UNIVERSITÉ LAVAL

SIO-6051
Data Mining

Final Project
Adult Dataset

Presented to
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Fives phases of CRISPDM of the Adult Dataset

1-Executive summary

1.1- Business Understanding Phase

In this project, we analyze the Adult dataset provided from the Census bureau in USA. The objective is to identify the best algorithm to be employed in order to predict whether a certain adult has annual income more than 50,000 $ based on several attributes such as: age, education, occupation, capital gain, and capital loss as well as other variables as illustrated in details within this document. Such prediction is required to decide if a certain adult could be granted a loan or be targeted by a specific marketing campaign.

1.2- Data Understanding Phase

The provided adult dataset contains 16281 observations of 15 variables: 6 numeric variables and 9 factor level variables. Certain numeric variables contain outliers whereas certain factor variables contain missing data.

1.3- Data Preparation Phase

Data preparation is done in order to clean and recover missing data and elimination of outliers.
Missed data are recovered using the method of *'Replace Missing Values with Random Values*', while outliers are removed using '*Min-max*' technique.

1.4- Modeling Phase

Three different models are applied on both training and validation datasets after data cleaning for the purpose of predicting the target variable and thereafter identifying the best algorithm:

1. K-nearest neighbour: for K= 5.
2. Decision trees: three different trees based of different sets of variables.
3. Neural networks: applied on three training sets of 4070, 8140 and 12210 observations (25%, 50% and 75%) respectively for 4,8, and 10 hidden layers respectively.

1.5- Evaluation Phase

The performance of each algorithm is initially evaluated for each model by getting the percentage between estimated values and actual values. False negative and false positive rates are also evaluated. With linear performance evaluation, we get the best performance 91.71% with neural network algorithm with 8 hidden layers and 4070 observations training set. The next best performance is obtained with a decision tree based on: Capital.gain, Capital.loss, Education.num, Marital.status variables. In such case, the recorded performance is 85.01%

2- Business understanding

2.1-Project objectives

The Adult dataset is from the Census bureau of United States (https://www.census.gov/) and the task is to predict whether a given adult makes more than 50 000$ a year based on attributes such as : (See Figure 1 in the appendix for the actual distribution)

1. Age;
2. Workclass;
3. Final weight;
4. Education (High School, Bachelors, Maters, etc.);
5. Education.num (the level of education : e.g. High School 1st year, Masters 2nd year, etc.);
6. Marital status;
7. Occupation;
8. Relationship;
9. Race;
10. Sex;
11. Capital gain;
12. Capital loss;
13. Hours of work per week;
14. Native country;
15. The income class that shows weither if the revenue is higher or lower than 50 000$.

According to the authors of the study made in 1996, Ronny Kohavi and Barry Becker, the data were split into :

> "train-test using MLC++ GenCVFiles (2/3, 1/3 random).| 48842 instances, mix of continuous and discrete (train=32561, test=16281) and 45222 if instances with unknown values are removed (train=30162, test=15060) "[i]

3- Data pre-processing and exploratory data analysis

Data preprocessing is taking place through two steps:

1. Data cleaning: for recovering missing values.
2. Elimination of outliers.

3.1- Data cleaning

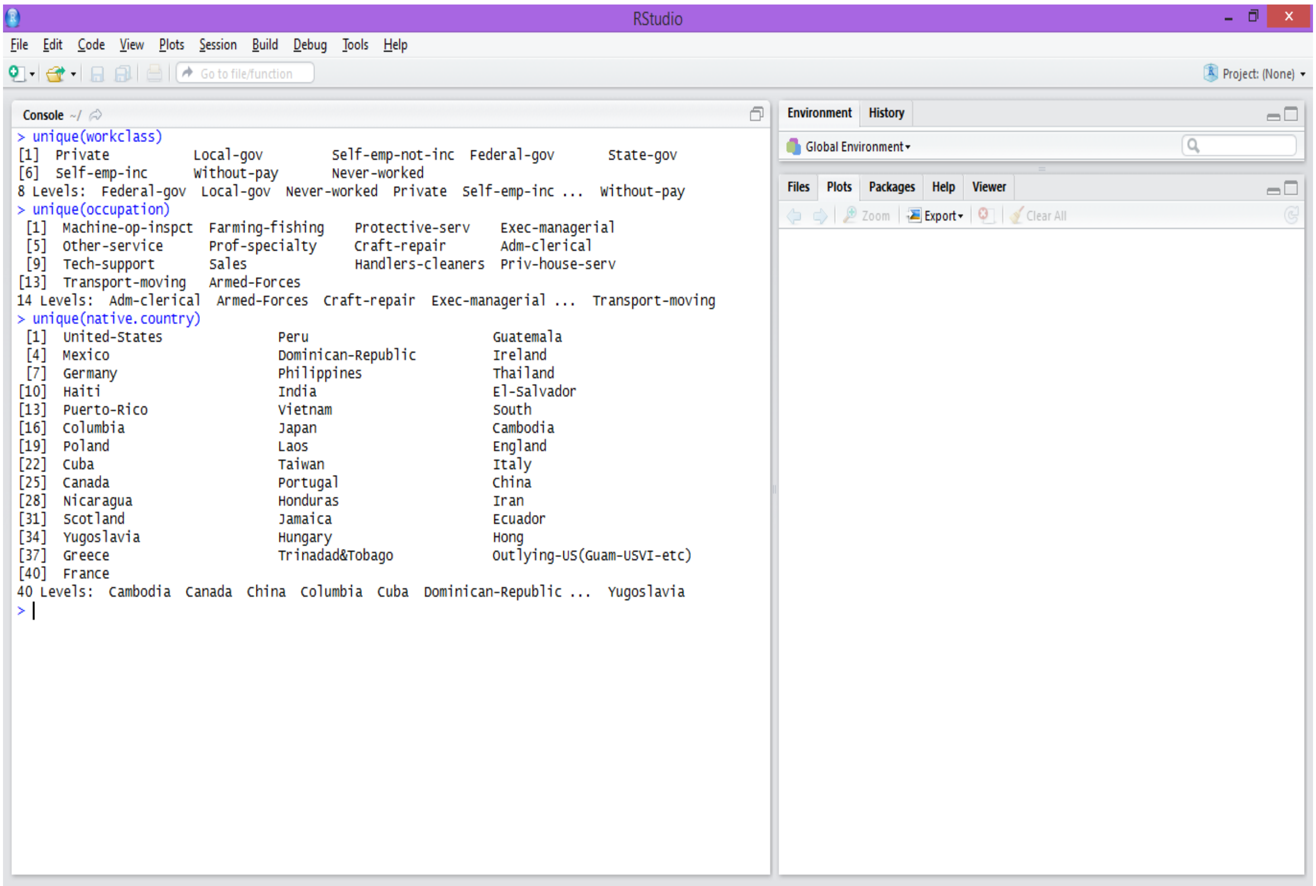
By examining the existing data of the adult dataset, we discover that there are missing data in three fields: workclass, occupation, and native.country. The missing data are marked as question marks '?'.

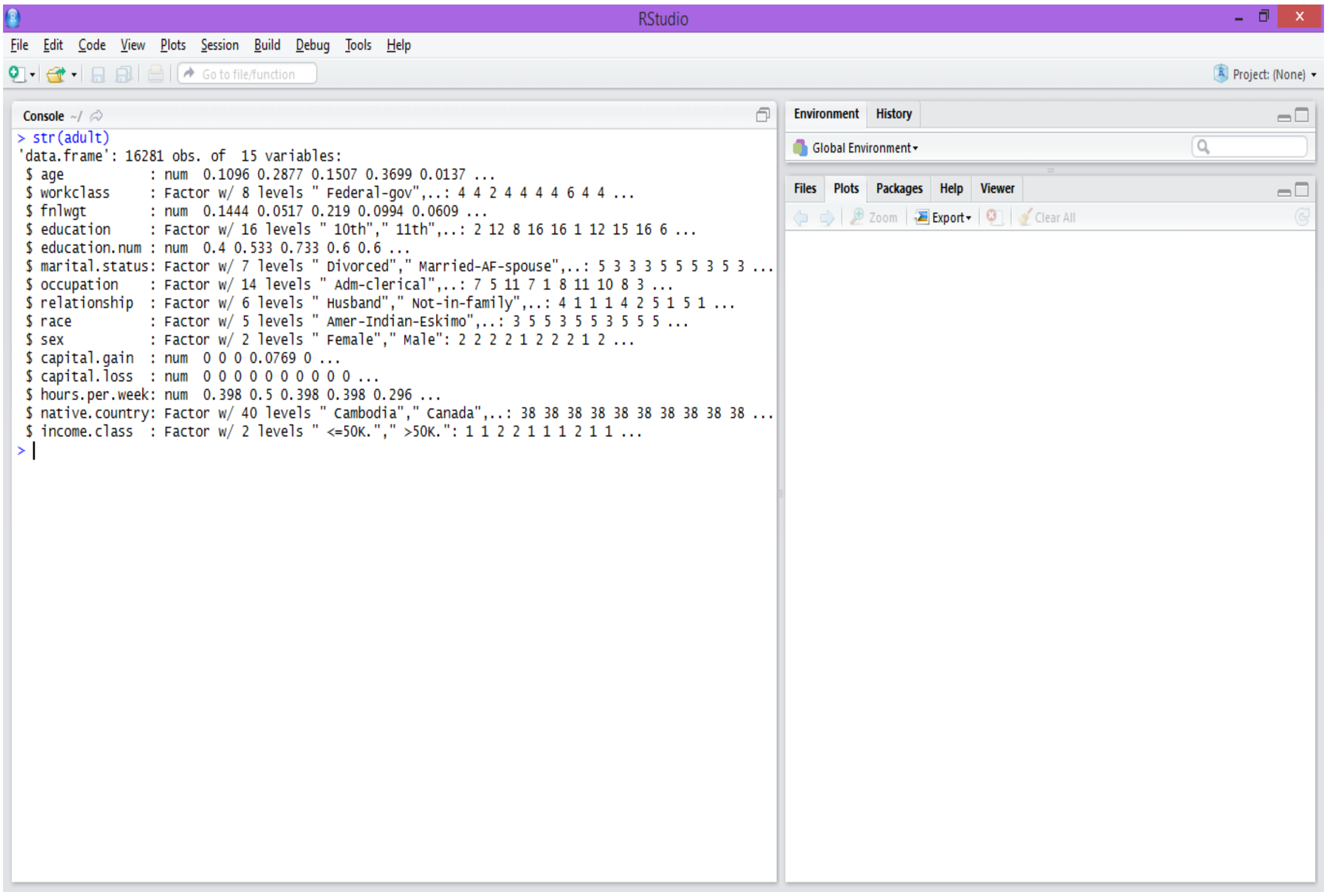
We employ the cleaning technique of Replacing Missing Values with Random Values. When applying this technique, we take in consideration the probability of occurrence for each variable in order to replace the missing values in order to keep the consistency of the dataset.

For each of the three variables containing missing data which are mentioned earlier, we go through the following steps:

1. Determination of the number of missed values for each of them
2. Transformation of the variable (the data field) into character instead of factor.
3. Selecting a random sample of dataset of other rows of the dataset which contain valid values. The probability of the presence of each value in the selected sample depends on its number of occurrence in the entire dataset.
4. Replacing the missed values, which are indicated by the question mark '?' by the random sample.
5. Returning the variable back into a factor variable instead of character.

Finally, we checked the resulting data by applying the command *unique* for each cleaned variable as well as viewing the summary of the entire dataset as shown in the figures below in order to insure the recovering of missing data before going through the next steps.


