```r
library(ggplot2)
library(caret)
library(rpart)
library(rpart.plot)
library(tree)
library(e1071)
library(kernlab)
library(neuralnet)
library(NeuralNetTools)
library(ROCR)
library(pROC)

G.data<-read.csv("/Users/GERMAN_DATA.csv",
                 header=TRUE)
str(G.data)
```

```
## 'data.frame':    1000 obs. of  21 variables:
##  $ CHK_ACCT_ST          : Factor w/ 4 levels "A11","A12","A13",..: 1 2 4 1
 1 4 4 2 4 2 ...
##  $ DUR                  : int  6 48 12 42 24 36 24 36 12 30 ...
##  $ CRED_HIST            : Factor w/ 5 levels "A30","A31","A32",..: 5 3 5 3
 4 3 3 3 3 5 ...
##  $ PURPOSE              : Factor w/ 10 levels "A40","A41","A410",..: 5 5 8
 4 1 8 4 2 5 1 ...
##  $ CRED_AMT             : int  1169 5951 2096 7882 4870 9055 2835 6948 305
9 5234 ...
##  $ SAV_ACCT_BOND        : Factor w/ 5 levels "A61","A62","A63",..: 5 1 1 1
 1 5 3 1 4 1 ...
##  $ EMPLYMT_ST           : Factor w/ 5 levels "A71","A72","A73",..: 5 3 4 4
 3 3 5 3 4 1 ...
##  $ INST_RT_PER_DISP_INCM: int  4 2 2 2 3 2 3 2 2 4 ...
##  $ PERS_ST_SEX          : Factor w/ 4 levels "A91","A92","A93",..: 3 2 3 3
 3 3 3 3 1 4 ...
##  $ COAPP_GURNTR         : Factor w/ 3 levels "A101","A102",..: 1 1 1 3 1 1
 1 1 1 1 ...
##  $ DUR_RES              : int  4 2 3 4 4 4 4 2 4 2 ...
##  $ PROPERTY             : Factor w/ 4 levels "A121","A122",..: 1 1 1 2 4 4
 2 3 1 3 ...
##  $ AGE                  : int  67 22 49 45 53 35 53 35 61 28 ...
##  $ OTHR_INSTL           : Factor w/ 3 levels "A141","A142",..: 3 3 3 3 3 3
 3 3 3 3 ...
##  $ HOUS_ST              : Factor w/ 3 levels "A151","A152",..: 2 2 2 3 3 3
 2 1 2 2 ...
##  $ NUM_CRED             : int  2 1 1 1 2 1 1 1 1 2 ...
##  $ JOB                  : Factor w/ 4 levels "A171","A172",..: 3 3 2 3 3 2
 3 4 2 4 ...
##  $ NUM_PEOP_LIABL       : int  1 1 2 2 2 2 1 1 1 1 ...
##  $ PHONE                : Factor w/ 2 levels "A191","A192": 2 1 1 1 1 2 1
2 1 1 ...
##  $ FRGN_WORKR           : Factor w/ 2 levels "A201","A202": 1 1 1 1 1 1 1
```

```
1 1 1 ...
##  $ Y                   : int  1 2 1 1 2 1 1 1 1 2 ...

summary(G.data)

##  CHK_ACCT_ST      DUR         CRED_HIST    PURPOSE       CRED_AMT
##  A11:274     Min.   : 4.0   A30: 40   A43    :280   Min.   :  250
##  A12:269     1st Qu.:12.0   A31: 49   A40    :234   1st Qu.: 1366
##  A13: 63     Median :18.0   A32:530   A42    :181   Median : 2320
##  A14:394     Mean   :20.9   A33: 88   A41    :103   Mean   : 3271
##              3rd Qu.:24.0   A34:293   A49    : 97   3rd Qu.: 3972
##              Max.   :72.0             A46    : 50   Max.   :18424
##                                       (Other): 55
##  SAV_ACCT_BOND EMPLYMT_ST INST_RT_PER_DISP_INCM PERS_ST_SEX COAPP_GURNTR
##  A61:603       A71: 62    Min.   :1.000         A91: 50     A101:907
##  A62:103       A72:172    1st Qu.:2.000         A92:310     A102: 41
##  A63: 63       A73:339    Median :3.000         A93:548     A103: 52
##  A64: 48       A74:174    Mean   :2.973         A94: 92
##  A65:183       A75:253    3rd Qu.:4.000
##                           Max.   :4.000
##
##     DUR_RES      PROPERTY        AGE        OTHR_INSTL HOUS_ST
##  Min.   :1.000   A121:282   Min.   :19.00   A141:139   A151:179
##  1st Qu.:2.000   A122:232   1st Qu.:27.00   A142: 47   A152:713
##  Median :3.000   A123:332   Median :33.00   A143:814   A153:108
##  Mean   :2.845   A124:154   Mean   :35.55
##  3rd Qu.:4.000              3rd Qu.:42.00
##  Max.   :4.000              Max.   :75.00
##
##     NUM_CRED       JOB      NUM_PEOP_LIABL   PHONE     FRGN_WORKR       Y

##  Min.   :1.000   A171: 22   Min.   :1.000   A191:596   A201:963   Min.   :
1.0
##  1st Qu.:1.000   A172:200   1st Qu.:1.000   A192:404   A202: 37   1st Qu.:
1.0
##  Median :1.000   A173:630   Median :1.000                         Median :
1.0
##  Mean   :1.407   A174:148   Mean   :1.155                         Mean   :
1.3
##  3rd Qu.:2.000              3rd Qu.:1.000                         3rd Qu.:
2.0
##  Max.   :4.000              Max.   :2.000                         Max.   :
2.0
##

G.data$DUR<-as.numeric(G.data$DUR)
G.data$CRED_AMT<-as.numeric(G.data$CRED_AMT)
G.data$INST_RT_PER_DISP_INCM<-as.numeric(G.data$INST_RT_PER_DISP_INCM)
G.data$DUR_RES<-as.numeric(G.data$DUR_RES)
G.data$AGE<-as.numeric(G.data$AGE)
