Case Study Final

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reading the dataset

```
German <- read.csv("C:/Users/sruth/Desktop/first sem/BAN 620/Final
Exam/GermanCredit.csv")
missing(German) #dataset is checking for any other missing values

## [1] FALSE

View(German)
str(German)

## 'data.frame':    1000 obs. of  32 variables:
##  $ OBS.           : int  1 2 3 4 5 6 7 8 9 10 ...
##  $ CHK_ACCT       : int  0 1 3 0 0 3 3 1 3 1 ...
##  $ DURATION       : int  6 48 12 42 24 36 24 36 12 30 ...
##  $ HISTORY        : int  4 2 4 2 3 2 2 2 2 4 ...
##  $ NEW_CAR        : int  0 0 0 0 1 0 0 0 0 1 ...
##  $ USED_CAR       : int  0 0 0 0 0 0 0 1 0 0 ...
##  $ FURNITURE      : int  0 0 0 1 0 0 1 0 0 0 ...
##  $ RADIO.TV       : int  1 1 0 0 0 0 0 0 1 0 ...
##  $ EDUCATION      : int  0 0 1 0 0 1 0 0 0 0 ...
##  $ RETRAINING     : int  0 0 0 0 0 0 0 0 0 0 ...
##  $ AMOUNT         : int  1169 5951 2096 7882 4870 9055 2835 6948 3059
5234 ...
##  $ SAV_ACCT       : int  4 0 0 0 0 4 2 0 3 0 ...
##  $ EMPLOYMENT     : int  4 2 3 3 2 2 4 2 3 0 ...
##  $ INSTALL_RATE   : int  4 2 2 2 3 2 3 2 2 4 ...
##  $ MALE_DIV       : int  0 0 0 0 0 0 0 0 1 0 ...
##  $ MALE_SINGLE    : int  1 0 1 1 1 1 1 1 0 0 ...
##  $ MALE_MAR_or_WID : int  0 0 0 0 0 0 0 0 0 1 ...
##  $ CO.APPLICANT   : int  0 0 0 0 0 0 0 0 0 0 ...
##  $ GUARANTOR      : int  0 0 0 1 0 0 0 0 0 0 ...
##  $ PRESENT_RESIDENT: int  4 2 3 4 4 4 4 2 4 2 ...
##  $ REAL_ESTATE    : int  1 1 1 0 0 0 0 0 1 0 ...
##  $ PROP_UNKN_NONE : int  0 0 0 0 1 1 0 0 0 0 ...
##  $ AGE            : int  67 22 49 45 53 35 53 35 61 28 ...
##  $ OTHER_INSTALL  : int  0 0 0 0 0 0 0 0 0 0 ...
##  $ RENT           : int  0 0 0 0 0 0 0 1 0 0 ...
##  $ OWN_RES        : int  1 1 1 0 0 0 1 0 1 1 ...
##  $ NUM_CREDITS    : int  2 1 1 1 2 1 1 1 1 2 ...
##  $ JOB            : int  2 2 1 2 2 1 2 3 1 3 ...
##  $ NUM_DEPENDENTS : int  1 1 2 2 2 2 1 1 1 1 ...
##  $ TELEPHONE      : int  1 0 0 0 0 1 0 1 0 0 ...
```

```
##  $ FOREIGN          : int  0 0 0 0 0 0 0 0 0 0 ...
##  $ RESPONSE         : int  1 0 1 1 0 1 1 1 1 0 ...
```