RStudio
File Edit Code View Plots Session Build Debug Tools Help
Console ~/
> unique(workclass)
[1] Private   Local-gov   Self-emp-not-inc Federal-gov   State-gov
[6] Self-emp-inc   Without-pay   Never-worked
8 Levels: Federal-gov Local-gov Never-worked Private Self-emp-inc ... Without-pay
> unique(occupation)
 [1] Machine-op-inspct Farming-fishing   Protective-serv   Exec-managerial
 [5] Other-service   Prof-specialty   Craft-repair   Adm-clerical
 [9] Tech-support   Sales   Handlers-cleaners Priv-house-serv
[13] Transport-moving   Armed-Forces
14 Levels: Adm-clerical Armed-Forces Craft-repair Exec-managerial ... Transport-moving
> unique(native.country)
 [1] United-States   Peru   Guatemala
 [4] Mexico   Dominican-Republic Ireland
 [7] Germany   Philippines   Thailand
[10] Haiti   India   El-Salvador
[13] Puerto-Rico   Vietnam   South
[16] Columbia   Japan   Cambodia
[19] Poland   Laos   England
[22] Cuba   Taiwan   Italy
[25] Canada   Portugal   China
[28] Nicaragua   Honduras   Iran
[31] Scotland   Jamaica   Ecuador
[34] Yugoslavia   Hungary   Hong
[37] Greece   Trinadad&Tobago   Outlying-US(Guam-USVI-etc)
[40] France
40 Levels: Cambodia Canada China Columbia Cuba Dominican-Republic ... Yugoslavia
Environment History
Global Environment
Files Plots Packages Help Viewer
Zoom Export Clear All
Project: (None)

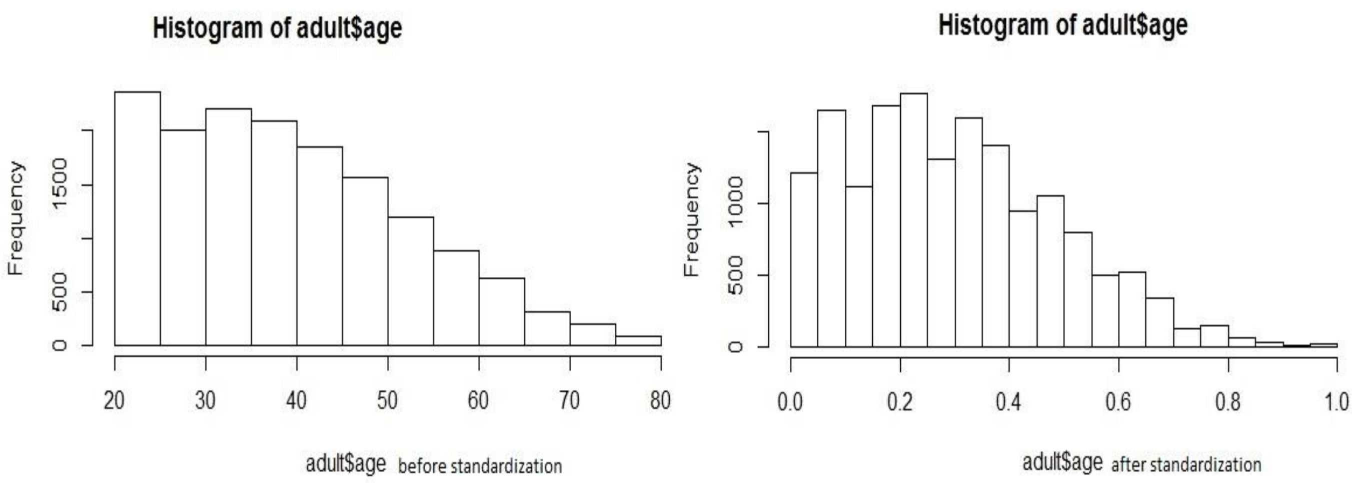

RStudio
File Edit Code View Plots Session Build Debug Tools Help
Console ~/
> str(adult)
'data.frame': 16281 obs. of 15 variables:
 $ age   : num 0.1096 0.2877 0.1507 0.3699 0.0137 ...
 $ workclass   : Factor w/ 8 levels " Federal-gov",..: 4 4 2 4 4 4 4 6 4 4 ...
 $ fnlwgt   : num 0.1444 0.0517 0.219 0.0994 0.0609 ...
 $ education   : Factor w/ 16 levels " 10th"," 11th",..: 2 12 8 16 16 1 12 15 16 6 ...
 $ education.num : num 0.4 0.533 0.733 0.6 0.6 ...
 $ marital.status: Factor w/ 7 levels " Divorced"," Married-AF-spouse",..: 5 3 3 3 5 5 5 3 5 3 ...
 $ occupation   : Factor w/ 14 levels " Adm-clerical",..: 7 5 11 7 1 8 11 10 8 3 ...
 $ relationship : Factor w/ 6 levels " Husband"," Not-in-family",..: 4 1 1 1 4 2 5 1 5 1 ...
 $ race   : Factor w/ 5 levels " Amer-Indian-Eskimo",..: 3 5 5 3 5 5 3 5 5 5 ...
 $ sex   : Factor w/ 2 levels " Female"," Male": 2 2 2 2 1 2 2 2 1 2 ...
 $ capital.gain : num 0 0 0 0.0769 0 ...
 $ capital.loss : num 0 0 0 0 0 0 0 0 0 0 ...
 $ hours.per.week: num 0.398 0.5 0.398 0.398 0.296 ...
 $ native.country: Factor w/ 40 levels " Cambodia"," Canada",..: 38 38 38 38 38 38 38 38 38 38 ...
 $ income.class : Factor w/ 2 levels " <=50K."," >50K.": 1 1 2 2 1 1 1 2 1 1 ...
Environment History
Global Environment
Files Plots Packages Help Viewer
Zoom Export Clear All
Project: (None)

3.2 - Elimination of outliers

Data transformation method was chosen in order to eliminate the outliers of the "adult" dataset. According to Daniel T. Larose, several techniques can be used depending on the objectifs and the analysis. For this project, the min-max normalization was applied to certain variables on the dataset in order to achieve the normalization. The concerning variables are the numeric variables such as: age, fnlwgt, education.num, hours.per.week, capital.loss and capital.gain.

The process consisted of applying the min-max formula to selected variable and assigning the current result to the corresponding variable. In order to achieve the transformation, the algorithm bellow is applied:

```
adult$age=(adult$age-min(adult$age))/(max(adult$age)-min(adult$age))
adult$fnlwgt=(adult$fnlwgt-min(adult$fnlwgt))/(max(adult$fnlwgt)-min(adult$fnlwgt))

adult$education.num=(adult$education.num-
min(adult$education.num))/(max(adult$education.num)-min(adult$education.num))
adult$hours.per.week=(adult$hours.per.week-
min(adult$hours.per.week))/(max(adult$hours.per.week)-min(adult$hours.per.week))

adult$capital.loss=(adult$capital.loss-min(adult$capital.loss))/(max(adult$capital.loss)-
min(adult$capital.loss))

adult$capital.gain=(adult$capital.gain-min(adult$capital.gain))/(max(adult$capital.gain)-
min(adult$capital.gain))
```



Histogram of variable age before and after standardization

4- Modeling section

Preparing and selecting the variables and applying the appropriate modeling techniques

4.1 – Training and validation

4.1.1 - Comparison of "mytreeadult" and "mytreeadult2"

```
all.equal(mytreeadult, mytreeadult2, use.edge.length = FALSE)
```

```
 [1] "Attributes: < Component 2: Names: 5 string mismatches >"
 [2] "Attributes: < Component 2: Length mismatch: comparison on first 5
components >"
 [3] "Attributes: < Component 2: Component 1: Lengths (16, 8) differ
(string compare on first 8) >"
 [4] "Attributes: < Component 2: Component 1: 8 string mismatches >"
 [5] "Attributes: < Component 2: Component 2: Lengths (8, 16) differ
(string compare on first 8) >"
 [6] "Attributes: < Component 2: Component 2: 8 string mismatches >"
 [7] "Attributes: < Component 2: Component 3: Lengths (14, 7) differ
(string compare on first 7) >"
 [8] "Attributes: < Component 2: Component 3: 7 string mismatches >"
 [9] "Attributes: < Component 2: Component 4: Lengths (2, 14) differ
(string compare on first 2) >"
[10] "Attributes: < Component 2: Component 4: 2 string mismatches >"
[11] "Attributes: < Component 2: Component 5: Lengths (5, 6) differ (string
compare on first 5) >"
[12] "Attributes: < Component 2: Component 5: 5 string mismatches >"
[13] "Component 1: Attributes: < Component 2: Numeric: lengths (9, 13)
differ >"
[14] "Component 1: Component 1: Lengths: 9, 13"
[15] "Component 1: Component 1: Attributes: < Component 2: 4 string
mismatches >"
[16] "Component 1: Component 1: Lengths (9, 13) differ (string compare on
first 9)"
[17] "Component 1: Component 1: 7 string mismatches"
[18] "Component 1: Component 2: Numeric: lengths (9, 13) differ"
[19] "Component 1: Component 3: Numeric: lengths (9, 13) differ"
[20] "Component 1: Component 4: Numeric: lengths (9, 13) differ"
[21] "Component 1: Component 5: Numeric: lengths (9, 13) differ"
[22] "Component 1: Component 6: Numeric: lengths (9, 13) differ"
[23] "Component 1: Component 7: Numeric: lengths (9, 13) differ"
[24] "Component 1: Component 8: Numeric: lengths (9, 13) differ"
[25] "Component 1: Component 9: Attributes: < Component 1: Mean relative
difference: 0.4444444 >"
[26] "Component 1: Component 9: Numeric: lengths (54, 78) differ"
[27] "Component 2: Mean relative difference: 1.183825"
[28] "Component 3: target, current do not match when deparsed"
[29] "Component 4: formulas differ in contents"
[30] "Component 5: Attributes: < Component 1: Mean relative difference:
0.6666667 >"
[31] "Component 5: Numeric: lengths (15, 25) differ"
[32] "Component 8: Component 1: Mean relative difference: 19"
[33] "Component 8: Component 2: Mean absolute difference: 7"
[34] "Component 11: Attributes: < Component 1: Mean relative difference:
0.9565217 >"
[35] "Component 11: Attributes: < Component 2: Component 1: 23 string
mismatches >"
[36] "Component 11: Numeric: lengths (115, 225) differ"
[37] "Component 12: Attributes: < Component 1: Mean relative difference:
0.7142857 >"
```

```
[38] "Component 12: Numeric: lengths (304, 800) differ"
[39] "Component 13: Names: 5 string mismatches"
[40] "Component 13: Numeric: lengths (5, 12) differ"
[41] "Component 15: Names: 5 string mismatches"
[42] "Component 15: Lengths (6, 14) differ (comparison on first 6
components)"
```

4.1.2 - Comparison of "mytreeadult" and "mytreeadult3"

```
> all.equal(mytreeadult, mytreeadult3, use.edge.length=FALSE)
```

```
 [1] "Attributes: < Component 2: Names: 3 string mismatches >"
 [2] "Attributes: < Component 2: Length mismatch: comparison on first 4
components >"
 [3] "Attributes: < Component 2: Component 1: Lengths (16, 8) differ
(string compare on first 8) >"
 [4] "Attributes: < Component 2: Component 1: 8 string mismatches >"
 [5] "Attributes: < Component 2: Component 2: Lengths (8, 7) differ (string
compare on first 7) >"
 [6] "Attributes: < Component 2: Component 2: 7 string mismatches >"
 [7] "Attributes: < Component 2: Component 3: Lengths (14, 5) differ
(string compare on first 5) >"
 [8] "Attributes: < Component 2: Component 3: 5 string mismatches >"
 [9] "Component 1: Attributes: < Component 2: Numeric: lengths (9, 13)
differ >"
[10] "Component 1: Component 1: Lengths: 9, 13"
[11] "Component 1: Component 1: Attributes: < Component 2: 4 string
mismatches >"
[12] "Component 1: Component 1: Lengths (9, 13) differ (string compare on
first 9)"
[13] "Component 1: Component 1: 7 string mismatches"
[14] "Component 1: Component 2: Numeric: lengths (9, 13) differ"
[15] "Component 1: Component 3: Numeric: lengths (9, 13) differ"
[16] "Component 1: Component 4: Numeric: lengths (9, 13) differ"
[17] "Component 1: Component 5: Numeric: lengths (9, 13) differ"
[18] "Component 1: Component 6: Numeric: lengths (9, 13) differ"
[19] "Component 1: Component 7: Numeric: lengths (9, 13) differ"
[20] "Component 1: Component 8: Numeric: lengths (9, 13) differ"
[21] "Component 1: Component 9: Attributes: < Component 1: Mean relative
difference: 0.4444444 >"
[22] "Component 1: Component 9: Numeric: lengths (54, 78) differ"
[23] "Component 2: Mean relative difference: 1.19961"
[24] "Component 3: target, current do not match when deparsed"
[25] "Component 4: formulas differ in contents"
[26] "Component 5: Attributes: < Component 1: Mean relative difference:
0.6666667 >"
[27] "Component 5: Numeric: lengths (15, 25) differ"
[28] "Component 8: Component 1: Mean relative difference: 19"
[29] "Component 8: Component 2: Mean absolute difference: 7"
[30] "Component 11: Attributes: < Component 1: Mean relative difference:
0.826087 >"
[31] "Component 11: Attributes: < Component 2: Component 1: 21 string
mismatches >"
[32] "Component 11: Numeric: lengths (115, 210) differ"
[33] "Component 12: Attributes: < Component 1: Mean relative difference:
0.5428571 >"
[34] "Component 12: Numeric: lengths (304, 64) differ"
[35] "Component 13: Names: 4 string mismatches"
[36] "Component 13: Numeric: lengths (5, 9) differ"
[37] "Component 15: Names: 5 string mismatches"
[38] "Component 15: Lengths (6, 9) differ (comparison on first 6
components)"
```