```

```
G.data$NUM_CRED<-as.numeric(G.data$NUM_CRED)
G.data$NUM_PEOP_LIABL<-as.numeric(G.data$NUM_PEOP_LIABL)
G.data$Y<-as.factor(G.data$Y)

sapply(G.data, function(x) sum(is.na(x)))
```

```
##           CHK_ACCT_ST                   DUR             CRED_HIST
##                     0                     0                     0
##               PURPOSE              CRED_AMT         SAV_ACCT_BOND
##                     0                     0                     0
##            EMPLYMT_ST INST_RT_PER_DISP_INCM           PERS_ST_SEX
##                     0                     0                     0
##          COAPP_GURNTR               DUR_RES              PROPERTY
##                     0                     0                     0
##                   AGE            OTHR_INSTL              HOUS_ST
##                     0                     0                     0
##              NUM_CRED                   JOB        NUM_PEOP_LIABL
##                     0                     0                     0
##                 PHONE            FRGN_WORKR                     Y
##                     0                     0                     0
```

```
# split data into training and test sets
set.seed(800)
index <- 1:nrow(G.data)
test_set_index <- sample(index, trunc(length(index)/3))
test_set <- G.data[test_set_index,]
train_set <- G.data[-test_set_index,]
train_set1 <- G.data[-test_set_index,]

# determine the max/min from the training set
d_max <- sapply(train_set[,c(2,5,8,11,13,16,18)], max)
d_min <- sapply(train_set[,c(2,5,8,11,13,16,18)], min)

# normalize the data to [0,1] use rescale function of scales package

# function for rescale the columns based on the training set max/min
rescale <- function(dat, d_min, d_max) {
  c <- ncol(dat)
  for (i in 1:c) {
    dat[,i] <- sapply(dat[,i], function(x) (x - d_min[i])/(d_max[i] - d_min[i
]))
  }
  return (dat)
}

# normalize the training/testing set
train_set[,c(2,5,8,11,13,16,18)] <- rescale(train_set[,c(2,5,8,11,13,16,18)],
 d_min, d_max)
test_set[,c(2,5,8,11,13,16,18)] <- rescale(test_set[,c(2,5,8,11,13,16,18)], d
_min, d_max)
```

```r
# Logistic Regression Model
log_fit1 <- train(Y~., data=train_set, method="glm", family="binomial")

summary(log_fit1)
```

```
##
## Call:
## NULL
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -2.1721  -0.6954  -0.3621   0.7162   2.6803
##
## Coefficients:
##                       Estimate Std. Error z value Pr(>|z|)
## (Intercept)            0.54252    1.28725   0.421 0.673423
## CHK_ACCT_STA12        -0.56660    0.27273  -2.077 0.037756 *
## CHK_ACCT_STA13        -1.18573    0.47393  -2.502 0.012352 *
## CHK_ACCT_STA14        -1.87698    0.29384  -6.388 1.68e-10 ***
## DUR                    1.55806    0.77860   2.001 0.045381 *
## CRED_HISTA31           0.15717    0.68800   0.228 0.819298
## CRED_HISTA32          -0.54026    0.54328  -0.994 0.320010
## CRED_HISTA33          -0.62625    0.57995  -1.080 0.280220
## CRED_HISTA34          -1.22520    0.53807  -2.277 0.022785 *
## PURPOSEA41            -1.64968    0.47894  -3.444 0.000572 ***
## PURPOSEA410           -0.68814    0.81065  -0.849 0.395951
## PURPOSEA42            -1.00982    0.33602  -3.005 0.002654 **
## PURPOSEA43            -0.89454    0.30958  -2.890 0.003858 **
## PURPOSEA44            -0.24180    0.76841  -0.315 0.753008
## PURPOSEA45            -0.17377    0.67317  -0.258 0.796301
## PURPOSEA46             0.27010    0.49799   0.542 0.587554
## PURPOSEA48            -2.32235    1.33729  -1.737 0.082457 .
## PURPOSEA49            -0.58741    0.40182  -1.462 0.143771
## CRED_AMT               1.76120    0.96808   1.819 0.068869 .
## SAV_ACCT_BONDA62      -0.64374    0.36922  -1.744 0.081244 .
## SAV_ACCT_BONDA63      -1.11515    0.56701  -1.967 0.049217 *
## SAV_ACCT_BONDA64      -1.32455    0.58407  -2.268 0.023342 *
## SAV_ACCT_BONDA65      -1.17164    0.32713  -3.582 0.000342 ***
## EMPLYMT_STA72         -0.18383    0.54978  -0.334 0.738096
## EMPLYMT_STA73         -0.29918    0.53181  -0.563 0.573731
## EMPLYMT_STA74         -0.56412    0.57329  -0.984 0.325116
## EMPLYMT_STA75          0.06347    0.53331   0.119 0.905265
## INST_RT_PER_DISP_INCM  0.53868    0.33081   1.628 0.103441
## PERS_ST_SEXA92        -0.42360    0.47689  -0.888 0.374402
## PERS_ST_SEXA93        -0.83222    0.47485  -1.753 0.079667 .
## PERS_ST_SEXA94         0.10197    0.56205   0.181 0.856030
## COAPP_GURNTRA102       0.01857    0.51516   0.036 0.971252
## COAPP_GURNTRA103      -0.86363    0.49838  -1.733 0.083120 .
## DUR_RES                0.13028    0.32519   0.401 0.688704
## PROPERTYA122           0.48987    0.31961   1.533 0.125341
```