Question 1. Review the predictor variables and guess what their role in a credit decision might be. Are there any surprise in the data?

```
German$PRESENT_RESIDENT <- German$PRESENT_RESIDENT - 1
German <- German[,c(-1,-22)]

German$ANOTHER_OBJECTIVE <-
ifelse(German$NEW_CAR+German$USED_CAR+German$FURNITURE+German$RADIO.TV+German
$EDUCATION+German$RETRAINING==0, 1, 0)

German$Female <-
ifelse(German$MALE_DIV+German$MALE_MAR_or_WID+German$MALE_SINGLE==0, 1, 0)

German$PRESENT_RESIDENT <- factor(German$PRESENT_RESIDENT, levels = c(0, 1,
2, 3), labels=c("<=1-year","1-2years","2-3years",">=3years"))

German$EMPLOYMENT <- factor(German$EMPLOYMENT, levels = c(0,1,2,3,4), labels
= c("Unemployed", "1years","1-3years","4-6year",">=7years"))

German$JOB <- factor(German$JOB, levels = c(0, 1, 2, 3),
labels=c("Uemployed","Unskilled-employee","Skilled-employee","highly
qualified employee/self employed"))

German$CHK_ACCT <- factor(German$CHK_ACCT, levels=c(0,1,2,3), labels =
c("<0DM","0-200DM","200DM","No_checking_Acct"))

German$HISTORY <- factor(German$HISTORY, levels = c(0,1,2,3,4), labels =
c("No_Credits","Paid","Existing_Paid","Unpaid","Important_Acct"))

German$SAV_ACCT <- factor(German$SAV_ACCT, levels=c(0,1,2,3,4), labels =
c("<100DM","101-500DM","501-1000DM","1000DM","No_Saving_Acct"))

New_German <- German
head(German)

##           CHK_ACCT DURATION        HISTORY NEW_CAR USED_CAR FURNITURE
## 1             <0DM        6 Important_Acct       0        0         0
## 2          0-200DM       48  Existing_Paid       0        0         0
## 3 No_checking_Acct       12 Important_Acct       0        0         0
## 4             <0DM       42  Existing_Paid       0        0         1
## 5             <0DM       24         Unpaid       1        0         0
## 6 No_checking_Acct       36  Existing_Paid       0        0         0
##   RADIO.TV EDUCATION RETRAINING AMOUNT       SAV_ACCT EMPLOYMENT
## 1        1         0          0   1169 No_Saving_Acct   >=7years
## 2        1         0          0   5951         <100DM   1-3years
```

```
## 3        0         1          0   2096         <100DM    4-6year
## 4        0         0          0   7882         <100DM    4-6year
## 5        0         0          0   4870         <100DM   1-3years
## 6        0         1          0   9055 No_Saving_Acct   1-3years
##   INSTALL_RATE MALE_DIV MALE_SINGLE MALE_MAR_or_WID CO.APPLICANT GUARANTOR
## 1            4        0           1               0            0         0
## 2            2        0           0               0            0         0
## 3            2        0           1               0            0         0
## 4            2        0           1               0            0         1
## 5            3        0           1               0            0         0
## 6            2        0           1               0            0         0
##   PRESENT_RESIDENT REAL_ESTATE AGE OTHER_INSTALL RENT OWN_RES NUM_CREDITS
## 1         >=3years           1  67             0    0       1           2
## 2         1-2years           1  22             0    0       1           1
## 3         2-3years           1  49             0    0       1           1
## 4         >=3years           0  45             0    0       0           1
## 5         >=3years           0  53             0    0       0           2
## 6         >=3years           0  35             0    0       0           1
##                  JOB NUM_DEPENDENTS TELEPHONE FOREIGN RESPONSE
## 1   Skilled-employee              1         1       0        1
## 2   Skilled-employee              1         0       0        0
## 3 Unskilled-employee              2         0       0        1
## 4   Skilled-employee              2         0       0        1
## 5   Skilled-employee              2         0       0        0
## 6 Unskilled-employee              2         1       0        1
##   ANOTHER_OBJECTIVE Female
## 1                 0      0
## 2                 0      1
## 3                 0      0
## 4                 0      0
## 5                 0      0
## 6                 0      0
```