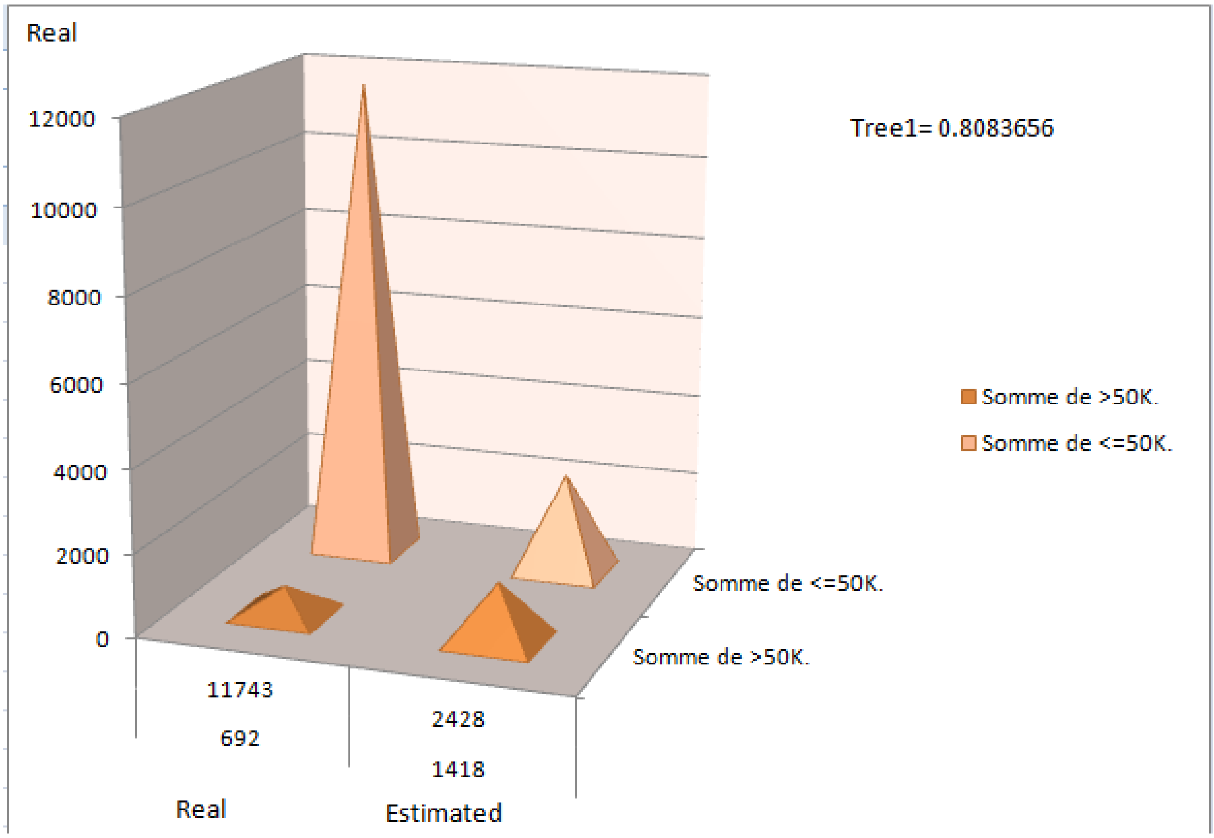
4.1.3 - Comparison of "mytreeadult2" and "mytreeadult3"

```
> all.equal(mytreeadult2, mytreeadult3, dist.edge.length=FALSE)

 [1] "Attributes: < Component 2: Names: 3 string mismatches >"
 [2] "Attributes: < Component 2: Length mismatch: comparison on first 4 
components >"
 [3] "Attributes: < Component 2: Component 2: Lengths (16, 7) differ 
(string compare on first 7) >"
 [4] "Attributes: < Component 2: Component 2: 7 string mismatches >"
 [5] "Attributes: < Component 2: Component 3: Lengths (7, 5) differ (string 
compare on first 5) >"
 [6] "Attributes: < Component 2: Component 3: 5 string mismatches >"
 [7] "Attributes: < Component 2: Component 4: Lengths (14, 2) differ 
(string compare on first 2) >"
 [8] "Attributes: < Component 2: Component 4: 2 string mismatches >"
 [9] "Component 1: Component 1: Attributes: < Component 2: 2 string 
mismatches >"
[10] "Component 1: Component 1: 3 string mismatches"
[11] "Component 1: Component 2: Mean relative difference: 0.01844142"
[12] "Component 1: Component 3: Mean relative difference: 0.01844142"
[13] "Component 1: Component 4: Mean relative difference: 0.009607994"
[14] "Component 1: Component 6: Mean relative difference: 0.0310192"
[15] "Component 1: Component 8: Mean relative difference: 0.3"
[16] "Component 1: Component 9: Mean relative difference: 0.0184811"
[17] "Component 2: Mean relative difference: 2.324051"
[18] "Component 3: target, current do not match when deparsed"
[19] "Component 4: formulas differ in contents"
[20] "Component 5: Mean relative difference: 0.002749724"
[21] "Component 11: Attributes: < Component 1: Mean relative difference: 
0.06666667 >"
[22] "Component 11: Attributes: < Component 2: Component 1: 41 string 
mismatches >"
[23] "Component 11: Numeric: lengths (225, 210) differ"
[24] "Component 12: Attributes: < Component 1: Mean relative difference: 
0.7333333 >"
[25] "Component 12: Numeric: lengths (800, 64) differ"
[26] "Component 13: Names: 9 string mismatches"
[27] "Component 13: Numeric: lengths (12, 9) differ"
[28] "Component 15: Names: 7 string mismatches"
[29] "Component 15: Lengths (14, 9) differ (comparison on first 9 
components)"


> printcp(mytreeadult)

Classification tree:
rpart(formula = income.class ~ education + workclass + occupation + 
    sex + age + race, data = adult, method = "class", control = 
rpart.control(minsplit = 1))

Variables actually used in tree construction:
[1] age        education  occupation sex      

Root node error: 3846/16281 = 0.23623

n= 16281 

        CP nsplit rel error  xerror     xstd
1 0.047322      0   1.00000 1.00000 0.014092
2 0.022361      3   0.83411 0.83801 0.013220
3 0.010000      4   0.81175 0.81955 0.013109

> printcp(mytreeadult2)

Classification tree:
rpart(formula = income.class ~ ., data = adult, method = "class")
```

```
Variables actually used in tree construction:
[1] capital.gain capital.loss education    relationship

Root node error: 3846/16281 = 0.23623

n= 16281

        CP nsplit rel error  xerror     xstd
1 0.125715      0   1.00000 1.00000 0.014092
2 0.054602      2   0.74857 0.74857 0.012658
3 0.037181      3   0.69397 0.69397 0.012282
4 0.010660      4   0.65679 0.65679 0.012011
5 0.010000      6   0.63547 0.64587 0.011929

> printcp(mytreeadult3)

Classification tree:
rpart(formula = income.class ~ age + workclass + education.num +
    marital.status + race + sex + capital.gain + capital.loss +
    hours.per.week, data = adult, method = "class")

Variables actually used in tree construction:
[1] capital.gain   capital.loss   education.num  marital.status

Root node error: 3846/16281 = 0.23623

n= 16281

        CP nsplit rel error  xerror     xstd
1 0.126365      0   1.00000 1.00000 0.014092
2 0.054862      2   0.74727 0.74805 0.012654
3 0.036661      3   0.69241 0.69319 0.012277
4 0.010660      4   0.65575 0.65627 0.012008
5 0.010000      6   0.63443 0.63833 0.011872
```