```
## PROPERTYA123           0.39319    0.29648   1.326 0.184780
## PROPERTYA124           1.20818    0.56079   2.154 0.031205 *
## AGE                   -1.55415    0.63953  -2.430 0.015093 *
## OTHR_INSTLA142         0.54688    0.52356   1.045 0.296239
## OTHR_INSTLA143        -0.25168    0.29864  -0.843 0.399380
## HOUS_STA152           -0.30417    0.29647  -1.026 0.304903
## HOUS_STA153           -0.83819    0.62275  -1.346 0.178323
## NUM_CRED               0.30724    0.80317   0.383 0.702063
## JOBA172                1.14655    0.95647   1.199 0.230636
## JOBA173                1.18793    0.93054   1.277 0.201742
## JOBA174                1.46394    0.92334   1.585 0.112854
## NUM_PEOP_LIABL         0.45206    0.31389   1.440 0.149810
## PHONEA192             -0.31518    0.24771  -1.272 0.203239
## FRGN_WORKRA202        -1.00380    0.69100  -1.453 0.146315
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 813.02  on 666  degrees of freedom
## Residual deviance: 592.12  on 618  degrees of freedom
## AIC: 690.12
##
## Number of Fisher Scoring iterations: 5

# Prediction
pred<-predict(log_fit1, newdata=test_set)

confusionMatrix(pred,test_set$Y)

## Confusion Matrix and Statistics
##
##           Reference
## Prediction   1   2
##          1 203  54
##          2  29  47
##
##                Accuracy : 0.7508
##                  95% CI : (0.7007, 0.7963)
##     No Information Rate : 0.6967
##     P-Value [Acc > NIR] : 0.01719
##
##                   Kappa : 0.3659
##
##  Mcnemar's Test P-Value : 0.00843
##
##             Sensitivity : 0.8750
##             Specificity : 0.4653
##          Pos Pred Value : 0.7899
##          Neg Pred Value : 0.6184
```

```
##              Prevalence : 0.6967
##          Detection Rate : 0.6096
##    Detection Prevalence : 0.7718
##       Balanced Accuracy : 0.6702
##
##        'Positive' Class : 1
##
```

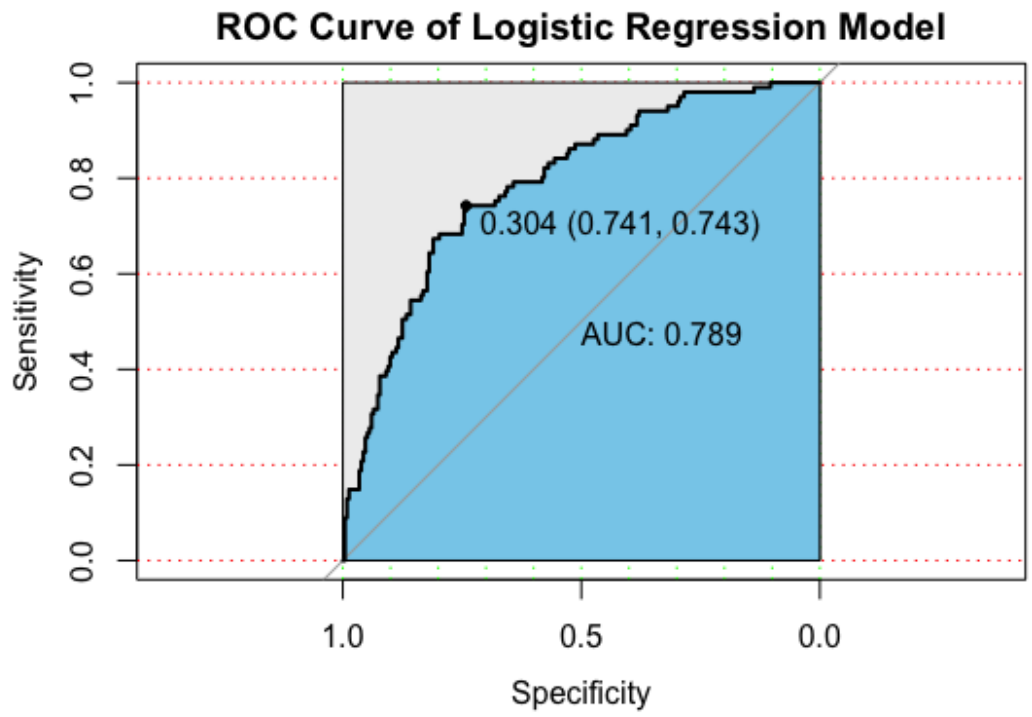
```
# 10-Fold Cross Validation:
ctrl <- trainControl(method = "repeatedcv", number = 10, savePredictions = TR
UE)

log_fit2 <- train(Y~.,data=train_set, method="glm", family="binomial",
                  trControl = ctrl, tuneLength = 5)

summary(log_fit2)
```

```
##
## Call:
## NULL
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -2.1721  -0.6954  -0.3621   0.7162   2.6803
##
## Coefficients:
##                       Estimate Std. Error z value Pr(>|z|)
## (Intercept)            0.54252    1.28725   0.421 0.673423
## CHK_ACCT_STA12        -0.56660    0.27273  -2.077 0.037756 *
## CHK_ACCT_STA13        -1.18573    0.47393  -2.502 0.012352 *
## CHK_ACCT_STA14        -1.87698    0.29384  -6.388 1.68e-10 ***
## DUR                    1.55806    0.77860   2.001 0.045381 *
## CRED_HISTA31           0.15717    0.68800   0.228 0.819298
## CRED_HISTA32          -0.54026    0.54328  -0.994 0.320010
## CRED_HISTA33          -0.62625    0.57995  -1.080 0.280220
## CRED_HISTA34          -1.22520    0.53807  -2.277 0.022785 *
## PURPOSEA41            -1.64968    0.47894  -3.444 0.000572 ***
## PURPOSEA410           -0.68814    0.81065  -0.849 0.395951
## PURPOSEA42            -1.00982    0.33602  -3.005 0.002654 **
## PURPOSEA43            -0.89454    0.30958  -2.890 0.003858 **
## PURPOSEA44            -0.24180    0.76841  -0.315 0.753008
## PURPOSEA45            -0.17377    0.67317  -0.258 0.796301
## PURPOSEA46             0.27010    0.49799   0.542 0.587554
## PURPOSEA48            -2.32235    1.33729  -1.737 0.082457 .
## PURPOSEA49            -0.58741    0.40182  -1.462 0.143771
## CRED_AMT               1.76120    0.96808   1.819 0.068869 .
## SAV_ACCT_BONDA62      -0.64374    0.36922  -1.744 0.081244 .
## SAV_ACCT_BONDA63      -1.11515    0.56701  -1.967 0.049217 *
## SAV_ACCT_BONDA64      -1.32455    0.58407  -2.268 0.023342 *
## SAV_ACCT_BONDA65      -1.17164    0.32713  -3.582 0.000342 ***
```