```
head(New_German)
```

```
##         CHK_ACCT DURATION        HISTORY NEW_CAR USED_CAR FURNITURE
## 1            <0DM        6 Important_Acct       0        0         0
## 2          0-200DM      48  Existing_Paid       0        0         0
## 3 No_checking_Acct      12 Important_Acct       0        0         0
## 4            <0DM       42  Existing_Paid       0        0         1
## 5            <0DM       24         Unpaid       1        0         0
## 6 No_checking_Acct      36  Existing_Paid       0        0         0
##   RADIO.TV EDUCATION RETRAINING AMOUNT       SAV_ACCT EMPLOYMENT
## 1        1         0          0   1169 No_Saving_Acct   >=7years
## 2        1         0          0   5951         <100DM   1-3years
## 3        0         1          0   2096         <100DM    4-6year
## 4        0         0          0   7882         <100DM    4-6year
## 5        0         0          0   4870         <100DM   1-3years
## 6        0         1          0   9055 No_Saving_Acct   1-3years
##   INSTALL_RATE MALE_DIV MALE_SINGLE MALE_MAR_or_WID CO.APPLICANT GUARANTOR
```

```
## 1              4        0           1               0             0          0
## 2              2        0           0               0             0          0
## 3              2        0           1               0             0          0
## 4              2        0           1               0             0          1
## 5              3        0           1               0             0          0
## 6              2        0           1               0             0          0
##   PRESENT_RESIDENT REAL_ESTATE AGE OTHER_INSTALL RENT OWN_RES NUM_CREDITS
## 1         >=3years           1  67             0    0       1           2
## 2         1-2years           1  22             0    0       1           1
## 3         2-3years           1  49             0    0       1           1
## 4         >=3years           0  45             0    0       0           1
## 5         >=3years           0  53             0    0       0           2
## 6         >=3years           0  35             0    0       0           1
##                  JOB NUM_DEPENDENTS TELEPHONE FOREIGN RESPONSE
## 1   Skilled-employee              1         1       0        1
## 2   Skilled-employee              1         0       0        0
## 3 Unskilled-employee              2         0       0        1
## 4   Skilled-employee              2         0       0        1
## 5   Skilled-employee              2         0       0        0
## 6 Unskilled-employee              2         1       0        1
##   ANOTHER_OBJECTIVE Female
## 1                 0      0
## 2                 0      1
## 3                 0      0
## 4                 0      0
## 5                 0      0
## 6                 0      0
```

```
library(dplyr)
```

```
##
## Attaching package: 'dplyr'

## The following objects are masked from 'package:stats':
##
##     filter, lag

## The following objects are masked from 'package:base':
##
##     intersect, setdiff, setequal, union
```

```
AMOUNT.mean = German %>% dplyr::select(AMOUNT,RESPONSE) %>%
group_by(RESPONSE) %>% summarise(m =mean(AMOUNT))
AMOUNT.mean
```

```
## # A tibble: 2 x 2
##   RESPONSE     m
##      <int> <dbl>
## 1        0 3938.
## 2        1 2985.
```

```
DURATION.mean = German %>% dplyr::select(DURATION,RESPONSE)
%>%group_by(RESPONSE) %>% summarise( m =mean(DURATION))
DURATION.mean
```

```
## # A tibble: 2 x 2
##   RESPONSE     m
##      <int> <dbl>
## 1        0  24.9
## 2        1  19.2
```

```
INSTALL_RATE.median = German %>% dplyr::select(INSTALL_RATE,RESPONSE)
%>%group_by(RESPONSE) %>% summarise( m =median(INSTALL_RATE))
INSTALL_RATE.median
```

```
## # A tibble: 2 x 2
##   RESPONSE     m
##      <int> <dbl>
## 1        0     4
## 2        1     3
```

```
AGE.median = German %>% dplyr::select(AGE,RESPONSE) %>%group_by(RESPONSE) %>%
summarise( m =median(AGE))
AGE.median
```

```
## # A tibble: 2 x 2
##   RESPONSE     m
##      <int> <dbl>
## 1        0    31
## 2        1    34
```