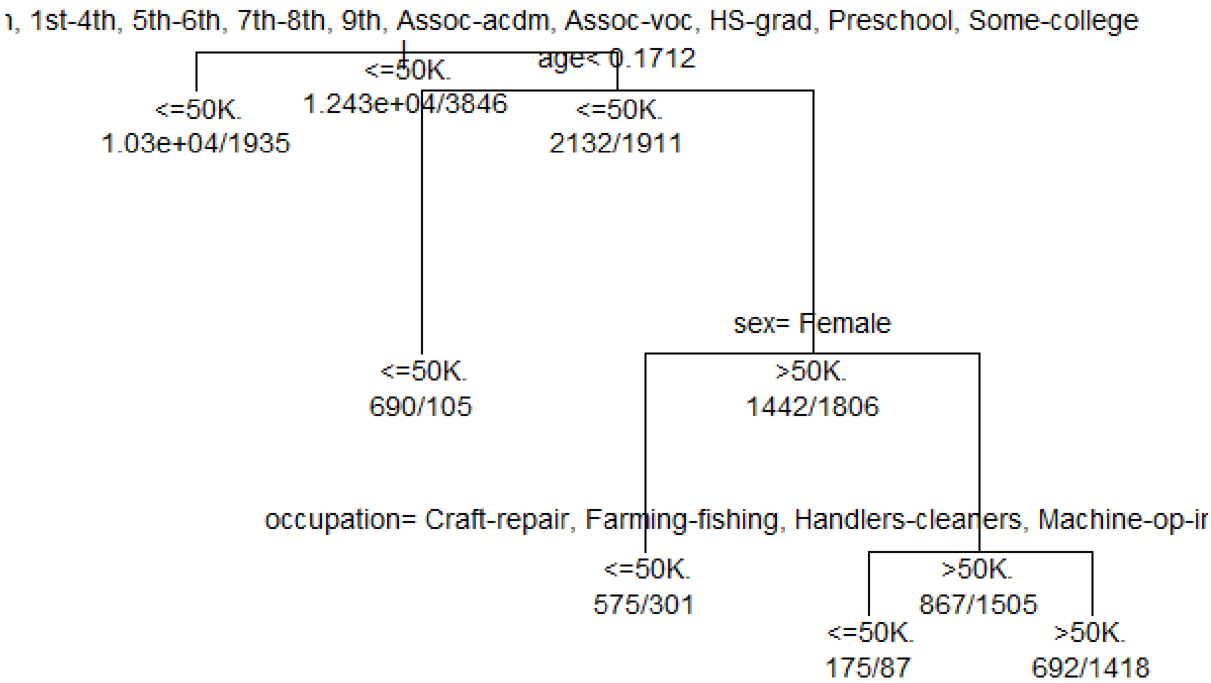
5- Algorithms

5.1- classification trees



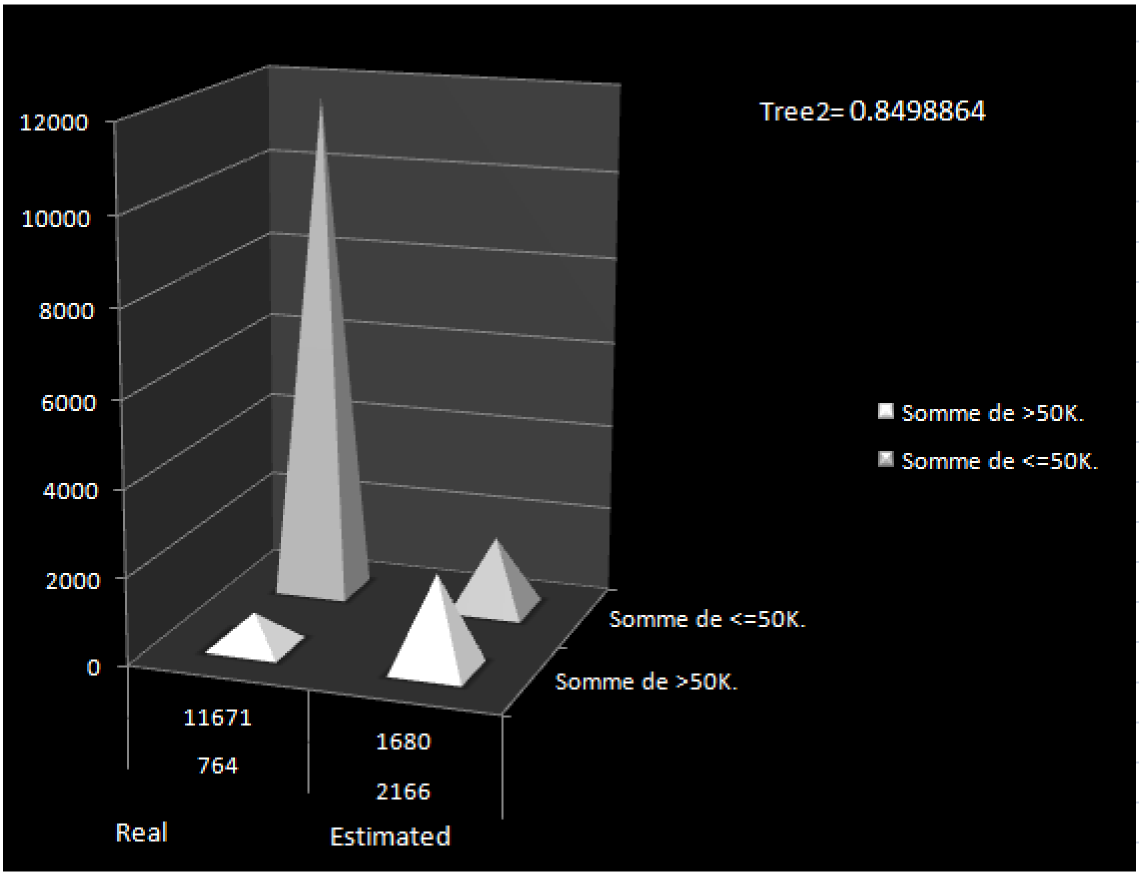

```
>mytreeadult=rpart(income.class~education+workclass+occupation+sex+age+race
, data=adult, method="class", control=rpart.control(minsplit=1))

> mytreeadult
n= 16281

node), split, n, loss, yval, (yprob)
      * denotes terminal node

 1) root 16281 3846  <=50K. (0.7637737 0.2362263)
   2) education= 10th, 11th, 12th, 1st-4th, 5th-6th, 7th-8th, 9th, Assoc-
acdm, Assoc-voc, HS-grad, Preschool, Some-college 12238 1935  <=50K.
(0.8418859 0.1581141) *
   3) education= Bachelors, Doctorate, Masters, Prof-school 4043 1911
<=50K. (0.5273312 0.4726688)
     6) age< 0.1712329 795  105  <=50K. (0.8679245 0.1320755) *
     7) age>=0.1712329 3248 1442  >50K. (0.4439655 0.5560345)
      14) sex= Female 876  301  <=50K. (0.6563927 0.3436073) *
      15) sex= Male 2372  867  >50K. (0.3655143 0.6344857)
        30) occupation= Craft-repair, Farming-fishing, Handlers-cleaners,
Machine-op-inspct, Other-service, Transport-moving 262   87  <=50K.
(0.6679389 0.3320611) *
        31) occupation= Adm-clerical, Armed-Forces, Exec-managerial, Priv-
house-serv, Prof-specialty, Protective-serv, Sales, Tech-support 2110  692
>50K. (0.3279621 0.6720379) *

> plot(mytreeadult)

> text(mytreeadult, use.n=T, all=T, pretty=0, cex=0.9, xpd=TRUE)

> estincome.class=predict(mytreeadult, data=adult, type="class")
```

```
> t1=table(income.class, estincome.class)

> t1
            estincome.class
income.class  <=50K.  >50K.
      <=50K.   11743    692
      >50K.     2428   1418

> (11743+1418)/16281
```



Mytreeadult1

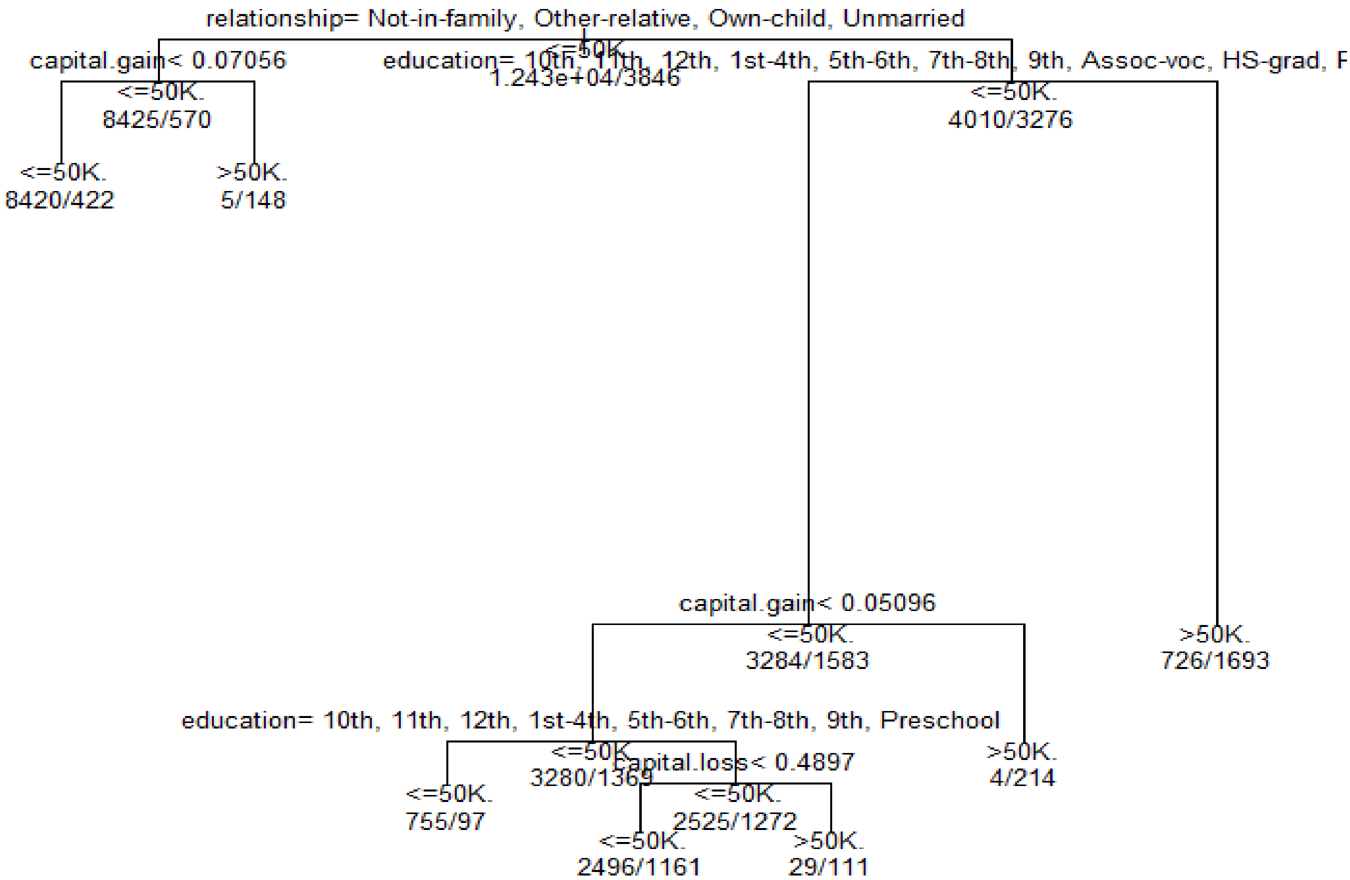
```
[1] 0.8083656
```

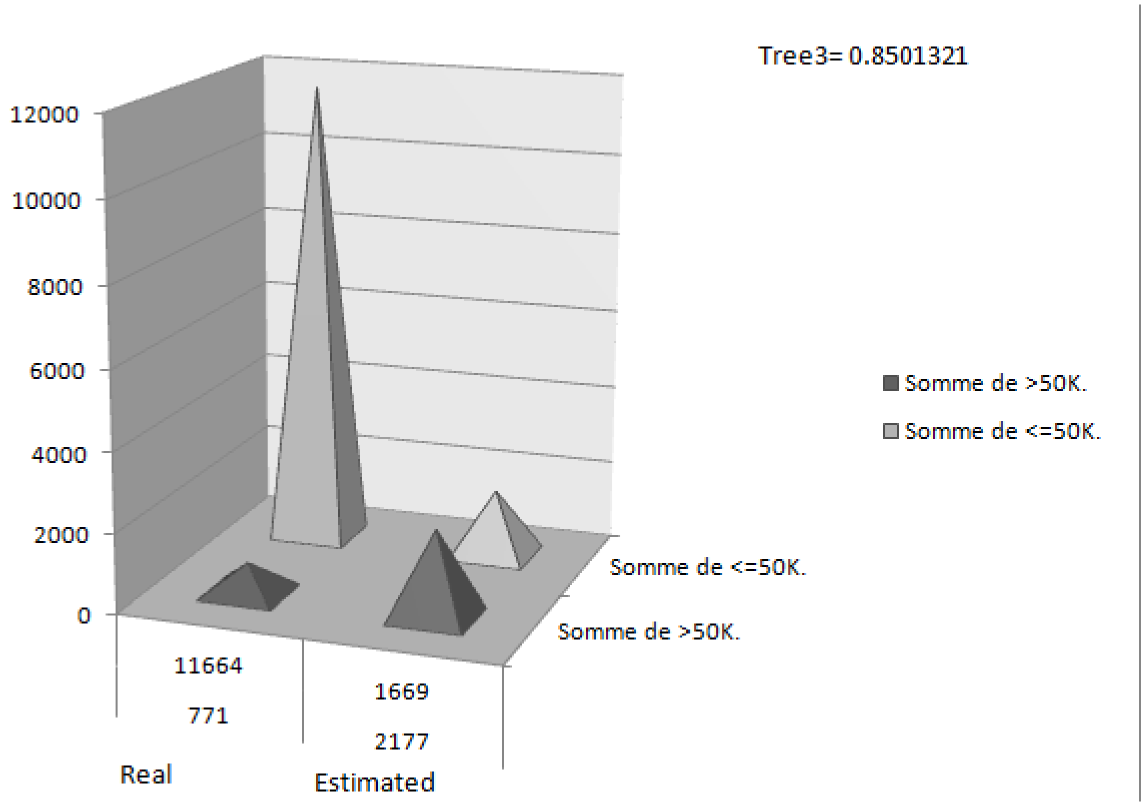



```
> mytreeadult2=rpart(income.class~., data=adult, method="class")

> mytreeadult2
n= 16281

node), split, n, loss, yval, (yprob)
      * denotes terminal node

 1) root 16281 3846  <=50K. (0.76377372 0.23622628)
   2) relationship= Not-in-family, Other-relative, Own-child, Unmarried
8995  570  <=50K. (0.93663146 0.06336854)
     4) capital.gain< 0.07055571 8842  422  <=50K. (0.95227324 0.04772676)
*
     5) capital.gain>=0.07055571 153    5  >50K. (0.03267974 0.96732026) *
   3) relationship= Husband, Wife 7286 3276  <=50K. (0.55037057 0.44962943)
     6) education= 10th, 11th, 12th, 1st-4th, 5th-6th, 7th-8th, 9th, Assoc-
voc, HS-grad, Preschool, Some-college 4867 1583  <=50K. (0.67474830
0.32525170)
      12) capital.gain< 0.05095551 4649 1369  <=50K. (0.70552807
0.29447193)
        24) education= 10th, 11th, 12th, 1st-4th, 5th-6th, 7th-8th, 9th,
Preschool 852   97  <=50K. (0.88615023 0.11384977) *
        25) education= Assoc-voc, HS-grad, Some-college 3797 1272  <=50K.
(0.66499868 0.33500132)
          50) capital.loss< 0.4896552 3657 1161  <=50K. (0.68252666
0.31747334) *
          51) capital.loss>=0.4896552 140   29  >50K. (0.20714286
0.79285714) *
      13) capital.gain>=0.05095551 218    4  >50K. (0.01834862 0.98165138)
*
     7) education= Assoc-acdm, Bachelors, Doctorate, Masters, Prof-school
2419  726  >50K. (0.30012402 0.69987598) *
```

```
> plot(mytreeadult2)

> text(mytreeadult2, use.n=T, all=T, pretty=0, cex=0.8, xpd=TRUE)

> estincome.class=predict(mytreeadult2, data=adult, type="class")

> t1=table(income.class, estincome.class)

> t1
            estincome.class
income.class  <=50K.  >50K.
      <=50K.   11671    764
      >50K.     1680   2166
```

```
> (11671+2166)/16281
[1] 0.8498864
```