```
## EMPLYMT_STA72          -0.18383    0.54978  -0.334 0.738096
## EMPLYMT_STA73          -0.29918    0.53181  -0.563 0.573731
## EMPLYMT_STA74          -0.56412    0.57329  -0.984 0.325116
## EMPLYMT_STA75           0.06347    0.53331   0.119 0.905265
## INST_RT_PER_DISP_INCM   0.53868    0.33081   1.628 0.103441
## PERS_ST_SEXA92         -0.42360    0.47689  -0.888 0.374402
## PERS_ST_SEXA93         -0.83222    0.47485  -1.753 0.079667 .
## PERS_ST_SEXA94          0.10197    0.56205   0.181 0.856030
## COAPP_GURNTRA102        0.01857    0.51516   0.036 0.971252
## COAPP_GURNTRA103       -0.86363    0.49838  -1.733 0.083120 .
## DUR_RES                 0.13028    0.32519   0.401 0.688704
## PROPERTYA122            0.48987    0.31961   1.533 0.125341
## PROPERTYA123            0.39319    0.29648   1.326 0.184780
## PROPERTYA124            1.20818    0.56079   2.154 0.031205 *
## AGE                    -1.55415    0.63953  -2.430 0.015093 *
## OTHR_INSTLA142          0.54688    0.52356   1.045 0.296239
## OTHR_INSTLA143         -0.25168    0.29864  -0.843 0.399380
## HOUS_STA152            -0.30417    0.29647  -1.026 0.304903
## HOUS_STA153            -0.83819    0.62275  -1.346 0.178323
## NUM_CRED                0.30724    0.80317   0.383 0.702063
## JOBA172                 1.14655    0.95647   1.199 0.230636
## JOBA173                 1.18793    0.93054   1.277 0.201742
## JOBA174                 1.46394    0.92334   1.585 0.112854
## NUM_PEOP_LIABL          0.45206    0.31389   1.440 0.149810
## PHONEA192              -0.31518    0.24771  -1.272 0.203239
## FRGN_WORKRA202         -1.00380    0.69100  -1.453 0.146315
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 813.02  on 666  degrees of freedom
## Residual deviance: 592.12  on 618  degrees of freedom
## AIC: 690.12
##
## Number of Fisher Scoring iterations: 5

# Prediction
pred <- predict(log_fit2, newdata=test_set)
confusionMatrix(data=pred, test_set$Y)

## Confusion Matrix and Statistics
##
##           Reference
## Prediction   1   2
##          1 203  54
##          2  29  47
##
##                Accuracy : 0.7508
##                  95% CI : (0.7007, 0.7963)
```

```
##     No Information Rate : 0.6967
##     P-Value [Acc > NIR] : 0.01719
##
##                   Kappa : 0.3659
##
##  Mcnemar's Test P-Value : 0.00843
##
##             Sensitivity : 0.8750
##             Specificity : 0.4653
##          Pos Pred Value : 0.7899
##          Neg Pred Value : 0.6184
##              Prevalence : 0.6967
##          Detection Rate : 0.6096
##    Detection Prevalence : 0.7718
##       Balanced Accuracy : 0.6702
##
##        'Positive' Class : 1
##
```

```
t1<-table(data=pred, test_set$Y)
log_acc<-(t1[1,1]+t1[2,2])/(t1[1,1]+t1[2,2]+t1[1,2]+t1[2,1])
log_spec<-t1[2,2]/(t1[1,2]+t1[2,2])

# Logistic ROC curve
log.predd <- predict(log_fit2, type='prob',test_set, probability = TRUE)

modelroc <- roc(test_set$Y,log.predd[,2])
plot(modelroc, type="S",print.auc=TRUE, auc.polygon=TRUE, grid=c(0.1, 0.2),
     grid.col=c("green", "red"), max.auc.polygon=TRUE,
     auc.polygon.col="skyblue", print.thres=TRUE, main="ROC Curve of Logistic
 Regression Model")
```

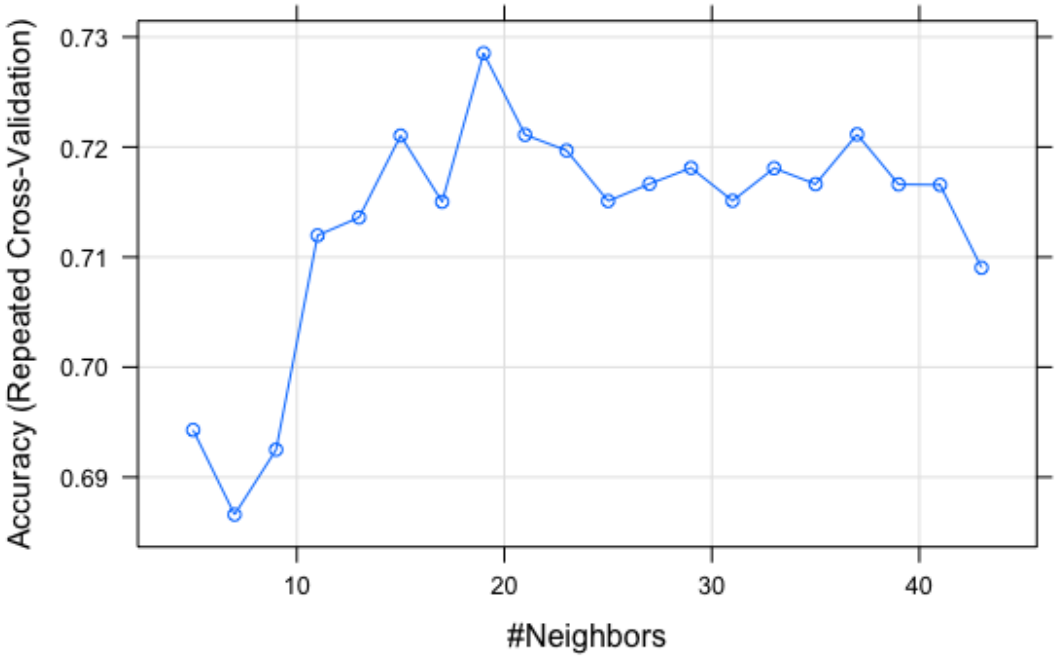



```
# kNN
ctrl <- trainControl(method = "repeatedcv", number = 10, savePredictions = TR
UE)

knn_fit <- train(Y ~ ., data = train_set, method = "knn",
                 trControl = ctrl, preProcess = c("center","scale"), tuneLeng
th = 20)

# Output of kNN fit
knn_fit
```

```
## k-Nearest Neighbors
##
## 667 samples
##  20 predictor
##   2 classes: '1', '2'
##
## Pre-processing: centered (48), scaled (48)
## Resampling: Cross-Validated (10 fold, repeated 1 times)
## Summary of sample sizes: 601, 600, 600, 600, 600, 600, ...
## Resampling results across tuning parameters:
##
##   k   Accuracy   Kappa
##    5  0.6942887  0.1876046
##    7  0.6865971  0.1494744
##    9  0.6924980  0.1543284
##   11  0.7119702  0.1976489
```

