

# EXERCISES - RANDOM FORESTS

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# EXERCISE: RANDOM FORESTS

## DOWNLOAD AND IMPORT EXAMPLE DATA

- 1) Download the Data from **here** and read in the `adult.csv` file with `header=FALSE`. Store this in `dat`. Use `str()` command to see the dataframe.
- 2) Get the column names from the **meta data** and add them to the data frame. Notice that `dat` is ordered - `V1,V2,V3,...`

## GET AN OVERVIEW OF THE DATA

- 3) Use the `table` command to get the distribution of the feature `class`.
- 4) Make a binary variable `class`.
- 5) Use the `cor()` command to see the correlation of all the numeric and integer columns including the `class` column.

# SOLUTION: DOWNLOAD AND IMPORT (I)

## SOLUTION EXERCISE 1: GET THE DATASET

```
l1 <- "http://www.r-exercises.com/wp-content"
```

```
l2 <- "/uploads/2016/11/adult.csv"
```

```
link <- paste0(l1,l2)
```

```
dat <- read.csv(link,header=FALSE)
```

```
str(dat)
```

```
## 'data.frame':    15916 obs. of  15 variables:
```

```
## $ V1 : int  39 50 38 53 28 37 49 52 31 42 ...
```

```
## $ V2 : Factor w/ 9 levels " ?"," Federal-gov",...: 8 7 5 5 5
```

```
## $ V3 : int  77516 83311 215646 234721 338409 284582 160187 2
```

```
## $ V4 : Factor w/ 16 levels " 10th"," 11th",...: 10 10 12 2 10
```

```
## $ V5 : int  13 13 9 7 13 14 5 9 14 13 ...
```

```
## $ V6 : Factor w/ 7 levels " Divorced"," Married-AF-spouse",..
```

```
## $ V7 : Factor w/ 15 levels " ?"," Adm-clerical",...: 2 5 7 7
```

```
## $ V8 : Factor w/ 6 levels " Husband"," Not-in-family",...: 2
```

```
## $ V9 : Factor w/ 5 levels " Amer-Indian-Eskimo",...: 5 5 5 3
```

## SOLUTION: DOWNLOAD AND IMPORT (II)

### SOLUTION EXERCISE 2 RENAME COLUMNS

```
colnames(dat) <- c("age", "workclass", "fnlwgt", "education",  
                  "education-num", "marital-status", "occupation",  
                  "relationship", "race", "sex", "capital-gain",  
                  "capital-loss", "hours-per-week",  
                  "native-country", "class")  
  
load("../data/meta_cnames.Rdata")  
colnames(dat) <- cnames_dat
```

# SOLUTION: GET OVERVIEW

## SOLUTION EXERCISE 3: GET DISTRIBUTION

```
table(dat$class)
```

```
##
```

```
##  <=50K  >50K
```

```
##  12097  3819
```

## SOLUTION EXERCISE 4

- ▶ A binary variable class

```
levels(dat$class) <- c(0,1)
```

```
dat$class <- as.numeric(dat$class)
```

# SOLUTION EXERCISE 5

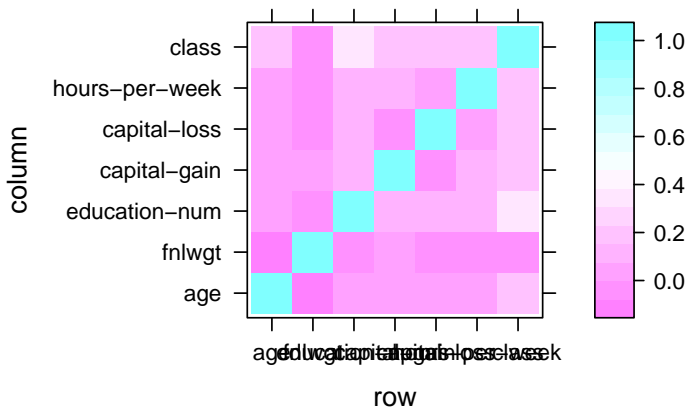
## CORRELATION OF ALL NUMERIC AND INTEGER VARIABLES

```
(cormat <- cor(dat[,c(1,3,5,11,12,13,15)]))
```