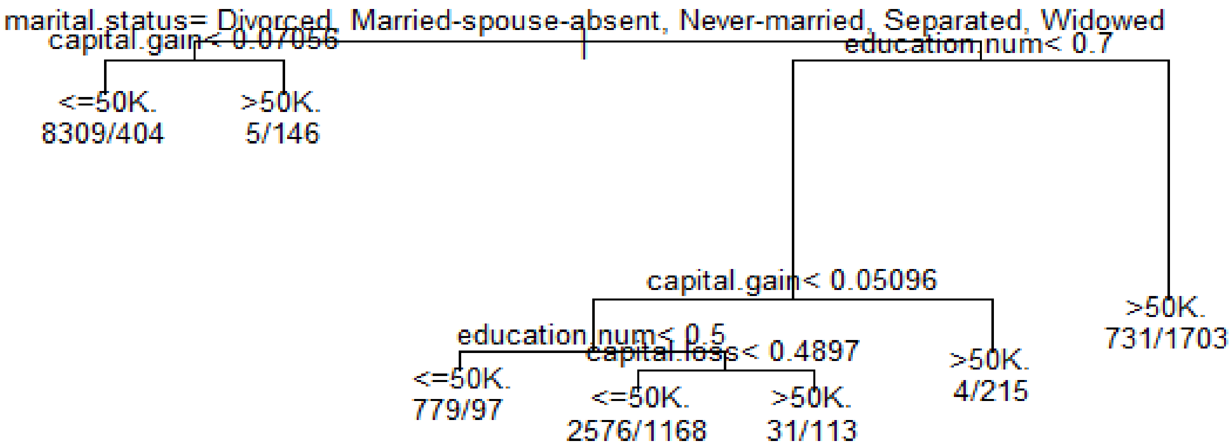



```
>mytreeadult3=rpart(income.class~age+workclass+education.num+marital.status
+race+sex+capital.gain+capital.loss+hours.per.week, data=adult,
method="class")
```

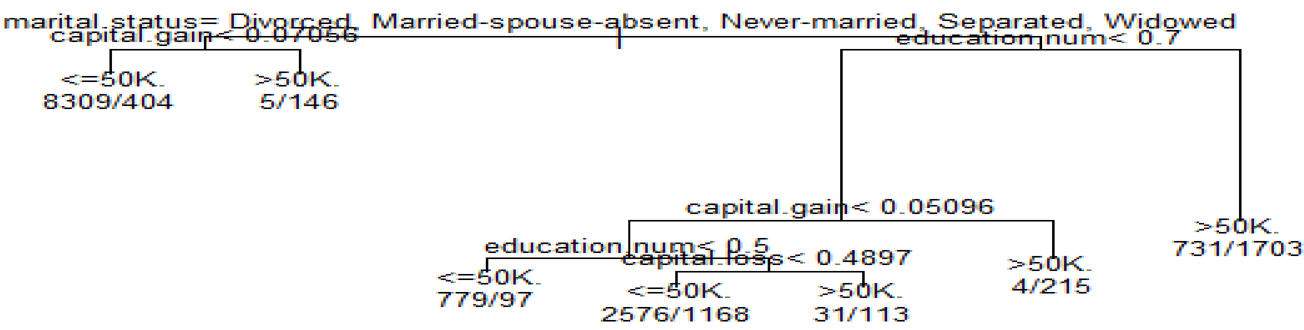
Mytreeadult2

```
> mytreeadult3
n= 16281

node), split, n, loss, yval, (yprob)
      * denotes terminal node

 1) root 16281 3846  <=50K. (0.76377372 0.23622628)
   2) marital.status= Divorced, Married-spouse-absent, Never-married,
Separated, Widowed 8864  550  <=50K. (0.93795126 0.06204874)
     4) capital.gain< 0.07055571 8713  404  <=50K. (0.95363250 0.04636750)
*
     5) capital.gain>=0.07055571 151    5  >50K. (0.03311258 0.96688742) *
   3) marital.status= Married-AF-spouse, Married-civ-spouse 7417 3296
<=50K. (0.55561548 0.44438452)
     6) education.num< 0.7 4983 1593  <=50K. (0.68031306 0.31968694)
      12) capital.gain< 0.05095551 4764 1378  <=50K. (0.71074727
0.28925273)
        24) education.num< 0.5 876   97  <=50K. (0.88926941 0.11073059) *
        25) education.num>=0.5 3888 1281  <=50K. (0.67052469 0.32947531)
          50) capital.loss< 0.4896552 3744 1168  <=50K. (0.68803419
0.31196581) *
          51) capital.loss>=0.4896552 144   31  >50K. (0.21527778
0.78472222) *
      13) capital.gain>=0.05095551 219    4  >50K. (0.01826484 0.98173516)
*
     7) education.num>=0.7 2434  731  >50K. (0.30032868 0.69967132) *

> estincome.class3=predict(mytreeadult3, data=adult, type="class")
```

```
> t3=table(income.class, estincome.class3)

> t3
             estincome.class3
income.class   <=50K.   >50K.
      <=50K.    11664     771
      >50K.      1669    2177

> (11664+2177)/16281
[1] 0.8501321

> plot(mytreeadult3)

> text(mytreeadult3, use.n=T, all=F, pretty=0, cex=0.8, xpd=TRUE)
```

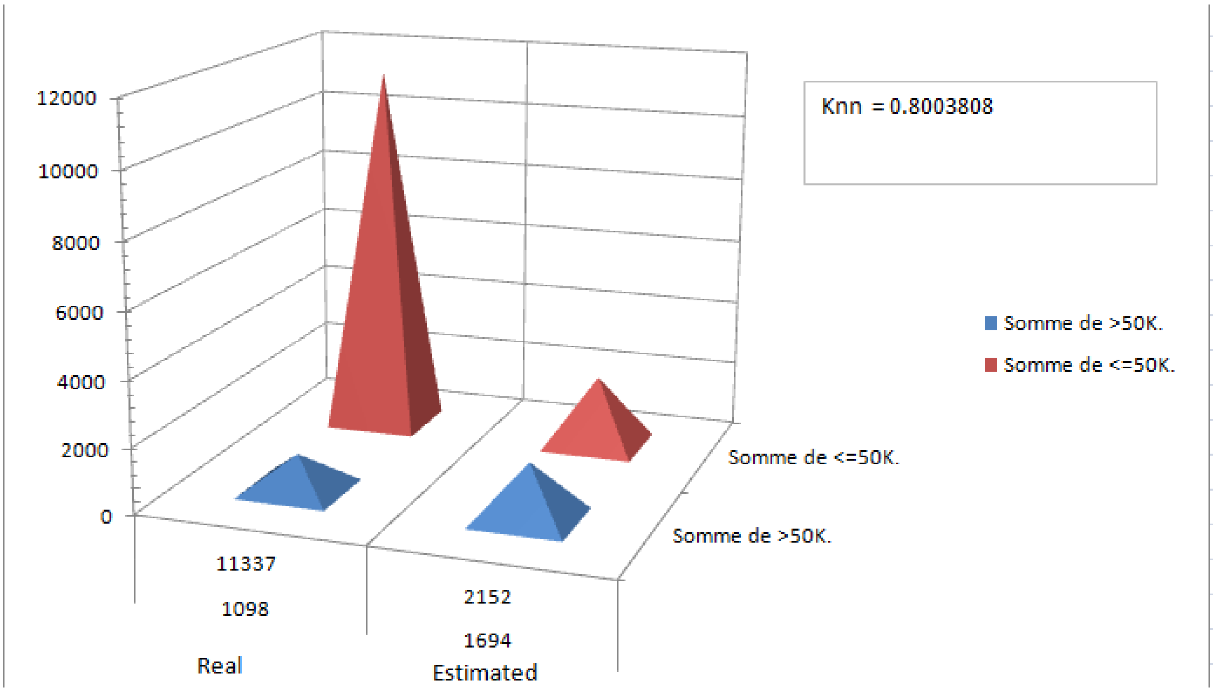


Mytreeadult3



Mytreeadult3

5.2 - k-nearest neighbor



KNN on variable "income.class"

Training set at 60 %, 9700 variables out of 16281

```
str(adult)

adult$workclass=NULL
adult$education=NULL
adult$marital.status=NULL
adult$occupation=NULL
adult$relationship=NULL
adult$race=NULL
adult$sex=NULL
adult$native.country=NULL

adult$income.class=as.factor(income.class)

adult$income.class=as.factor(adult$income.class)

str(adult)

estincome.class=knn.cv(adult[,-7], adult[,7], 5)

estincome.class


> t1=table(income.class, estincome.class)


> str(adult)

'data.frame':   16281 obs. of  7 variables:
 $ age           : num  0.1096 0.2877 0.1507 0.3699 0.0137 ...
```

```
 $ fnlwgt        : num  0.1444 0.0517 0.219 0.0994 0.0609 ...
 $ education.num : num  0.4 0.533 0.733 0.6 0.6 ...
 $ capital.gain  : num  0 0 0 0.0769 0 ...
 $ capital.loss  : num  0 0 0 0 0 0 0 0 0 0 ...
 $ hours.per.week: num  0.398 0.5 0.398 0.398 0.296 ...
 $ income.class  : Factor w/ 2 levels " <=50K."," >50K.": 1 1 2 2 1 1 1 2 1
1 ...
```

```
> t1
```

```
            estincome.class
income.class  <=50K.  >50K.
      <=50K.   11337   1098
      >50K.     2152   1694
```

```
> (11337+1694)/16281
```

```
[1] 0.8003808
```