```
##    13  0.7135998  0.1806212
##    15  0.7210399  0.1942151
##    17  0.7150238  0.1781192
##    19  0.7285259  0.2134942
##    21  0.7211084  0.1985490
##    23  0.7196851  0.1940685
##    25  0.7150931  0.1623568
##    27  0.7166541  0.1432209
##    29  0.7181015  0.1519827
##    31  0.7151164  0.1303891
##    33  0.7180781  0.1392873
##    35  0.7166315  0.1224959
##    37  0.7211544  0.1413605
##    39  0.7166082  0.1155436
##    41  0.7165623  0.1113073
##    43  0.7090311  0.0833919
##
## Accuracy was used to select the optimal model using the largest value.
## The final value used for the model was k = 19.
```

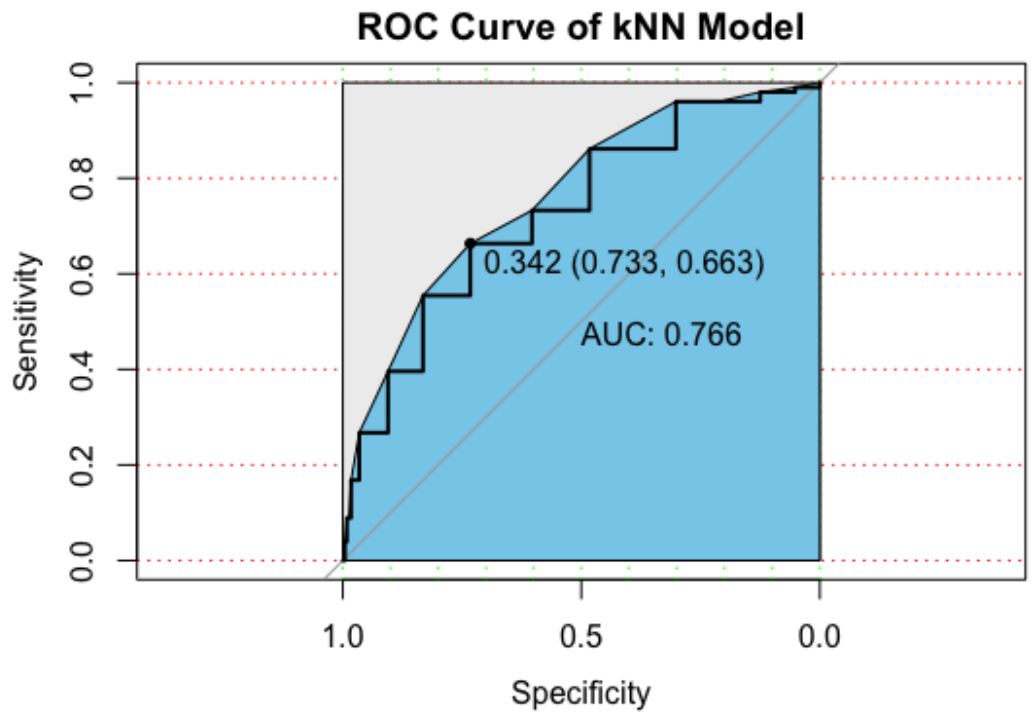
```
# Plotting yields Number of Neighbours Vs accuracy (based on repeated cross v
alidation)
plot(knn_fit)
```



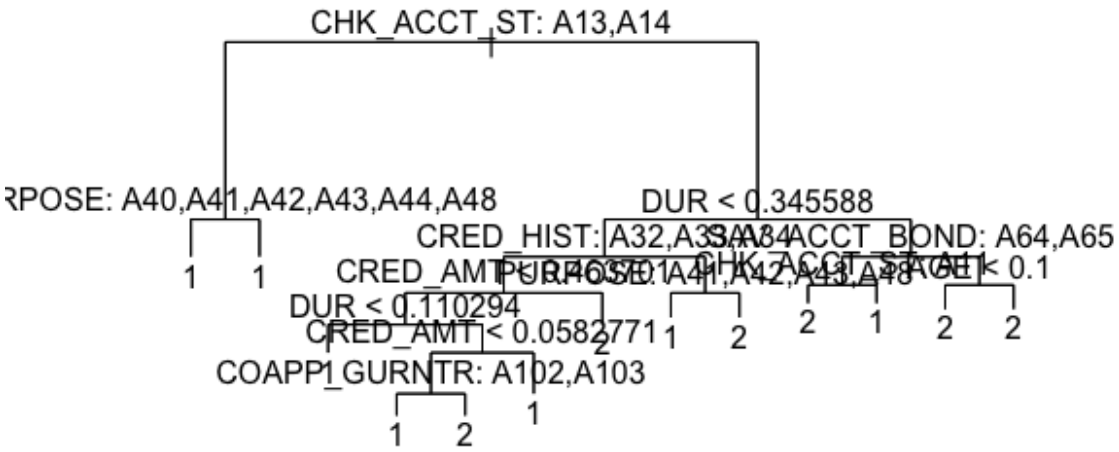

```
knnPredict <- predict(knn_fit,newdata = test_set )
#Get the confusion matrix to see accuracy value and other parameter values
confusionMatrix(knnPredict, test_set$Y )
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction   1   2
##          1 224  74
##          2   8  27
##
##                Accuracy : 0.7538
##                  95% CI : (0.7038, 0.7991)
##     No Information Rate : 0.6967
##     P-Value [Acc > NIR] : 0.01256
##
##                   Kappa : 0.2855
##
##  Mcnemar's Test P-Value : 7.071e-13
##
##             Sensitivity : 0.9655
##             Specificity : 0.2673
##          Pos Pred Value : 0.7517
##          Neg Pred Value : 0.7714
##              Prevalence : 0.6967
##          Detection Rate : 0.6727
##    Detection Prevalence : 0.8949
##       Balanced Accuracy : 0.6164
##
##        'Positive' Class : 1
##
```

```
t1<-table(knnPredict, test_set$Y)
knn_acc<-(t1[1,1]+t1[2,2])/(t1[1,1]+t1[2,2]+t1[1,2]+t1[2,1])
knn_spec<-t1[2,2]/(t1[1,2]+t1[2,2])

# kNN ROC curve
knn.predd <- predict(knn_fit, type='prob',test_set, probability = TRUE)

modelroc <- roc(test_set$Y,knn.predd[,2])
plot(modelroc, type="S",print.auc=TRUE, auc.polygon=TRUE, grid=c(0.1, 0.2),
     grid.col=c("green", "red"), max.auc.polygon=TRUE,
     auc.polygon.col="skyblue", print.thres=TRUE, main="ROC Curve of kNN Mode
l")
```



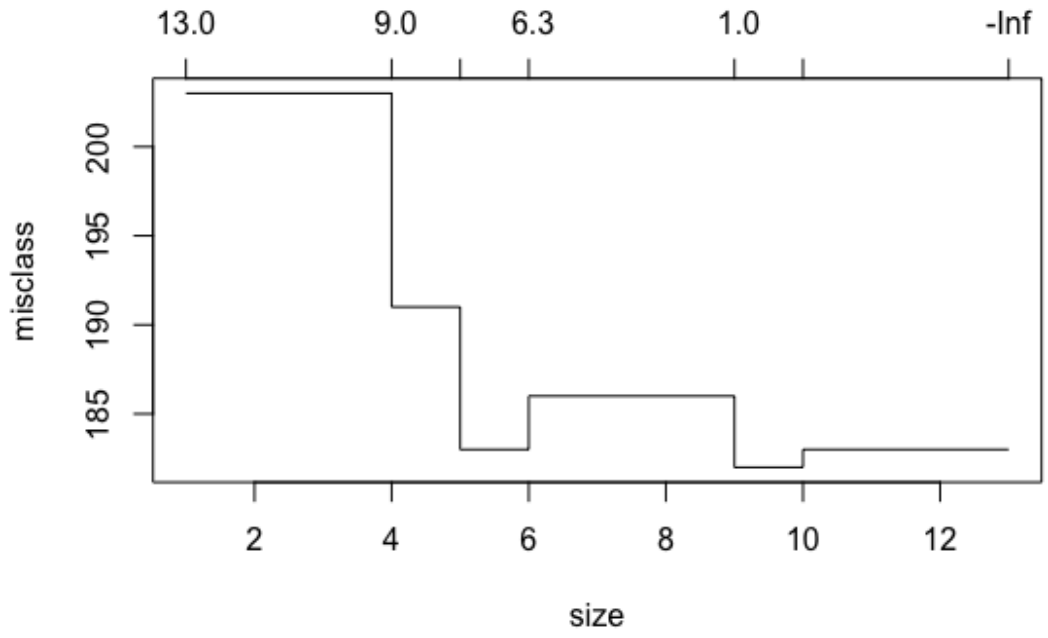

```r
# Decision Tree

trees <- tree(Y~., train_set)
plot(trees)
text(trees, pretty=0)
```



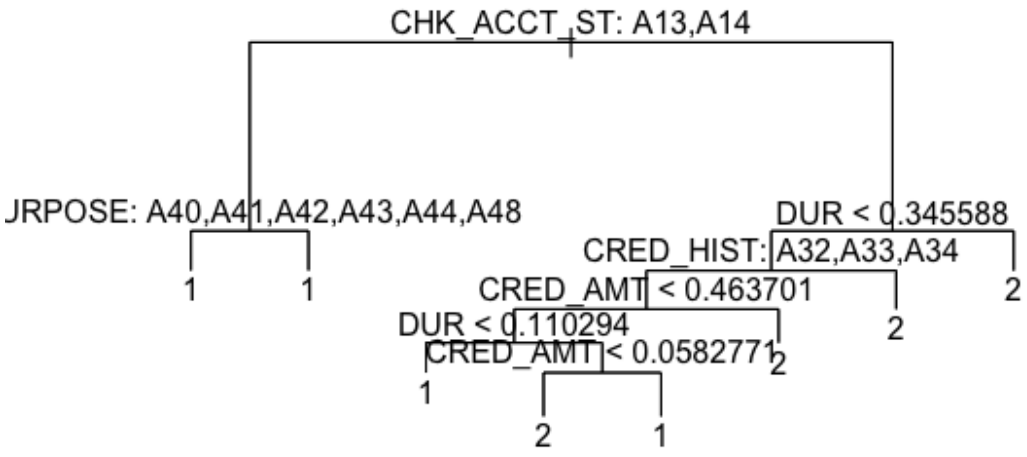
```r
# Prediction and confusion matrix
treesPredict <- predict(trees,newdata = test_set , type="class")
confusionMatrix(treesPredict, test_set$Y )
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction   1   2
##          1 203  58
##          2  29  43
##
##                Accuracy : 0.7387
##                  95% CI : (0.6881, 0.7851)
##     No Information Rate : 0.6967
##     P-Value [Acc > NIR] : 0.052290
##
##                   Kappa : 0.3273
##
##  Mcnemar's Test P-Value : 0.002683
##
##             Sensitivity : 0.8750
##             Specificity : 0.4257
##          Pos Pred Value : 0.7778
##          Neg Pred Value : 0.5972
##              Prevalence : 0.6967
##          Detection Rate : 0.6096
##    Detection Prevalence : 0.7838
##       Balanced Accuracy : 0.6504
##
##        'Positive' Class : 1
##
```

```r