In this case, classification problem is there which is the target variable of response column. In this dataset there were 4 categories in Present_Resident so one has to be substracted in order to have 0 to 3 levels. Real_estate and Prop_Unkn_none- either of them can be 0 but cannot be 0 at the same time. the Another-objective option is need and should be added to the data set. So the Female option has been added. At the end of this chunk, meadian values for bad records is lesser than that of good records in age variable, it might be premature to say young people tend to have bad credit records, but we can safely assume it tends to be riskier. In case of installment_rate variable great difference between the good and bad records, we see that bad records have more median value than good ones.For the amount variable, we observe that the amount for bad records is larger in general as compared to good ones.

#Question 2. Divide the data into trainning and validatin partitions, and develop classification models using following data mining techniques in R: logistic regression, classification trees, and neural networks.

#Question 3.Choose one modelfrom each technique and report the confusion matrix and the cost/gain matrix for the validation data. Which technique has the highest net profit?

```
#creating model for logistic regression
set.seed(2)
dim(German)

## [1] 1000   32

train1_rows <- sample(c(1:1000), 800) #first 1000 rows
train1_data <- German[train1_rows,]#training data
valid1_data <- German[-train1_rows,]#test data

#logistic regression model
g <- glm(RESPONSE~., data = train1_data, family="binomial") #logistic model
was created
options(scipen = 999)
summary(g) #summary of the model

##
## Call:
## glm(formula = RESPONSE ~ ., family = "binomial", data = train1_data)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -2.8202  -0.5702   0.3339   0.6433   2.6268
##
## Coefficients: (2 not defined because of singularities)
##                                               Estimate  Std. Error z value
## (Intercept)                                 2.11214477  1.20608385   1.751
## CHK_ACCT0-200DM                             0.29107351  0.26019593   1.119
## CHK_ACCT200DM                               0.83669433  0.40974880   2.042
## CHK_ACCTNo_checking_Acct                    1.74864373  0.27114315   6.449
## DURATION                                   -0.04129844  0.01096185  -3.767
## HISTORYPaid                                -0.53216904  0.64625498  -0.823
## HISTORYExisting_Paid                        0.45262152  0.52563200   0.861
## HISTORYUnpaid                               0.93837640  0.57996762   1.618
## HISTORYImportant_Acct                       1.74311947  0.55201223   3.158
## NEW_CAR                                    -1.21943853  0.44985977  -2.711
## USED_CAR                                    0.28640087  0.55961942   0.512
## FURNITURE                                  -0.50103443  0.46516888  -1.077
## RADIO.TV                                   -0.26949220  0.45286263  -0.595
## EDUCATION                                  -1.71204797  0.58389101  -2.932
## RETRAINING                                 -0.62627216  0.50930540  -1.230
## AMOUNT                                     -0.00009651  0.00005174  -1.865
## SAV_ACCT101-500DM                           0.65628338  0.34873255   1.882
## SAV_ACCT501-1000DM                          0.08790008  0.41729739   0.211
## SAV_ACCT1000DM                              1.52075531  0.59928769   2.538
## SAV_ACCTNo_Saving_Acct                      1.27755014  0.31641209   4.038
## EMPLOYMENT1years                            0.55675493  0.51244797   1.086
## EMPLOYMENT1-3years                          0.91584377  0.49825398   1.838
## EMPLOYMENT4-6year                           1.48245532  0.53767085   2.757
## EMPLOYMENT>=7years                          0.95716512  0.49695760   1.926
```

```
## INSTALL_RATE                                  -0.32647427  0.10327849  -3.161
## MALE_DIV                                      -0.49739632  0.46739684  -1.064
## MALE_SINGLE                                    0.47954953  0.24332160   1.971
## MALE_MAR_or_WID                                0.29487588  0.37460866   0.787
## CO.APPLICANT                                  -0.52781097  0.47492591  -1.111
## GUARANTOR                                      1.60909207  0.53569671   3.004
## PRESENT_RESIDENT1-2years                      -0.89870048  0.34755735  -2.586
## PRESENT_RESIDENT2-3years                      -0.60297426  0.39077102  -1.543
## PRESENT_RESIDENT>=3years                      -0.36738986  0.35719395  -1.029
## REAL_ESTATE                                    0.24298658  0.24930449   0.975
## AGE                                            0.01465486  0.01081263   1.355
## OTHER_INSTALL                                 -0.50768698  0.24671306  -2.058
## RENT                                           0.06479400  0.41056146   0.158
## OWN_RES                                        0.39652354  0.35390425   1.120
## NUM_CREDITS                                   -0.57066899  0.22981372  -2.483
## JOBUnskilled-employee                         -0.91072238  0.71230295  -1.279
## JOBSkilled-employee                           -0.77042787  0.68233358  -1.129
## JOBhighly qualified employee/self employed -0.71717781  0.69277231  -1.035
## NUM_DEPENDENTS                                -0.19850678  0.28670864  -0.692
## TELEPHONE                                      0.49001752  0.23544794   2.081
## FOREIGN                                        1.15430233  0.64120810   1.800
## ANOTHER_OBJECTIVE                                      NA          NA      NA
## Female                                                 NA          NA      NA
##                                                  Pr(>|z|)
## (Intercept)                                      0.079904 .
## CHK_ACCT0-200DM                                  0.263281
## CHK_ACCT200DM                                    0.041155 *
## CHK_ACCTNo_checking_Acct                   0.000000000112 ***
## DURATION                                         0.000165 ***
## HISTORYPaid                                      0.410243
## HISTORYExisting_Paid                             0.389183
## HISTORYUnpaid                                    0.105667
## HISTORYImportant_Acct                            0.001590 **
## NEW_CAR                                          0.006714 **
## USED_CAR                                         0.608806
## FURNITURE                                        0.281435
## RADIO.TV                                         0.551786
## EDUCATION                                        0.003366 **
## RETRAINING                                       0.218825
## AMOUNT                                           0.062125 .
## SAV_ACCT101-500DM                                0.059848 .
## SAV_ACCT501-1000DM                               0.833167
## SAV_ACCT1000DM                                   0.011161 *
## SAV_ACCTNo_Saving_Acct                     0.000053997425 ***
## EMPLOYMENT1years                                 0.277275
## EMPLOYMENT1-3years                               0.066047 .
## EMPLOYMENT4-6year                                0.005830 **
## EMPLOYMENT>=7years                               0.054098 .
## INSTALL_RATE                                     0.001572 **
## MALE_DIV                                         0.287245
```

```
## MALE_SINGLE                                       0.048741 *
## MALE_MAR_or_WID                                   0.431190
## CO.APPLICANT                                      0.266416
## GUARANTOR                                         0.002667 **
## PRESENT_RESIDENT1-2years                          0.009716 **
## PRESENT_RESIDENT2-3years                          0.122822
## PRESENT_RESIDENT>=3years                          0.303694
## REAL_ESTATE                                       0.329730
## AGE                                               0.175307
## OTHER_INSTALL                                     0.039609 *
## RENT                                              0.874600
## OWN_RES                                           0.262532
## NUM_CREDITS                                       0.013022 *
## JOBUnskilled-employee                             0.201052
## JOBSkilled-employee                               0.258853
## JOBhighly qualified employee/self employed        0.300562
## NUM_DEPENDENTS                                    0.488709
## TELEPHONE                                         0.037414 *
## FOREIGN                                           0.071829 .
## ANOTHER_OBJECTIVE                                       NA
## Female                                                  NA
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 965.23  on 799  degrees of freedom
## Residual deviance: 671.65  on 755  degrees of freedom
## AIC: 761.65
##
## Number of Fisher Scoring iterations: 5
```

```
pred <- predict(g, valid1_data[,-30], type = "response")#prediction of the
model was done
```

```
## Warning in predict.lm(object, newdata, se.fit, scale = 1, type = if (type
## == : prediction from a rank-deficient fit may be misleading
```

```
library(caret)
```

```
## Loading required package: lattice
```

```
## Loading required package: ggplot2
```

```
library(ggplot2)
confusionMatrix(as.factor(ifelse(pred>0.5, 1, 0)),
as.factor(valid1_data$RESPONSE))#confusion matrix was created
```