##	age	fnlwgt	education-num	capital
## age	1.00000000	-0.079506361	0.02668698	0.0664
## fnlwgt	-0.07950636	1.000000000	-0.04671504	0.0006
## education-num	0.02668698	-0.046715043	1.00000000	0.1174
## capital-gain	0.06646649	0.000653693	0.11745307	1.0000
## capital-loss	0.06176551	-0.012139341	0.08090257	-0.0316
## hours-per-week	0.05659864	-0.012345724	0.14528405	0.0757
## class	0.22920766	-0.013067759	0.32856870	0.2210
##	capital-loss	hours-per-week	class	
## age	0.06176551	0.05659864	0.22920766	
## fnlwgt	-0.01213934	-0.01234572	-0.01306776	
## education-num	0.08090257	0.14528405	0.32856870	
## capital-gain	-0.03168533	0.07571567	0.22104995	
## capital-loss	1.00000000	0.05439109	0.15366554	
## hours-per-week	0.05439109	1.00000000	0.22544319	

# A LEVELPLOT OF THE CORRELATION MATRIX

```
lattice::levelplot(cormat)
```



# EXERCISE: RANDOM FORESTS

## SPLIT THE DATASET

- 6) Split the dataset into train and test sample. You may use `caTools::sample.split()` and use the ratio as 0.7 and set the seed to be 1000.
- 7) Check the number of rows of train and test
- 8) We are ready to use decision tree in our dataset. Load the package `rpart` and `rpart.plot`
- 9) Use `rpart` to build the decision tree on the train set. Include all features. Store this model in `dec`
- 10) Use `prp()` to plot the decision tree.



# SOLUTIONS

## SOLUTION EXERCISE 6 - SPLIT DATASET

```
dat$class <- as.factor(dat$class)

set.seed(1000)
library(caTools)
split <- sample.split(dat$class, SplitRatio=0.8)
Train <- dat[split==TRUE,]
Test <- dat[split==FALSE,]
```

## SOLUTION EXERCISE 7 - NUMBER OF ROWS

```
nrow(Train)

## [1] 12733

nrow(Test)

## [1] 3183
```

# SOLUTIONS EXERCISE

## SOLUTION EXERCISE 8 - LOAD PACKAGES

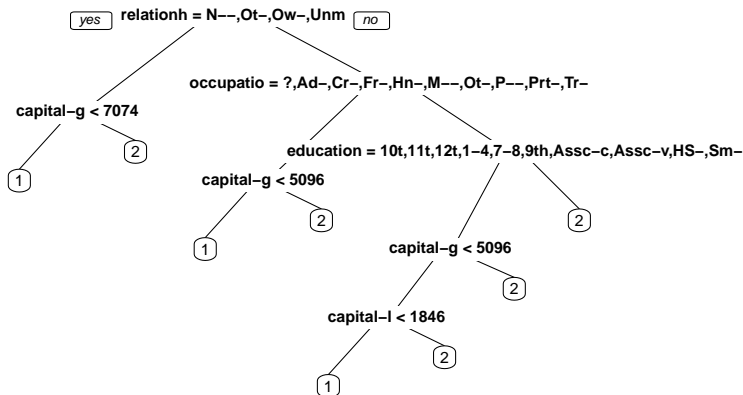
```
library(rpart)
library(rpart.plot)
```

## SOLUTION EXERCISE 9 - FIRST MODEL

```
dec <- rpart(class~., data=Train)
```

# SOLUTION EXERCISE 10 - PLOT THE RESULTING TREE

`prp(dec)`



## EXERCISE - PREDICT AND PRODUCE CONFUSION MATRIX

- 11) use the `predict()` command to make predictions on the Train data. Set the method to `class`. Class returns classifications instead of probability scores. Store this prediction in `pred_dec`.
- 12) Create a **confusion matrix** (4 different combinations of predicted and actual values - see figure below) and print it.