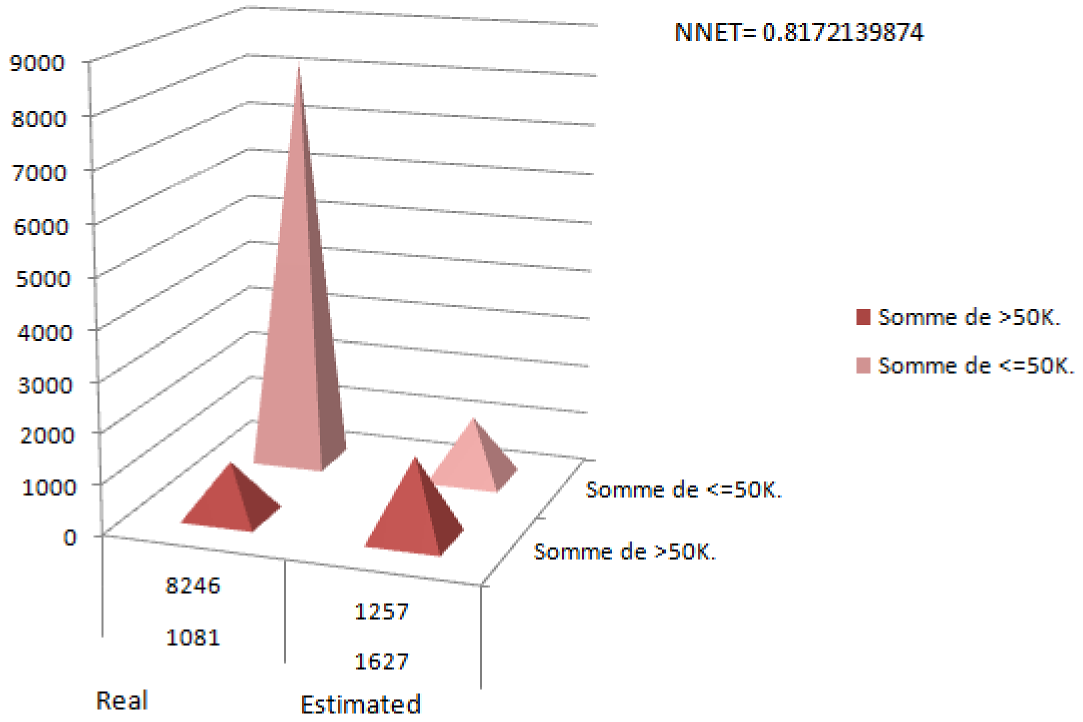
```
> indtrain=sample(1:16281, 9700)
```

```
> ls.str()
adult : 'data.frame':  16281 obs. of  7 variables:
 $ age           : num  0.1096 0.2877 0.1507 0.3699 0.0137 ...
 $ fnlwgt        : num  0.1444 0.0517 0.219 0.0994 0.0609 ...
 $ education.num : num  0.4 0.533 0.733 0.6 0.6 ...
 $ capital.gain  : num  0 0 0 0.0769 0 ...
 $ capital.loss  : num  0 0 0 0 0 0 0 0 0 0 ...
 $ hours.per.week: num  0.398 0.5 0.398 0.398 0.296 ...
 $ income.class  : Factor w/ 2 levels " <=50K."," >50K.": 1 1 2 2 1 1 1 2 1
1 ...
estincome.class :  Factor w/ 2 levels " <=50K."," >50K.": 1 1 1 2 1 1 1 2 1
1 ...
income.class :  Factor w/ 2 levels " <=50K."," >50K.": 1 1 2 2 1 1 1 2 1 1
...
indtrain :  int [1:9700] 6203 15486 6667 13874 10072 9913 3408 3915 15131
4107 ...
native.country :  Factor w/ 40 levels " Cambodia"," Canada",..: 38 38 38 38
38 38 38 38 38 38 ...
occupation :  Factor w/ 14 levels " Adm-clerical",..: 7 5 11 7 4 8 7 10 8 3
...
t1 :  'table' int [1:2, 1:2] 11337 2152 1098 1694
test : 'data.frame':   6581 obs. of  7 variables:
 $ age           : num  0.1507 0.3699 0.0137 0.2329 0.0959 ...
 $ fnlwgt        : num  0.219 0.0994 0.0609 0.1254 0.2412 ...
 $ education.num : num  0.733 0.6 0.6 0.333 0.6 ...
 $ capital.gain  : num  0 0.0769 0 0 0 ...
 $ capital.loss  : num  0 0 0 0 0 0 0 0 0 0 ...
 $ hours.per.week: num  0.398 0.398 0.296 0.296 0.398 ...
 $ income.class  : Factor w/ 2 levels " <=50K."," >50K.": 2 2 1 1 1 2 1 2 2
1 ...
train : 'data.frame':  9700 obs. of  7 variables:
 $ age           : num  0.1507 0.7945 0.0822 0.274 0.2192 ...
 $ fnlwgt        : num  0.1532 0.0588 0.0722 0.2525 0.1292 ...
 $ education.num : num  0.533 0.333 0.533 0.133 0.867 ...
 $ capital.gain  : num  0 0 0 0 0 0 0 0 0 0 ...
 $ capital.loss  : num  0 0 0 0 0 0 0 0 0 0 ...
 $ hours.per.week: num  0.398 0.143 0.48 0.449 0.378 ...
 $ income.class  : Factor w/ 2 levels " <=50K."," >50K.": 1 1 1 1 1 2 1 1 1
1 ...
workclass :  Factor w/ 8 levels " Federal-gov",..: 4 4 2 4 4 4 4 6 4 4 ...
```

```
> realincome.class=adult[indtrain, 7]

> realtest=adult[-indtrain, 7]

> estincome.class=knn(train, train, realincome.class, 5)

> train=adult[indtrain, 1:6]
```

```
> test=adult[-indtrain, 1:6]

> estincome.class=knn(train, train, realincome.class, 5)

> t2=table(estincome.class, realincome.class)

> t2
               realincome.class
estincome.class  <=50K.  >50K.
         <=50K.    6975   1010
         >50K.      400   1315

> (6975+1315)/9700
[1] 0.8546392

> esttest=knn(train, test, realincome.class, 5)

> t3=table(esttest, realtest)

> t3
         realtest
esttest    <=50K.  >50K.
   <=50K.    4604    875
   >50K.      456    646

> (4604+646)/9700
[1] 0.5412371
```

5.3- neural networks



We apply the neural network on variable “income.class” of the adult dataset.

After inputting the dataset in R, we prepare a training set of 9700 observations (60%). The rest will constitute the validation set.

```
> set.seed(99999999)
> index <- sample(1:nrow(adult), 9700)
> adult.test = adult[index,]
> adult.valid = adult[-index,]
```

Then we set up our neural network with 10 for the size of the hidden layer:

```
> adult.net = nnet(income.class~.,data=adult.test,size=10)
# weights:  981
initial  value 10111.087684
iter  10 value 3505.577504
iter  20 value 3112.728652
iter  30 value 2909.482290
iter  40 value 2805.980720
iter  50 value 2750.823741
iter  60 value 2686.060553
iter  70 value 2633.928168
iter  80 value 2592.264548
iter  90 value 2517.967758
iter 100 value 2456.290412
final  value 2456.290412
stopped after 100 iterations
```

Then we try our model on the validation set and use a cross validation table to assess the performance:

```
adult.valid$est.income = predict(adult.net,adult.valid,type="class")
> T=table(adult.valid$income.class,adult.valid$est.income)
> T

           <=50K.  >50K.
   <=50K.    4650    395
   >50K.      656    880
> (4650+880)/(16281-9700)
[1] 0.8402978
```

We get a pretty good 84.03% correct classification.

Now we do the same again with a smaller hidden layer (5):

```
> adult.net = nnet(income.class~.,data=adult.test,size=5)
# weights:  491
initial  value 5853.263152
iter  10 value 3455.243801
iter  20 value 3154.626569
iter  30 value 3005.342318
iter  40 value 2935.386984
iter  50 value 2886.353716
iter  60 value 2824.031681
iter  70 value 2774.114975
iter  80 value 2745.270426
iter  90 value 2728.753792
iter 100 value 2713.742806
final  value 2713.742806
stopped after 100 iterations
> adult.valid$est.income =
predict(adult.net,adult.valid,type="class")
> T=table(adult.valid$income.class,adult.valid$est.income)
> T
```

```
            <=50K.  >50K.
  <=50K.     4633    412
  >50K.       635    901
> (4633+901)/(16281-9700)
[1] 0.8409056
```

The result is slightly better with an 84.09% correct classification.

5.4- analyze the effect of varying parameters

The performance of each algorithm is initially evaluated for each model by getting the percentage between estimated values and actual values. False negative and false positive rates are also evaluated. With linear performance evaluation, we get the best performance 91.71% with neural network algorithm with 8 hidden layers and 4070 observations training set. The next best performance is obtained with a decision tree based on: Capital.gain, Capital.loss, Education.num, Marital.status variables. In such case, the recorded performance is 85.01%

Algorithme KNN sur la variable "income.class"

Training set is à 60 %, 9700 variables on16281

Almost same results with 25%

```
> t2=table(estincome.class, realincome.class)
> t2
             realincome.class
estincome.class  <=50K.  >50K.
        <=50K.    2910    443
        >50K.      191    526
> (2910+526)/4070
[1] 0.844226
```

```
str(adult)

adult$workclass=NULL
adult$education=NULL
adult$marital.status=NULL
adult$occupation=NULL
adult$relationship=NULL
adult$race=NULL
adult$sex=NULL
adult$native.country=NULL

adult$income.class=as.factor(income.class)

adult$income.class=as.factor(adult$income.class)

str(adult)

estincome.class=knn.cv(adult[,-7], adult[,7], 5)

estincome.class


> t1=table(income.class, estincome.class)
```

```
> str(adult)

'data.frame':	16281 obs. of  7 variables:
 $ age           : num  0.1096 0.2877 0.1507 0.3699 0.0137 ...
 $ fnlwgt        : num  0.1444 0.0517 0.219 0.0994 0.0609 ...
 $ education.num : num  0.4 0.533 0.733 0.6 0.6 ...
 $ capital.gain  : num  0 0 0 0.0769 0 ...
 $ capital.loss  : num  0 0 0 0 0 0 0 0 0 0 ...
 $ hours.per.week: num  0.398 0.5 0.398 0.398 0.296 ...
 $ income.class  : Factor w/ 2 levels " <=50K."," >50K.": 1 1 2 2 1 1 1 2 1
1 ...

> t1

            estincome.class
income.class  <=50K.  >50K.
      <=50K.   11337   1098
      >50K.     2152   1694


> (11337+1694)/16281

[1] 0.8003808

> indtrain=sample(1:16281, 9700)

> ls.str()
adult : 'data.frame':	16281 obs. of  7 variables:
 $ age           : num  0.1096 0.2877 0.1507 0.3699 0.0137 ...
 $ fnlwgt        : num  0.1444 0.0517 0.219 0.0994 0.0609 ...
 $ education.num : num  0.4 0.533 0.733 0.6 0.6 ...
 $ capital.gain  : num  0 0 0 0.0769 0 ...
 $ capital.loss  : num  0 0 0 0 0 0 0 0 0 0 ...
 $ hours.per.week: num  0.398 0.5 0.398 0.398 0.296 ...
 $ income.class  : Factor w/ 2 levels " <=50K."," >50K.": 1 1 2 2 1 1 1 2 1
1 ...
estincome.class :  Factor w/ 2 levels " <=50K."," >50K.": 1 1 1 2 1 1 1 2 1
1 ...
income.class :  Factor w/ 2 levels " <=50K."," >50K.": 1 1 2 2 1 1 1 2 1 1
...
indtrain :  int [1:9700] 6203 15486 6667 13874 10072 9913 3408 3915 15131
4107 ...
native.country :  Factor w/ 40 levels " Cambodia"," Canada",..: 38 38 38 38
38 38 38 38 38 38 ...
occupation :  Factor w/ 14 levels " Adm-clerical",..: 7 5 11 7 4 8 7 10 8 3
...
t1 :  'table' int [1:2, 1:2] 11337 2152 1098 1694
test : 'data.frame':	6581 obs. of  7 variables:
 $ age           : num  0.1507 0.3699 0.0137 0.2329 0.0959 ...
 $ fnlwgt        : num  0.219 0.0994 0.0609 0.1254 0.2412 ...
 $ education.num : num  0.733 0.6 0.6 0.333 0.6 ...
 $ capital.gain  : num  0 0.0769 0 0 0 ...
 $ capital.loss  : num  0 0 0 0 0 0 0 0 0 0 ...
 $ hours.per.week: num  0.398 0.398 0.296 0.296 0.398 ...
 $ income.class  : Factor w/ 2 levels " <=50K."," >50K.": 2 2 1 1 1 2 1 2 2
1 ...
train : 'data.frame':	9700 obs. of  7 variables:
 $ age           : num  0.1507 0.7945 0.0822 0.274 0.2192 ...
 $ fnlwgt        : num  0.1532 0.0588 0.0722 0.2525 0.1292 ...
 $ education.num : num  0.533 0.333 0.533 0.133 0.867 ...
 $ capital.gain  : num  0 0 0 0 0 0 0 0 0 0 ...
 $ capital.loss  : num  0 0 0 0 0 0 0 0 0 0 ...
 $ hours.per.week: num  0.398 0.143 0.48 0.449 0.378 ...
 $ income.class  : Factor w/ 2 levels " <=50K."," >50K.": 1 1 1 1 1 2 1 1 1
1 ...
workclass :  Factor w/ 8 levels " Federal-gov",..: 4 4 2 4 4 4 4 6 4 4 ...

> realincome.class=adult[indtrain, 7]
```

```
> realtest=adult[-indtrain, 7]
> estincome.class=knn(train, train, realincome.class, 5)
> train=adult[indtrain, 1:6]
> test=adult[-indtrain, 1:6]
> estincome.class=knn(train, train, realincome.class, 5)
> t2=table(estincome.class, realincome.class)
> t2
               realincome.class
estincome.class  <=50K.  >50K.
         <=50K.    6975   1010
         >50K.      400   1315

> (6975+1315)/9700
[1] 0.8546392

> esttest=knn(train, test, realincome.class, 5)
> t3=table(esttest, realtest)
> t3
         realtest
esttest    <=50K.  >50K.
   <=50K.    4604    875
   >50K.      456    646

> (4604+646)/9700
[1] 0.5412371
```

6- Conclusions on the best model(s) and their absolute significance

Evaluating those models and determining whether they achieve the business objectives and answer the research questions

Impacts of variables on income class estimation			
Decision tree	Mytreeadult	Mytreeadult2	Mytreeadult3
Variables used in the tree construction	Age Education Occupation Sex	Capital.gain Capital.loss Education Relationship	Capital.gain Capital.loss Education.num Marital.status
Efficiency rate	80.83 %	84.98%	85.01%

We apply the neural network on variable "income.class" of the adult dataset.