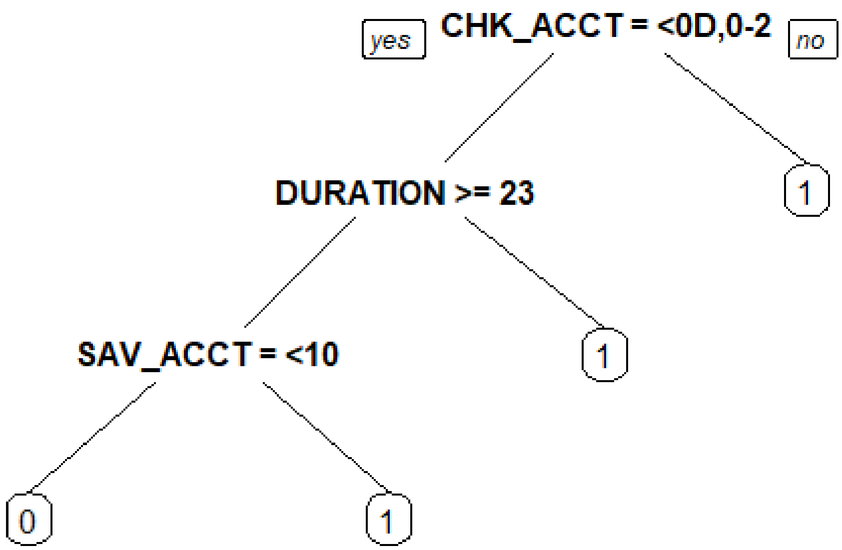
```
## Confusion Matrix and Statistics
##
##           Reference
```

```
## Prediction   0   1
##          0  33  26
##          1  34 107
##
##                Accuracy : 0.7
##                  95% CI : (0.6314, 0.7626)
##     No Information Rate : 0.665
##     P-Value [Acc > NIR] : 0.1652
##
##                   Kappa : 0.3061
##
##  Mcnemar's Test P-Value : 0.3662
##
##             Sensitivity : 0.4925
##             Specificity : 0.8045
##          Pos Pred Value : 0.5593
##          Neg Pred Value : 0.7589
##              Prevalence : 0.3350
##          Detection Rate : 0.1650
##    Detection Prevalence : 0.2950
##       Balanced Accuracy : 0.6485
##
##        'Positive' Class : 0
##
```

Logistic regression model Cost Metrix: Reference Bad Good Predited Bad 0 100*26=2600 Good 34*500=17000 0 Gain Matrix: Reference Bad Good Predicted
Bad 0 0 Good -500*34=-17000 100*107=10700 Logistic Regression model, net profit is -6300.

