pos)],],
              neg_data[s_neg[(1 + (i-1)*fold.size.neg):(i*fold.size.neg)],])
  }
  return(f.idx)
}
## Use the function to create the 10 test datasets
split_data <- prepare_cv_folds(10)
```

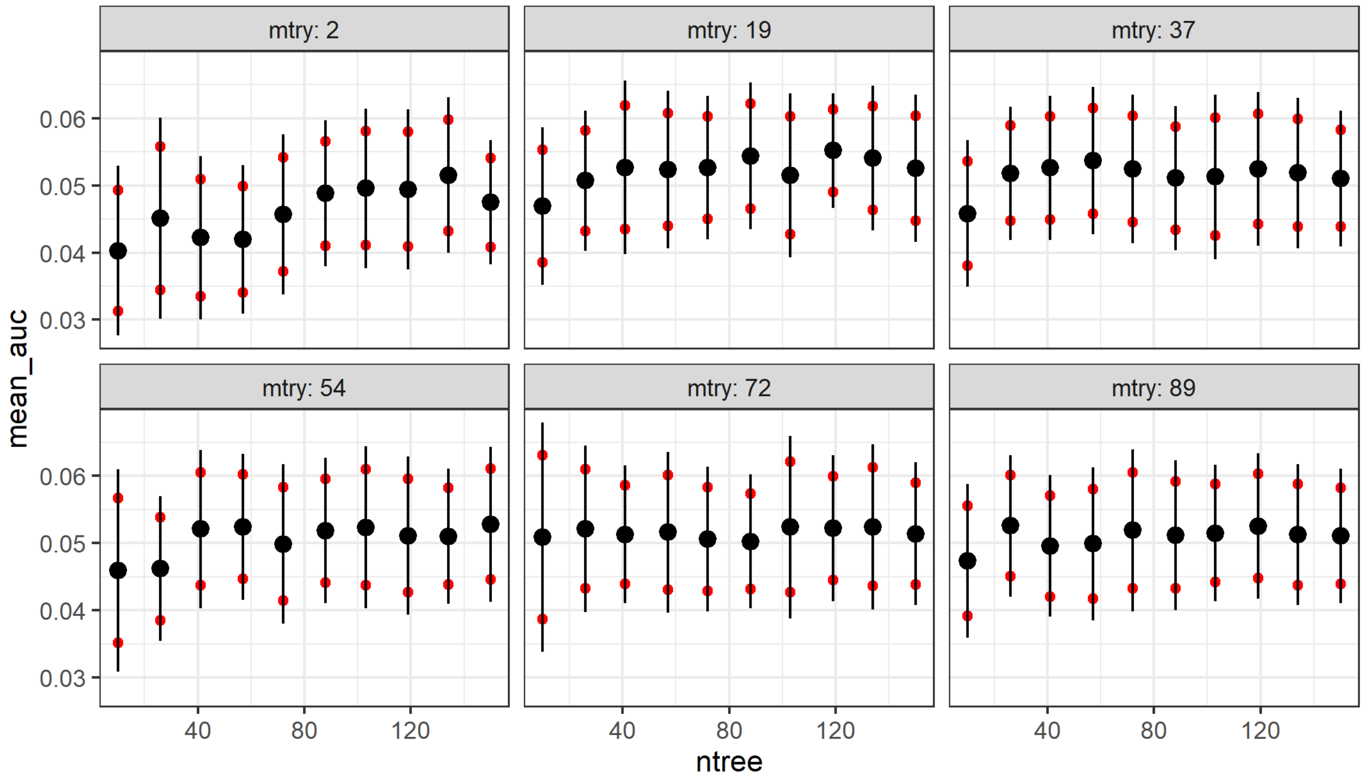
2.1 Decision tree



The graphique above shows the mean AUC as a function of different values of cp. The black lines represent the standard deviation and the red dots the Confidence Intervals. As we can see on this plot, reducing the complexity parameter below $cp = 0.001$ doesn't change the mean $AUC_{0.2}$. This means that $cp = 0.001$ is already sufficiently low. As a low cp means a more complex model, we are looking for the highest value of cp maximizing the mean AUC. Thus, we can select $cp = 0.001$ to learn the decision tree.