		Actual Values	
		Positive (1)	Negative (0)
Predicted Values	Positive (1)	TP	FP
	Negative (0)	FN	TN

## EXERCISES - ACCURACY

- 13) What is the **accuracy of the model** (ACC). Hint: all necessary information is in the confusion matrix.
- 14) What is the **misclassification rate**? Hint:  $(FP+FN)/total$

# EXERCISES

- 15) Remember the `predict()` command in question 11. We will use the same mode and same command except we will set the method to “regression”. This gives us a probability estimates. Store this in `pred_dec_reg`
- 16) Load the `ROCR` package. Use the `prediction()`, `performance()` and `plot()` command to print the **ROC curve**. Use `pred_dec_reg` variable from question 7. You can also refer to the previous exercise to see the code.
- 17) `plot()` the same ROC curve but set `colorize=TRUE`
- 18) Comment on your findings using ROC curve and accuracy. Is it a good model? Did you notice that `ROC prediction()` command only takes probability predictions as one of its arguments. Why is that so?

# SOLUTION EXERCISE 11

## SPLIT THE DATASET

```
split <- caTools::sample.split(Y = dat$class, SplitRatio=0.7)
Train <- dat[split==TRUE,]
Test <- dat[split==FALSE,]

library(rpart)
library(rpart.plot)

dec <- rpart(class~., data=Train)

pred_dec <- predict(dec,newdata = Test,type="class")
```

# SOLUTIONS

## EXERCISE 12 - CONFUSION MATRIX

```
(confmat <- table(Test$class,pred_dec))
```

```
##      pred_dec  
##           1      2  
##    1 3427  202  
##    2  556  590
```

## SOLUTION EXERCISE 13 - MODEL ACCURACY

```
(confmat[1,1] + confmat[2,2])/(sum(confmat))
```

```
## [1] 0.8412565
```

## SOLUTION EXERCISE 14 - MISCLASSIFICATION ERROR

```
mean(as.factor(Test$class)!=pred_dec)
```

```
## [1] 0.1587435
```



# FURTHER SOLUTIONS

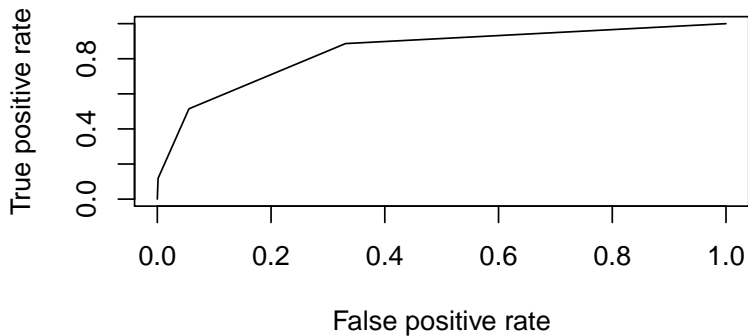
## SOLUTION EXERCISE 15 - MAKE PREDICTION

```
pred_dec_reg <- predict(dec,newdata = Test,type="prob")
```

## SOLUTION EXERCISE 16 - ROC CURVE

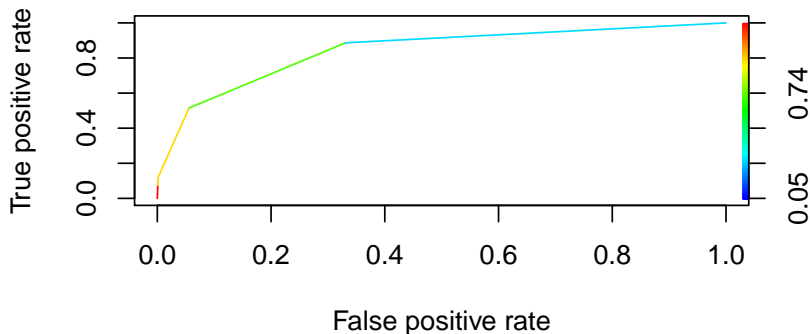
```
library(ROCR)
pred <- prediction(predictions=as.numeric(pred_dec_reg[,2]),
                    Test$class)
perf <- performance(pred,"tpr","fpr")
plot(perf)
```

# PERFORMANCE PLOT



## SOLUTION EXERCISE 17

```
plot(perf,colorize=TRUE)
```



## SOLUTION EXERCISE 18

- ▶ It is a good model. The initial accuracy is 0.85 which is pretty good.
- ▶ The ROC curve is also leaning more towards the true positive side which is also a good sign. `ROC prediction()` command takes probability score predictions because it is used to give a visual representation of a range of threshold values.
- ▶ We can use ROC also to interpret what threshold value to chose and decide the ratio of true positive to false positives based on the problem at hand. That is for another exercise