After inputting the dataset in R, we prepare 3 training sets of 4070, 8140 and 12210 observations (25%, 50% and 75%) respectively. The rest will constitute the validation sets.

```
> set.seed(1234)
> index <- sample(1:nrow(adult), 12210)
> adult.test = adult[index,]
> adult.valid = adult[-index,]
```

Then we set up our neural network with 4, 8 and then 10 for the size of the hidden layer:

```
> adult.net = nnet(income.class~.,data=adult.test,size=10)
# weights:  981
initial  value 3135.995213
iter  10 value 1465.151519
iter  20 value 1291.414488
iter  30 value 1171.231809
iter  40 value 1079.722209
iter  50 value 1001.254668
iter  60 value 937.061026
iter  70 value 882.046138
iter  80 value 843.915509
iter  90 value 823.209449
iter 100 value 807.510902
final  value 807.510902
stopped after 100 iterations
```

Then we try our model on the validation set and use a cross validation table to assess the performance:

```
> adult.valid$est.income =
predict(adult.net,adult.valid,type="class")
>
Cross.Table.Validation=table(adult.valid$income.class,adult.valid$es
t.income)
> Cross.Table.Validation

           <=50K.  >50K.
  <=50K.    2844    236
  >50K.      383    608
> (2844+608)/(16281-12210)
[1] 0.8479489
```

We get a pretty good 84.79% correct classification for this model.

Now we do the same again with the 8 other experiences and compute the false negative and false positive rates. Results are shown in the tables below:

Overall Score	Training Set Size		
Hidden Layer Size	4070	8140	12210
4	83.12%	84.38%	85.21%
8	91.17%	83.50%	84.30%
10	80.85%	84.56%	84.79%

False Negative Rate	Training Set Size		
Hidden Layer Size	4070	8140	12210
4	11.70%	12.14%	12.20%
8	1.62%	12.23%	12.25%
10	13.23%	11.45%	11.87%

False Positive Rate	Training Set Size		
Hidden Layer Size	4070	8140	12210
4	65.10%	70.65%	64.15%
8	67.65%	71.00%	60.08%
10	60.08%	69.93%	72.04%

We see that overall, our nine models have similar performance (around 84% success rate) except for one at 91% and another at 80%. The models have a rather low false negative rate around 12% except for an outstanding 1.62% with model (8, 4070). Differences are more on the side of false positive rates where 2 models perform at 60% and the others around 70%.

To make a wise choice we would need more business insights. Model (8, 4070) performs very well but if false positive errors are costly, models (10, 4070) and (8, 12210) would be preferred.

R commands history:

```
> set.seed(1234)
```

```
> index <- sample(1:nrow(adult), 4070)
> adult.test = adult[index,]
> adult.valid = adult[-index,]
> adult.net = nnet(income.class~.,data=adult.test,size=4)
# weights:  393
initial  value 2459.108513
iter  10 value 1442.041597
iter  20 value 1330.688498
iter  30 value 1275.115072
iter  40 value 1243.071689
iter  50 value 1224.722375
iter  60 value 1197.039751
iter  70 value 1155.090450
iter  80 value 1115.225276
iter  90 value 1089.683483
iter 100 value 1074.793746
final  value 1074.793746
stopped after 100 iterations
> adult.valid$est.income = predict(adult.net,adult.valid,type="class")
> adult.valid$est.income = predict(adult.net,adult.valid,type="class")
>
Cross.Table.Validation=table(adult.valid$income.class,adult.valid$est.incom
e)
> Cross.Table.Validation

           <=50K.  >50K.
  <=50K.    8376    951
   >50K.    1110   1774
> set.seed(12345)
> index <- sample(1:nrow(adult), 8140)
> adult.test = adult[index,]
> adult.valid = adult[-index,]
> adult.net = nnet(income.class~.,data=adult.test,size=4)
# weights:  393
initial  value 6119.813088
iter  10 value 2898.599148
iter  20 value 2626.897882
iter  30 value 2480.079774
iter  40 value 2413.075999
iter  50 value 2364.028423
iter  60 value 2336.402275
iter  70 value 2307.687463
iter  80 value 2294.885504
iter  90 value 2282.884777
iter 100 value 2276.811490
final  value 2276.811490
stopped after 100 iterations
> adult.valid$est.income = predict(adult.net,adult.valid,type="class")
> adult.valid$est.income = predict(adult.net,adult.valid,type="class")
>
Cross.Table.Validation=table(adult.valid$income.class,adult.valid$est.incom
e)
> Cross.Table.Validation

           <=50K.  >50K.
  <=50K.    5704    484
   >50K.     788   1165
> set.seed(123456)
> index <- sample(1:nrow(adult), 12210)
> adult.test = adult[index,]
> adult.valid = adult[-index,]
> adult.net = nnet(income.class~.,data=adult.test,size=4)
# weights:  393
initial  value 10471.002627
iter  10 value 4474.494058
iter  20 value 4076.006072
iter  30 value 3877.872209
iter  40 value 3734.606720
iter  50 value 3679.767884
iter  60 value 3623.159544
```

```
iter  70 value 3592.314267
iter  80 value 3571.323756
iter  90 value 3559.412370
iter 100 value 3545.174976
final  value 3545.174976
stopped after 100 iterations
> adult.valid$est.income = predict(adult.net,adult.valid,type="class")
> adult.valid$est.income = predict(adult.net,adult.valid,type="class")
>
Cross.Table.Validation=table(adult.valid$income.class,adult.valid$est.incom
e)
> Cross.Table.Validation

           <=50K.  >50K.
  <=50K.    2878    202
  >50K.      400    591
> set.seed(1234)
> index <- sample(1:nrow(adult), 4070)
> adult.test = adult[index,]
> adult.valid = adult[-index,]
> adult.net = nnet(income.class~.,data=adult.test,size=8)
# weights:  785
initial  value 2287.018750
iter  10 value 1627.926927
iter  20 value 1283.700990
iter  30 value 1157.988898
iter  40 value 1070.517132
iter  50 value 1009.628010
iter  60 value 965.731174
iter  70 value 935.132515
iter  80 value 911.736968
iter  90 value 890.600135
iter 100 value 876.674629
final  value 876.674629
stopped after 100 iterations
> adult.valid$est.income = predict(adult.net,adult.valid,type="class")
> adult.valid$est.income = predict(adult.net,adult.valid,type="class")
>
Cross.Table.Validation=table(adult.valid$income.class,adult.valid$est.incom
e)
> Cross.Table.Validation

           <=50K.  >50K.
  <=50K.    8501    826
  >50K.     1406   1478
> set.seed(12345)
> index <- sample(1:nrow(adult), 8140)
> adult.test = adult[index,]
> adult.valid = adult[-index,]
> adult.net = nnet(income.class~.,data=adult.test,size=8)
# weights:  785
initial  value 5785.640588
iter  10 value 3042.512614
iter  20 value 2685.571641
iter  30 value 2496.644827
iter  40 value 2401.234562
iter  50 value 2335.151536
iter  60 value 2280.621117
iter  70 value 2211.052535
iter  80 value 2167.950338
iter  90 value 2138.814242
iter 100 value 2099.496987
final  value 2099.496987
stopped after 100 iterations
> adult.valid$est.income = predict(adult.net,adult.valid,type="class")
> adult.valid$est.income = predict(adult.net,adult.valid,type="class")
>
Cross.Table.Validation=table(adult.valid$income.class,adult.valid$est.incom
e)
> Cross.Table.Validation
```

```
              <=50K.  >50K.
   <=50K.     5629    559
   >50K.       784   1169
> set.seed(123456)
> index <- sample(1:nrow(adult), 12210)
> adult.test = adult[index,]
> adult.valid = adult[-index,]
> adult.net = nnet(income.class~.,data=adult.test,size=8)
# weights:  785
initial  value 10858.504549
iter  10 value 4289.889326
iter  20 value 3932.774901
iter  30 value 3703.149854
iter  40 value 3616.784994
iter  50 value 3542.756767
iter  60 value 3449.070057
iter  70 value 3397.384907
iter  80 value 3351.014643
iter  90 value 3323.158446
iter 100 value 3302.889626
final  value 3302.889626
stopped after 100 iterations
> adult.valid$est.income = predict(adult.net,adult.valid,type="class")
> adult.valid$est.income = predict(adult.net,adult.valid,type="class")
>
Cross.Table.Validation=table(adult.valid$income.class,adult.valid$est.incom
e)
> Cross.Table.Validation

              <=50K.  >50K.
   <=50K.     2837    243
   >50K.       396    595
> set.seed(1234)
> index <- sample(1:nrow(adult), 4070)
> adult.test = adult[index,]
> adult.valid = adult[-index,]
> adult.net = nnet(income.class~.,data=adult.test,size=10)
# weights:  981
initial  value 2397.471223
iter  10 value 1468.756862
iter  20 value 1299.158308
iter  30 value 1172.898342
iter  40 value 1075.467612
iter  50 value 1008.177348
iter  60 value 951.346606
iter  70 value 878.801162
iter  80 value 820.238921
iter  90 value 780.151173
iter 100 value 744.367379
final  value 744.367379
stopped after 100 iterations
> adult.valid$est.income = predict(adult.net,adult.valid,type="class")
> adult.valid$est.income = predict(adult.net,adult.valid,type="class")
>
Cross.Table.Validation=table(adult.valid$income.class,adult.valid$est.incom
e)
> Cross.Table.Validation

              <=50K.  >50K.
   <=50K.     8246   1081
   >50K.      1257   1627
> set.seed(12345)
> index <- sample(1:nrow(adult), 8140)
> adult.test = adult[index,]
> adult.valid = adult[-index,]
> adult.net = nnet(income.class~.,data=adult.test,size=10)
# weights:  981
initial  value 10935.744667
iter  10 value 3408.853241
```

```
iter  20 value 2786.442454
iter  30 value 2641.101986
iter  40 value 2566.489040
iter  50 value 2525.891694
iter  60 value 2479.240222
iter  70 value 2437.018291
iter  80 value 2398.966117
iter  90 value 2373.295341
iter 100 value 2337.661751
final  value 2337.661751
stopped after 100 iterations
> adult.valid$est.income = predict(adult.net,adult.valid,type="class")
> adult.valid$est.income = predict(adult.net,adult.valid,type="class")
>
Cross.Table.Validation=table(adult.valid$income.class,adult.valid$est.incom
e)
> Cross.Table.Validation

           <=50K.  >50K.
   <=50K.    5663    525
   >50K.      732   1221
> set.seed(123456)
> index <- sample(1:nrow(adult), 12210)
> adult.test = adult[index,]
> adult.valid = adult[-index,]
> adult.net = nnet(income.class~.,data=adult.test,size=10)
# weights:  981
initial  value 9431.329023
iter  10 value 4370.103027
iter  20 value 3974.326523
iter  30 value 3733.639628
iter  40 value 3628.923494
iter  50 value 3526.704198
iter  60 value 3418.288646
iter  70 value 3320.457069
iter  80 value 3253.267738
iter  90 value 3204.914289
iter 100 value 3161.658111
final  value 3161.658111
stopped after 100 iterations
> adult.valid$est.income = predict(adult.net,adult.valid,type="class")
> adult.valid$est.income = predict(adult.net,adult.valid,type="class")
>
Cross.Table.Validation=table(adult.valid$income.class,adult.valid$est.incom
e)
> Cross.Table.Validation

           <=50K.  >50K.
   <=50K.    2844    236
   >50K.      383    608
```

7- Reference

Daniel T. Larose, *Discovering knowledge in data an introduction to data mining*, Wiley online , 2005, 241 pages

Daniel T. Larose, *Data mining Methods and Models*, Wiley-Interscience Ed., 2006, 340 pages

Robert I. Kabacoff, *R in action: Data analysis and graphics with R*, Manning Ed. 2011. 474 pages