# Cross validation and plot the tree
cv.trees <- cv.tree(trees, FUN = prune.misclass)
plot(cv.trees)
```



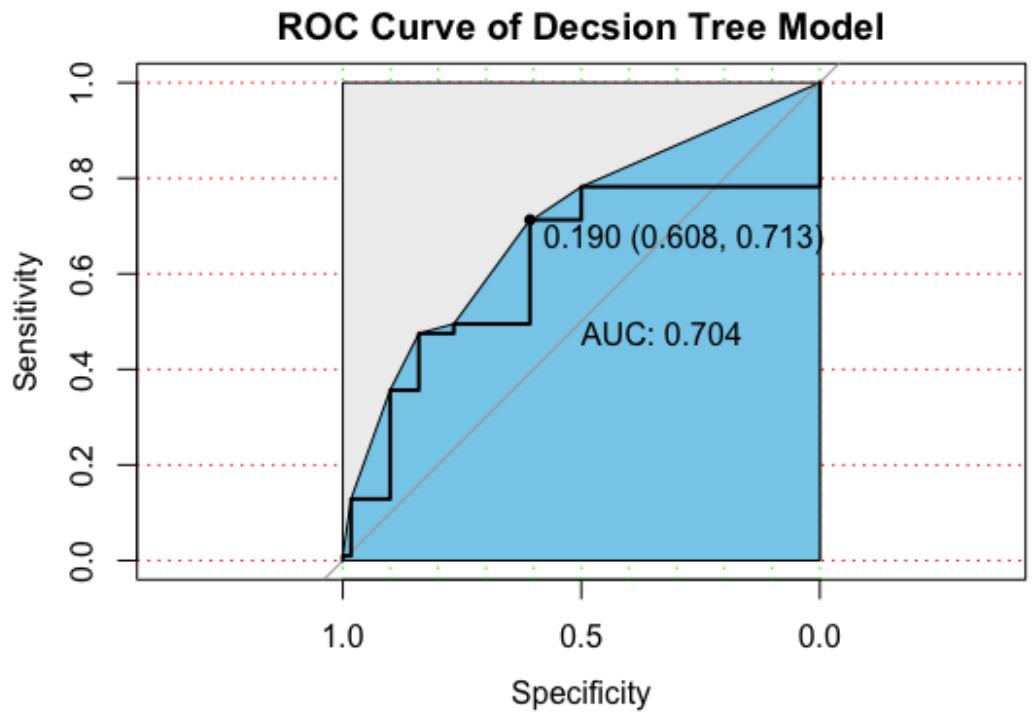

```
prune.trees <- prune.tree(trees, best=6)
plot(prune.trees)
text(prune.trees, pretty=0)
```



```r
prune.treesPredict <- predict(prune.trees,newdata = test_set , type="class")
confusionMatrix(prune.treesPredict, test_set$Y )
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction   1   2
##          1 195  53
##          2  37  48
##
##                Accuracy : 0.7297
##                  95% CI : (0.6786, 0.7767)
##     No Information Rate : 0.6967
##     P-Value [Acc > NIR] : 0.1045
##
##                   Kappa : 0.3305
##
##  Mcnemar's Test P-Value : 0.1138
##
##             Sensitivity : 0.8405
##             Specificity : 0.4752
##          Pos Pred Value : 0.7863
##          Neg Pred Value : 0.5647
##              Prevalence : 0.6967
##          Detection Rate : 0.5856
##    Detection Prevalence : 0.7447
##       Balanced Accuracy : 0.6579
##
##        'Positive' Class : 1
##
```

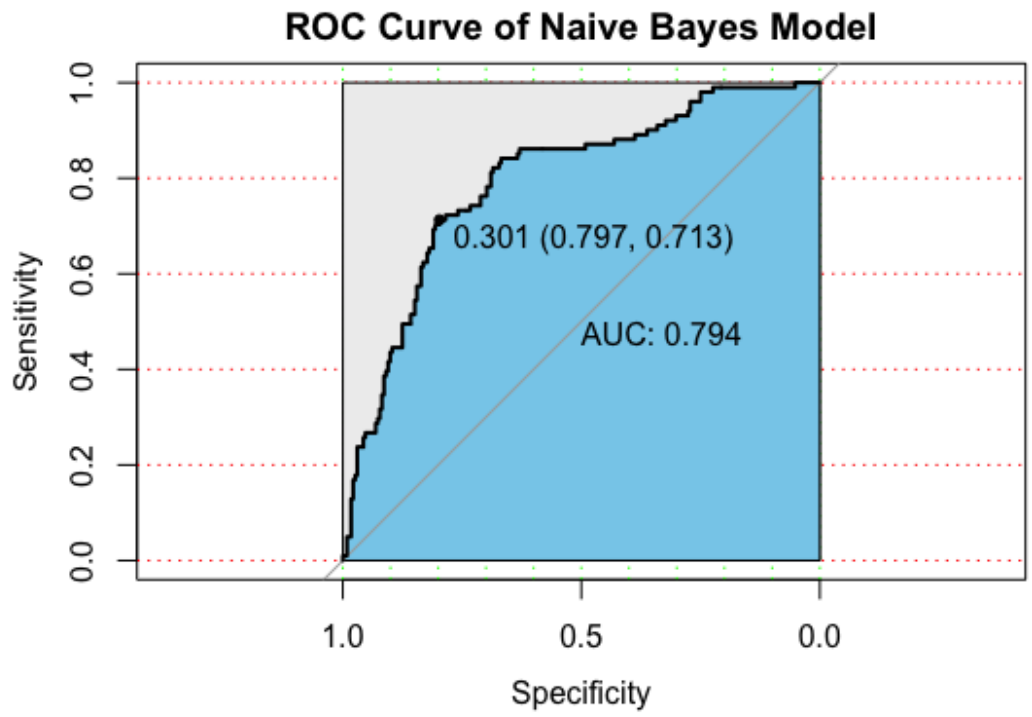
```r
t1<-table(prune.treesPredict, test_set$Y)
dt_acc<-(t1[1,1]+t1[2,2])/(t1[1,1]+t1[2,2]+t1[1,2]+t1[2,1])
dt_spec<-t1[2,2]/(t1[1,2]+t1[2,2])

# Decision Tree ROC curve
dt.predd <- predict(prune.trees,newdata = test_set)

modelroc <- roc(test_set$Y,dt.predd[,2])
plot(modelroc, type="S",print.auc=TRUE, auc.polygon=TRUE, grid=c(0.1, 0.2),
     grid.col=c("green", "red"), max.auc.polygon=TRUE,
     auc.polygon.col="skyblue", print.thres=TRUE, main="ROC Curve of Decsion
Tree Model")
```




```
# Naive Bayes
ctrl <- trainControl(method = "repeatedcv", number = 10, savePredictions = TR
UE)
nb_fit = train(train_set[,1:20],train_set[,21],'nb',
               trControl=ctrl)
nb_fit
```

```
## Naive Bayes
##
## 667 samples
##  20 predictor
##   2 classes: '1', '2'
##
## No pre-processing
## Resampling: Cross-Validated (10 fold, repeated 1 times)
## Summary of sample sizes: 600, 601, 600, 600, 600, 601, ...
## Resampling results across tuning parameters:
##
##   usekernel  Accuracy   Kappa
##   FALSE      0.7513116  0.3792598
##    TRUE      0.7316373  0.2645873
##
## Tuning parameter 'fL' was held constant at a value of 0
## Tuning
##  parameter 'adjust' was held constant at a value of 1
## Accuracy was used to select the optimal model using the largest value.
## The final values used for the model were fL = 0, usekernel = FALSE and adj
```

```
ust
##  = 1.

nbPredict <- predict(nb_fit$finalModel,newdata = test_set[,1:20] )$class
#Get the confusion matrix to see accuracy value and other parameter values
confusionMatrix(nbPredict, test_set$Y )

## Confusion Matrix and Statistics
##
##           Reference
## Prediction   1   2
##          1 203  55
##          2  29  46
##
##                Accuracy : 0.7477
##                  95% CI : (0.6975, 0.7935)
##     No Information Rate : 0.6967
##     P-Value [Acc > NIR] : 0.023181
##
##                   Kappa : 0.3563
##
##  Mcnemar's Test P-Value : 0.006377
##
##             Sensitivity : 0.8750
##             Specificity : 0.4554
##          Pos Pred Value : 0.7868
##          Neg Pred Value : 0.6133
##              Prevalence : 0.6967
##          Detection Rate : 0.6096
##    Detection Prevalence : 0.7748
##       Balanced Accuracy : 0.6652
##
##        'Positive' Class : 1
##

t1<-table(nbPredict, test_set$Y)