Classification Tree

```r
library(rpart)
library(rpart.plot)
set.seed(1)
training_rows <- sample(c(1:1000), 800)
train_data_tree <- New_German[training_rows,]
valid_data <- New_German[-training_rows,]

#classification tree model
train_tree <- rpart(RESPONSE ~ ., data = train_data_tree, minbucket = 50,
maxdepth = 10, model=TRUE, method = "class")
train_tree$cptable[which.min(train_tree$cptable[,"xerror"]),"CP"]

## [1] 0.01

pfit_tree <- prune(train_tree, cp =
train_tree$cptable[which.min(train_tree$cptable[,"xerror"]),"CP"])
prp(train_tree)
```




```
# predictions on validation set
pred_valid <- predict(train_tree, valid_data[,-30])
confusionMatrix(as.factor(1*(pred_valid[,2]>0.5)),
as.factor(valid_data$RESPONSE), positive = "1")

## Confusion Matrix and Statistics
##
##            Reference
## Prediction   0   1
##          0  17  11
##          1  50 122
##
##                Accuracy : 0.695
##                  95% CI : (0.6261, 0.758)
##     No Information Rate : 0.665
##     P-Value [Acc > NIR] : 0.2058
##
##                   Kappa : 0.1999
##
##  Mcnemar's Test P-Value : 0.000001142
##
##             Sensitivity : 0.9173
##             Specificity : 0.2537
##          Pos Pred Value : 0.7093
##          Neg Pred Value : 0.6071
##              Prevalence : 0.6650
##          Detection Rate : 0.6100
```

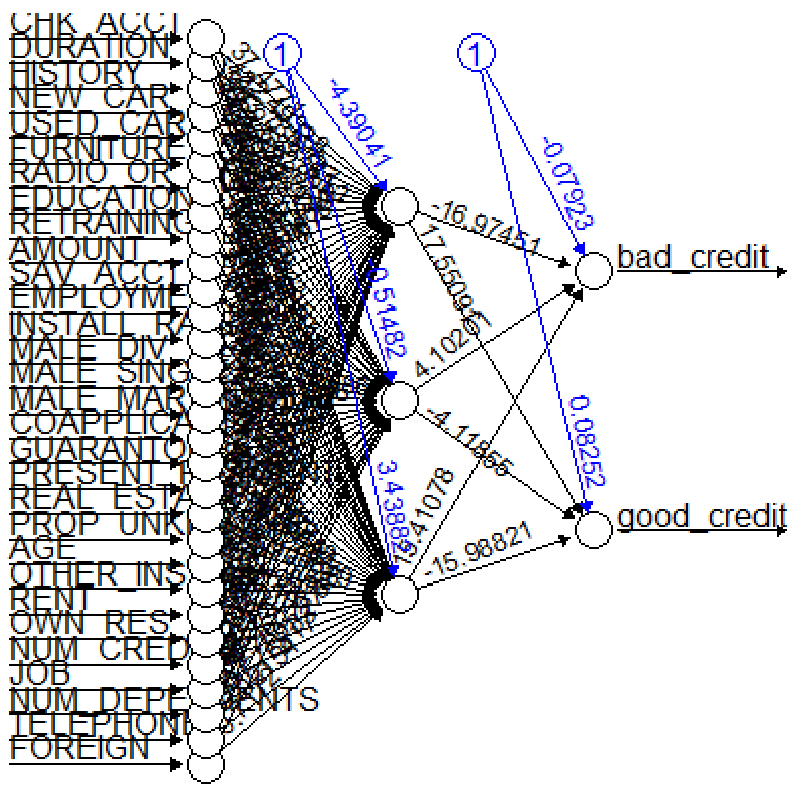
```
##    Detection Prevalence : 0.8600
##       Balanced Accuracy : 0.5855
##
##        'Positive' Class : 1
##
```