However, as we can see, the mean AUC is always equal to 0.027, which is rather disappointing.

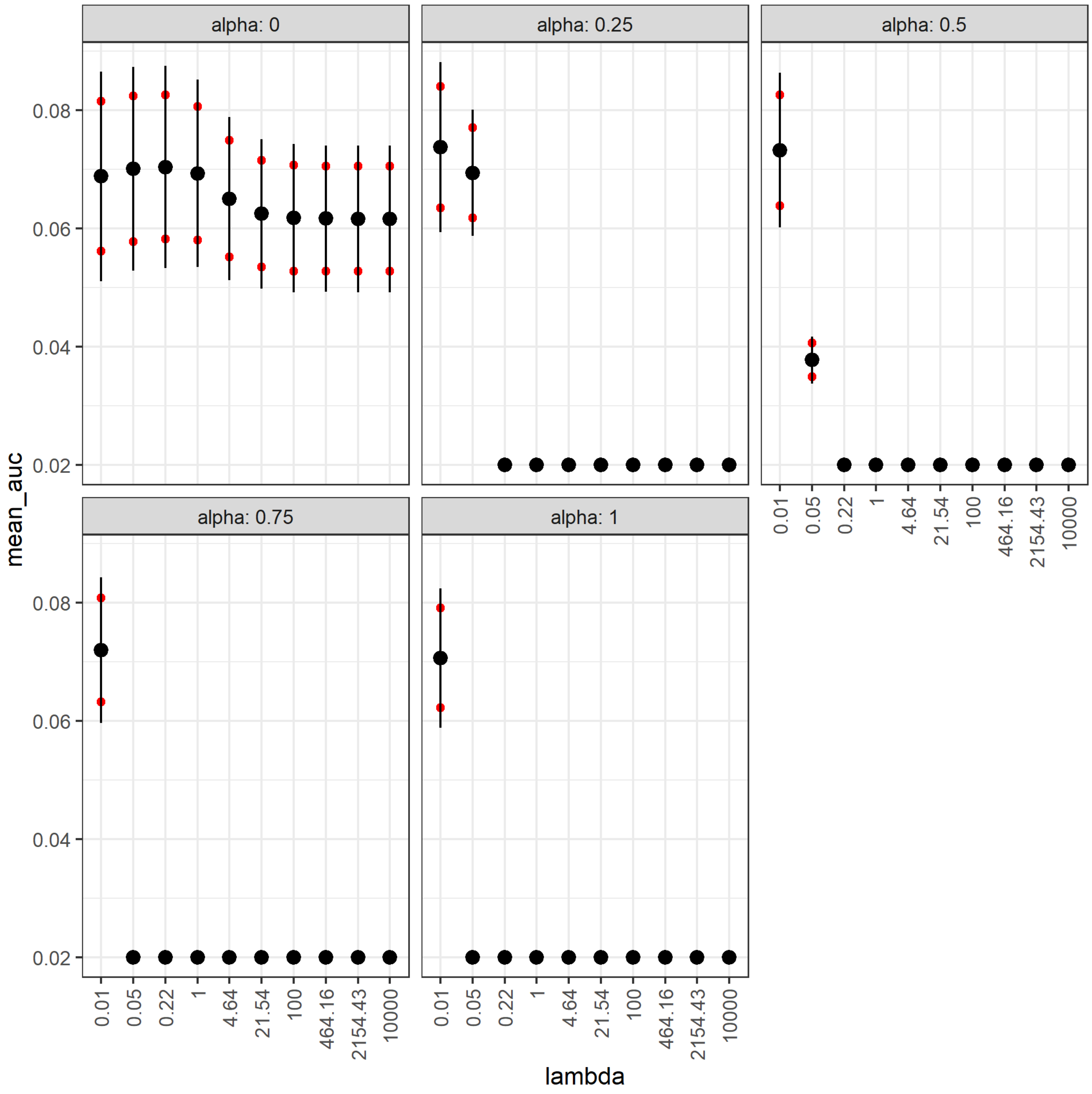
2.2 Random Forest



This plot shows the mean auc as a function of the number of trees. Each square correspond to a value of mtry indicated in the grey square. As we can see, the highest value of $AUC_{0.2}$ is for $mtry = 72$ and $ntree = 10$.