nb_acc<-(t1[1,1]+t1[2,2])/(t1[1,1]+t1[2,2]+t1[1,2]+t1[2,1])
nb_spec<-t1[2,2]/(t1[1,2]+t1[2,2])

# Naive Bayes ROC curve
nb.predd <- predict(nb_fit$finalModel, type='prob',test_set, probability = TR
UE)

modelroc <- roc(test_set$Y,nb.predd$posterior[,2])
plot(modelroc, type="S",print.auc=TRUE, auc.polygon=TRUE, grid=c(0.1, 0.2),
     grid.col=c("green", "red"), max.auc.polygon=TRUE,
     auc.polygon.col="skyblue", print.thres=TRUE, main="ROC Curve of Naive Ba
yes Model")
```




```
# Support Vector Machine

tc <- tune.control(cross = 10)
tune.out <- tune(svm, Y~.,
                 data = train_set, kernel = "radial",
                 ranges = list(cost = 10^(-1:2),
                               gamma = c(0.25,0.5,1,2,5)),
                 tunecontrol = tc)
summary(tune.out)

##
## Parameter tuning of 'svm':
##
## - sampling method: 10-fold cross validation
##
## - best parameters:
##  cost gamma
##     1  0.25
##
## - best performance: 0.2638851
##
## - Detailed performance results:
##     cost gamma     error dispersion
## 1    0.1  0.25 0.2983265 0.04829376
## 2    1.0  0.25 0.2638851 0.03877373
## 3   10.0  0.25 0.2743329 0.03580819
## 4  100.0  0.25 0.2743329 0.03580819
## 5    0.1  0.50 0.2983265 0.04829376
```

```
## 6    1.0  0.50 0.2968114 0.04941090
## 7   10.0  0.50 0.2922886 0.04187982
## 8  100.0  0.50 0.2922886 0.04187982
## 9    0.1  1.00 0.2983265 0.04829376
## 10   1.0  1.00 0.2983265 0.04829376
## 11  10.0  1.00 0.2953189 0.04805805
## 12 100.0  1.00 0.2953189 0.04805805
## 13   0.1  2.00 0.2983265 0.04829376
## 14   1.0  2.00 0.2983265 0.04829376
## 15  10.0  2.00 0.2983265 0.04829376
## 16 100.0  2.00 0.2983265 0.04829376
## 17   0.1  5.00 0.2983265 0.04829376
## 18   1.0  5.00 0.2983265 0.04829376
## 19  10.0  5.00 0.2983265 0.04829376
## 20 100.0  5.00 0.2983265 0.04829376
```

```
print(tune.out) # best parameters: cost=1, gamma=0.25
```

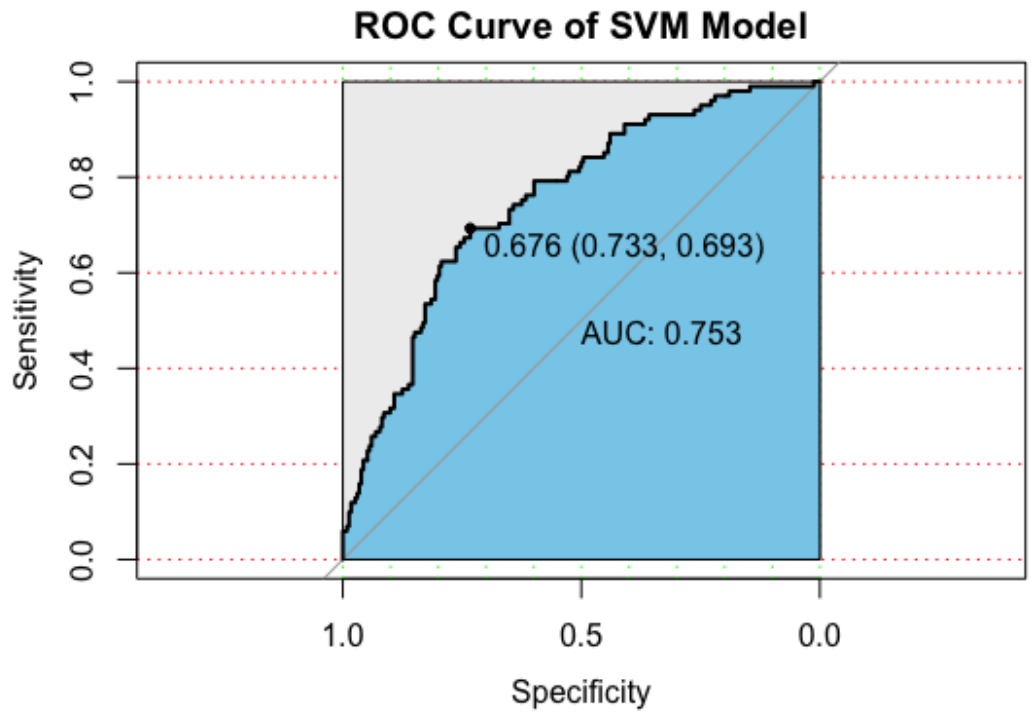
```
##
## Parameter tuning of 'svm':
##
## - sampling method: 10-fold cross validation
##
## - best parameters:
##  cost gamma
##     1  0.25
##
## - best performance: 0.2638851
```

```
svm.prediction = predict(tune.out$best.model,newdata=test_set,type='class')
confusionMatrix(svm.prediction,as.factor(test_set$Y))
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction   1   2
##          1 228  89
##          2   4  12
##
##                Accuracy : 0.7207
##                  95% CI : (0.6692, 0.7683)
##     No Information Rate : 0.6967
##     P-Value [Acc > NIR] : 0.1861
##
##                   Kappa : 0.1332
##
##  Mcnemar's Test P-Value : <2e-16
##
##             Sensitivity : 0.9828
##             Specificity : 0.1188
##          Pos Pred Value : 0.7192
```

```
##          Neg Pred Value : 0.7500
##              Prevalence : 0.6967
##          Detection Rate : 0.6847
##    Detection Prevalence : 0.9520
##       Balanced Accuracy : 0.5508
##
##        'Positive' Class : 1
##
```

```
t1<-table(svm.prediction,as.factor(test_set$Y))
svm_acc<-(t1[1,1]+t1[2,2])/(t1[1,1]+t1[2,2]+t1[1,2]+t1[2,1])