Classification tree model, Cost Metrix: Reference Bad Good Predited Bad 0 100*12=1200 Good 48*500=31500 0 Gain Matrix: Reference Bad Good Predicted
Bad 0 0 Good -500*48=-31500 100*121=19200 Classification Tree model, net profit is -12300.

neuralnet model

```
library("neuralnet")

##
## Attaching package: 'neuralnet'

## The following object is masked from 'package:dplyr':
##
##     compute

NN_German <- read.csv("C:/Users/sruth/Desktop/first sem/BAN 620/Final Exam/GermanCredit.csv")
scale <- preProcess(NN_German, method = c("range"))
German_scale <- predict(scale, NN_German)
German_scale$good_credit <- German_scale$RESPONSE == 1
German_scale$bad_credit <- German_scale$RESPONSE == 0

set.seed(1)
training_rows <- sample(c(1:1000), 800)
train_data_nn <- German_scale[training_rows,]
valid_data_nn <- German_scale[-training_rows,]

colnames(train_data_nn)[8] <- "RADIO_OR_TV"
colnames(train_data_nn)[18] <- "COAPPLICANT"
colnames(train_data_nn)

##  [1] "OBS."             "CHK_ACCT"         "DURATION"
##  [4] "HISTORY"          "NEW_CAR"          "USED_CAR"
##  [7] "FURNITURE"        "RADIO_OR_TV"      "EDUCATION"
## [10] "RETRAINING"       "AMOUNT"           "SAV_ACCT"
## [13] "EMPLOYMENT"       "INSTALL_RATE"     "MALE_DIV"
## [16] "MALE_SINGLE"      "MALE_MAR_or_WID"  "COAPPLICANT"
## [19] "GUARANTOR"        "PRESENT_RESIDENT" "REAL_ESTATE"
## [22] "PROP_UNKN_NONE"   "AGE"              "OTHER_INSTALL"
## [25] "RENT"             "OWN_RES"          "NUM_CREDITS"
## [28] "JOB"              "NUM_DEPENDENTS"   "TELEPHONE"
## [31] "FOREIGN"          "RESPONSE"         "good_credit"
## [34] "bad_credit"
```

```
nn <-
neuralnet(bad_credit+good_credit~CHK_ACCT+DURATION+HISTORY+NEW_CAR+USED_CAR+F
URNITURE+RADIO_OR_TV+EDUCATION+RETRAINING+AMOUNT+SAV_ACCT+EMPLOYMENT+INSTALL_
RATE+MALE_DIV+MALE_SINGLE+MALE_MAR_or_WID+COAPPLICANT+GUARANTOR+PRESENT_RESID
ENT+REAL_ESTATE+PROP_UNKN_NONE+AGE+OTHER_INSTALL+RENT+OWN_RES+NUM_CREDITS+JOB
+NUM_DEPENDENTS+TELEPHONE+FOREIGN, data = train_data_nn, linear.output = F,
hidden = 3)

plot(nn, rep="best")
```




```
predict <- neuralnet::compute(nn, valid_data_nn[,2:31])

predicted.class <- apply(predict$net.result,1,which.max)-1
confusionMatrix(as.factor(predicted.class),
as.factor(valid_data_nn$RESPONSE))

## Confusion Matrix and Statistics
##
##           Reference
## Prediction   0   1
##          0  26  19
##          1  41 114
##
##                Accuracy : 0.7
##                  95% CI : (0.6314, 0.7626)
##     No Information Rate : 0.665
##     P-Value [Acc > NIR] : 0.165172
```

```
##
##                   Kappa : 0.267
##
##  Mcnemar's Test P-Value : 0.006706
##
##             Sensitivity : 0.3881
##             Specificity : 0.8571
##          Pos Pred Value : 0.5778
##          Neg Pred Value : 0.7355
##              Prevalence : 0.3350
##          Detection Rate : 0.1300
##    Detection Prevalence : 0.2250
##       Balanced Accuracy : 0.6226
##
##        'Positive' Class : 0
##
```

Neural network model, Cost Metrix: Reference Bad Good Predited Bad 0 100*19=1900 Good 41*500=20500 0 Gain Matrix: Reference Bad Good Predicted Bad 0 0 Good -500*41=-20500 100*114=11400 neuralnet model, net profit is -9100.

So by looking over all the models,the logistic regression model provides the best net profit.