However, we must keep in mind that the Confidence Intervals always overlap, which means that the difference between the mean $AUC_{0.2}$ are not significant.

2.3 Regularized logistic regression



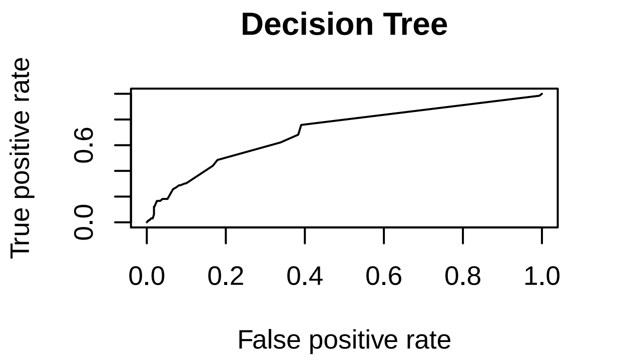
2.4 Evaluation on the test dataset

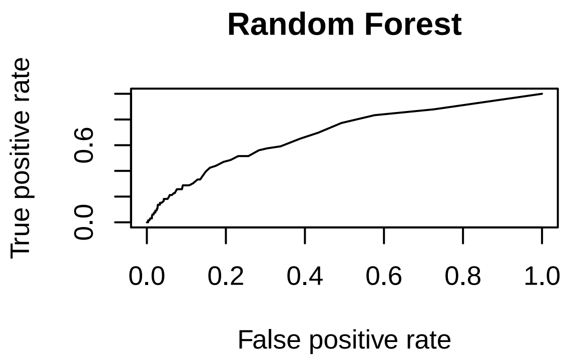
Thanks to the previous steps, we have chosen:

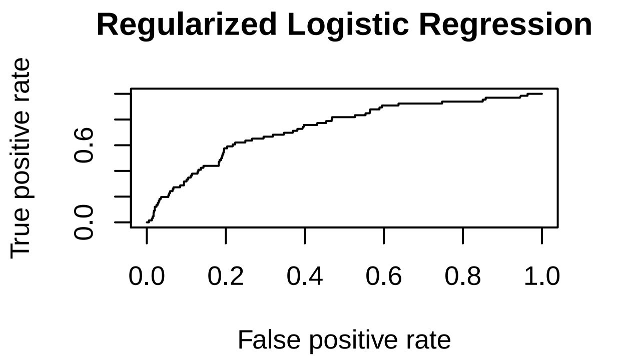
1. A decision tree with $cp = 0.00067$

2. A random forest with $ntree = 120$ and $mtry = 19$

3. A regularized logistic regression with $\lambda = 0.01$ and $\alpha = 0.25$





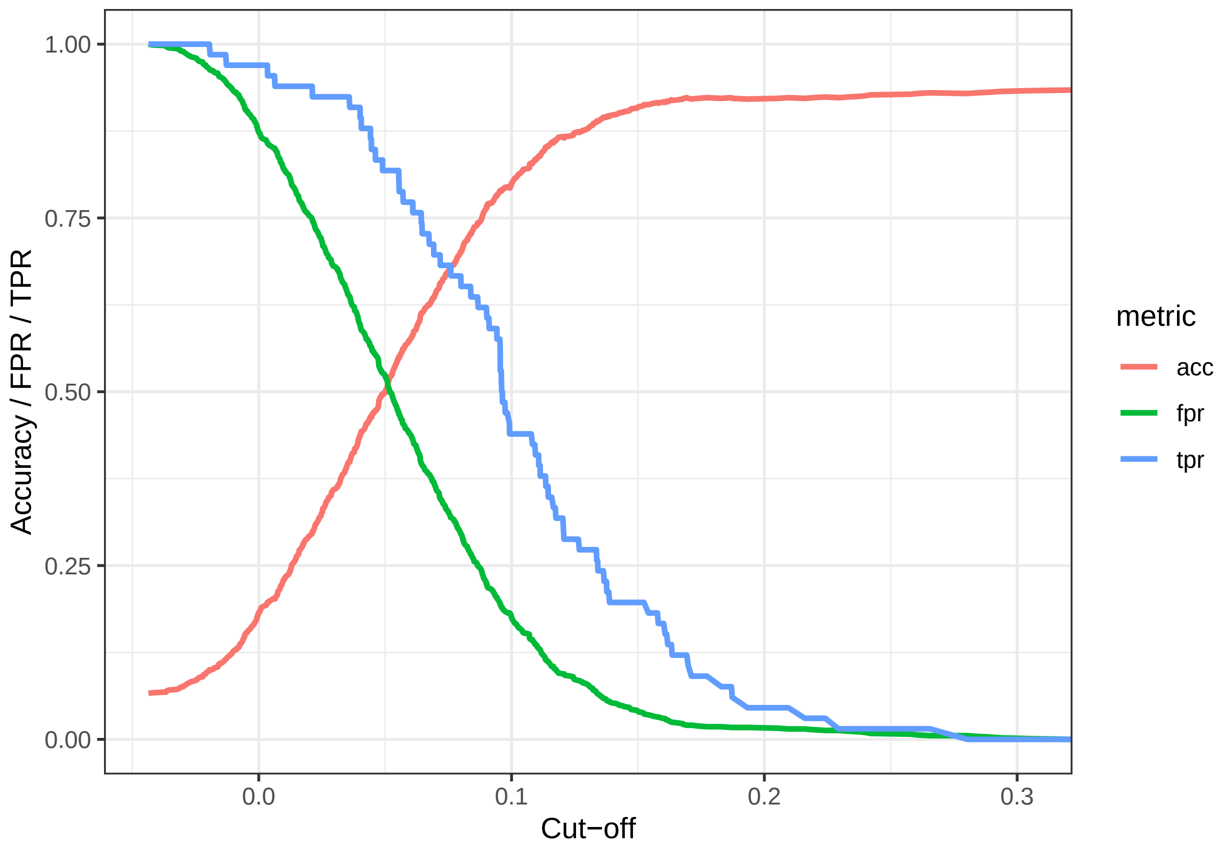


model	auc
Decision Tree	0.060
Random Forest	0.055
Regularized Logistic Regression	0.062

2.5 Setting cutoff threshold

```
## regularized logistic regression
perf.acc.log <- performance(p, measure = "acc", )
perf.tpr.log <- performance(p, measure = "tpr")
perf.fpr.log <- performance(p, measure = "fpr")
```

```
rbind(cbind(x = unlist(perf.acc.log@x.values),
      y = unlist(perf.acc.log@y.values), metric = "acc"),
cbind(x = unlist(perf.tpr.log@x.values),
      y = unlist(perf.tpr.log@y.values), metric = "tpr"),
cbind(x = unlist(perf.fpr.log@x.values),
      y = unlist(perf.fpr.log@y.values), metric = "fpr")) %>% as_tibble() %>%
  mutate(x = as.numeric(x), y = as.numeric(y)) %>%
  ggplot(aes(x, y, color = metric)) + geom_line(size = 1)+theme_bw()+
  xlab("Cut-off")+ ylab("Accuracy / FPR / TPR")
```



The optimal cut-oof seems to be 0.15 **1)** because we can see that this is the value where the accuracy is reaching a threshold and **2)** because this is where the difference between the True Positive Rate and the False Positive Rate is the greatest. This second remark is important because here, we are looking for maximizing the number of true positive while minimizing the number of False Positive.

Now, we can compute the confusion matrix with a threshold of 0.15:

```
##      obs
## pred   0   1
##    0 897  53
##    1  37  13
```