Stéphane Tufféry, *Data Mining and statistics for decision-making*, Wiley Ed., 2011, 717 pages

Ron Lohavi, Scaling *Up The Accuracy of Naïve-Bayes Classifiers: a Decision-Tree hybrid*, 2011, 6 pages

Everything on the course site SIO-6051

http://archive.ics.uci.edu/ml/datasets/Adult

http://archive.ics.uci.edu/ml/machine-learning-databases/adult/adult.names

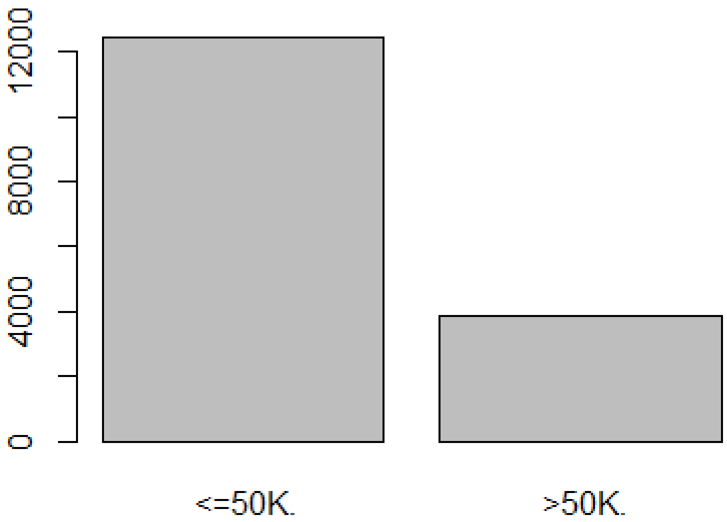
8-Appendices

Graphs and R commands

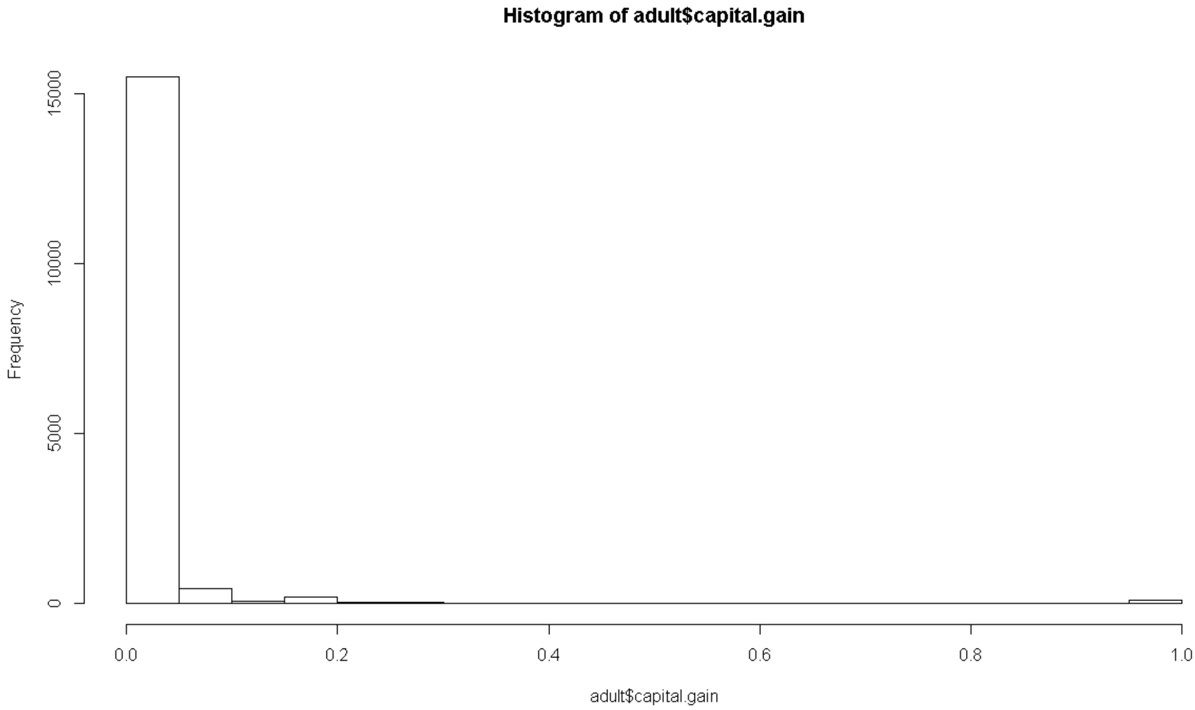
```
> summary(Provided.dataset)
      age                       workclass          fnlwgt                 education      education.num
 Min.   :17.00   Private            :11210   Min.   :  13492   HS-grad     :5283   Min.   : 1.00
 1st Qu.:28.00   Self-emp-not-inc: 1321   1st Qu.: 116736   Some-college:3587   1st Qu.: 9.00
 Median :37.00   Local-gov         : 1043   Median : 177831   Bachelors   :2670   Median :10.00
 Mean   :38.77   ?                 :  963   Mean   : 189436   Masters     : 934   Mean   :10.07
 3rd Qu.:48.00   State-gov         :  683   3rd Qu.: 238384   Assoc-voc   : 679   3rd Qu.:12.00
 Max.   :90.00   Self-emp-inc      :  579   Max.   :1490400   11th        : 637   Max.   :16.00
                (Other)            :  482                     (Other)     :2491
               marital.status              occupation            relationship                    race
  Divorced             :2190   Prof-specialty :2032   Husband       :6523   Amer-Indian-Eskimo:  159
  Married-AF-spouse    :  14   Exec-managerial:2020   Not-in-family :4278   Asian-Pac-Islander:  480
  Married-civ-spouse   :7403   Craft-repair   :2013   Other-relative: 525   Black             : 1561
  Married-spouse-absent: 210   Sales          :1854   Own-child     :2513   Other             :  135
  Never-married        :5434   Adm-clerical   :1841   Unmarried     :1679   White             :13946
  Separated            : 505   Other-service  :1628   Wife          : 763
  Widowed              : 525  (Other)         :4893
      sex          capital.gain     capital.loss      hours.per.week         native.country     income.class
  Female: 5421   Min.   :    0   Min.   :   0.0   Min.   : 1.00   United-States:14662   <=50K.:12435
  Male  :10860   1st Qu.:    0   1st Qu.:   0.0   1st Qu.:40.00   Mexico       :  308   >50K. : 3846
                 Median :    0   Median :   0.0   Median :40.00   ?            :  274
                 Mean   : 1082   Mean   :  87.9   Mean   :40.39   Philippines  :   97
                 3rd Qu.:    0   3rd Qu.:   0.0   3rd Qu.:45.00   Puerto-Rico  :   70
                 Max.   :99999   Max.   :3770.0   Max.   :99.00   Germany      :   69
                                                                 (Other)       :  801
```

```
> ls.str()
Provided.dataset : 'data.frame': 16281 obs. of  15 variables:
 $ age           : int  25 38 28 44 18 34 29 63 24 55 ...
 $ workclass     : Factor w/ 9 levels " ?"," Federal-gov",..: 5 5 3 5 1 5 1 7 5 5 ...
 $ fnlwgt        : int  226802 89814 336951 160323 103497 198693 227026 104626 369667 104996 ...
 $ education     : Factor w/ 16 levels " 10th"," 11th",..: 2 12 8 16 16 1 12 15 16 6 ...
 $ education.num : int  7 9 12 10 10 6 9 15 10 4 ...
 $ marital.status: Factor w/ 7 levels " Divorced"," Married-AF-spouse",..: 5 3 3 3 5 5 5 3 5 3 ...
 $ occupation    : Factor w/ 15 levels " ?"," Adm-clerical",..: 8 6 12 8 1 9 1 11 9 4 ...
 $ relationship  : Factor w/ 6 levels " Husband"," Not-in-family",..: 4 1 1 1 4 2 5 1 5 1 ...
 $ race          : Factor w/ 5 levels " Amer-Indian-Eskimo",..: 3 5 5 3 5 5 3 5 5 5 ...
 $ sex           : Factor w/ 2 levels " Female"," Male": 2 2 2 2 1 2 2 2 1 2 ...
 $ capital.gain  : int  0 0 0 7688 0 0 0 3103 0 0 ...
 $ capital.loss  : int  0 0 0 0 0 0 0 0 0 0 ...
 $ hours.per.week: int  40 50 40 40 30 30 40 32 40 10 ...
 $ native.country: Factor w/ 41 levels " ?"," Cambodia",..: 39 39 39 39 39 39 39 39 39 39 ...
 $ income.class  : Factor w/ 2 levels " <=50K."," >50K.": 1 1 2 2 1 1 1 2 1 1 ...
```

Figure 1: Distribution of the Dataset : Salary higher than 50K$ VS. lower lower or egal to 50k$



The most correlated variable among the dataset:



History of R commands

```
Churn.dataset.from.Larose <- read.csv("~/Rdata/Churn dataset from Larose.csv")

View(Churn.dataset.from.Larose)

setwd("/Users/Dom/Documents/Rdata")

View(Churn.dataset.from.Larose)

load("~/Rdata/cleaned.RData")

library(class)

attach(cleaned)

load("C:/Users/Pidory/Desktop/Projet_mahmoud_with_Min Max (1).RData")

load("C:/Users/Pidory/Desktop/Projet_mahmoud_with_Min Max (1).RData")

str(adult)

summary(adult)

adult$occupation [3,]
```

```
adult$occupation [2,]

adult$occupation

hist(adult$capitalgain)

str(adult)

hist(adult$capital.gain)

str(adult)

adult$workclass=NULL

adult$education=NULL

adult$marital.status=NULL

adult$occupation=NULL

adult$relationship=NULL

adult$race=NULL

adult$sex=NULL

adult$native.country=NULL

adult$income.class=as.factor(income.class)

adult$income.class=as.factor(adult$income.class)

str(adult)

estincome.class=knn.cv(adult[,-7], adult[,7], 5)

estincome.class


> t1=table(income.class, estincome.class)

> str(adult)

str(adult)

adult$workclass=NULL

adult$education=NULL

adult$marital.status=NULL

adult$occupation=NULL

adult$relationship=NULL

adult$race=NULL

adult$sex=NULL

adult$native.country=NULL

adult$income.class=as.factor(income.class)
```

```
adult$income.class=as.factor(adult$income.class)

str(adult)

estincome.class=knn.cv(adult[,-7], adult[,7], 5)

estincome.class

str(adult)

adult$workclass=NULL

adult$education=NULL

adult$marital.status=NULL

adult$occupation=NULL

adult$relationship=NULL

adult$race=NULL

adult$sex=NULL

adult$native.country=NULL

adult$income.class=as.factor(income.class)

adult$income.class=as.factor(adult$income.class)

str(adult)

estincome.class=knn.cv(adult[,-7], adult[,7], 5)

knn?

help knn

library(class)

adult$income.class=as.factor(income.class)

hist(adult)

estincome.class=knn.cv(adult[,-7], adult[,7], 5)

estincome.class

t1=table(income.class, estincome.class)

t1=table(income.class, estincome.class)

str(adult)

estincome.class=knn.cv(adult[,-7], adult[,7], 5)

t1=table(income.class, estincome.class)

adult = read.csv("adult.csv", header = TRUE)

attach(adult)

str(adult)
```

```
summary(adult)

table(workclass)

table(occupation)

table(native.country)

adult$workclass = as.character(adult$workclass)

adult$workclass[adult$workclass==" ?"] = as.character(sample(adult$workclass[which(adult$workclass !=" ?")], 963, replace = FALSE))

adult$workclass = as.factor(adult$workclass)

unique(adult$workclass)

adult$occupation = as.character(adult$occupation)

adult$occupation[adult$occupation==" ?"] = as.character(sample(occupation[which(adult$occupation !=" ?")], 966, replace = FALSE))

adult$occupation = as.factor(adult$occupation)

unique(adult$occupation)

adult$native.country = as.character(adult$native.country)

adult$native.country[adult$native.country==" ?"] = as.character(sample(adult$native.country[which(adult$native.country !=" ?")], 274,
replace = FALSE))

adult$native.country = as.factor(adult$native.country)

unique(adult$native.country)

str(adult)

summary(adult)
```

[i] http://archive.ics.uci.edu/ml/machine-learning-databases/adult/adult.names