svm_spec<-t1[2,2]/(t1[1,2]+t1[2,2])

# SVM ROC curve
svm_fit2 <- svm(Y~., data =train_set, cost=1, gamma=0.25, probability = TRUE)

svm.predd <- predict(svm_fit2, type='prob',test_set, probability = TRUE)

modelroc <- roc(test_set$Y,attr(svm.predd, "probabilities")[,2])
plot(modelroc, type="S",print.auc=TRUE, auc.polygon=TRUE, grid=c(0.1, 0.2),
     grid.col=c("green", "red"), max.auc.polygon=TRUE,
     auc.polygon.col="skyblue", print.thres=TRUE, main="ROC Curve of SVM Mode
l")
```




```
# Neural Network
ctrl <- trainControl(method = "repeatedcv", number = 10, savePredictions = TR
UE)
```

```r
nn_fit <- train(Y~., data = train_set,
                method = 'nnet', preProcess = c('center', 'scale'), trControl =
 ctrl,
                tuneGrid=expand.grid(size=c(10), decay=c(0.1)))
```

```
## # weights:  501
## initial  value 378.551862
## iter  10 value 229.345916
## iter  20 value 140.148831
## iter  30 value 102.800617
## iter  40 value 84.044160
## iter  50 value 75.353764
## iter  60 value 70.603753
## iter  70 value 68.100085
## iter  80 value 65.951893
## iter  90 value 64.374881
## iter 100 value 63.469051
## final  value 63.469051
## stopped after 100 iterations
## # weights:  501
## initial  value 420.305694
## iter  10 value 220.711299
## iter  20 value 136.128495
## iter  30 value 97.915459
## iter  40 value 82.491493
## iter  50 value 75.510341
## iter  60 value 71.897257
## iter  70 value 69.858317
## iter  80 value 67.928207
## iter  90 value 65.434115
## iter 100 value 64.457521
## final  value 64.457521
## stopped after 100 iterations
## # weights:  501
## initial  value 552.360593
## iter  10 value 220.909124
## iter  20 value 131.060228
## iter  30 value 95.513050
## iter  40 value 81.269554
## iter  50 value 75.141856
## iter  60 value 71.792300
## iter  70 value 69.183298
## iter  80 value 66.450365
## iter  90 value 65.187997
## iter 100 value 64.297136
## final  value 64.297136
## stopped after 100 iterations
## # weights:  501
## initial  value 402.502539
## iter  10 value 231.395112
```

```
## iter  20 value 140.503706
## iter  30 value 107.517453
## iter  40 value 89.699414
## iter  50 value 80.142133
## iter  60 value 74.823809
## iter  70 value 71.839871
## iter  80 value 68.396420
## iter  90 value 65.405487
## iter 100 value 63.357552
## final  value 63.357552
## stopped after 100 iterations
## # weights:  501
## initial  value 405.172051
## iter  10 value 220.868294
## iter  20 value 134.407466
## iter  30 value 97.560551
## iter  40 value 83.137364
## iter  50 value 77.157712
## iter  60 value 73.817408
## iter  70 value 71.311964
## iter  80 value 69.376511
## iter  90 value 68.485206
## iter 100 value 67.480413
## final  value 67.480413
## stopped after 100 iterations
## # weights:  501
## initial  value 407.348070
## iter  10 value 252.482362
## iter  20 value 152.334322
## iter  30 value 117.264633
## iter  40 value 101.258846
## iter  50 value 89.565782
## iter  60 value 79.640363
## iter  70 value 73.608504
## iter  80 value 68.623819
## iter  90 value 65.813268
## iter 100 value 63.472290
## final  value 63.472290
## stopped after 100 iterations
## # weights:  501
## initial  value 423.486007
## iter  10 value 217.319835
## iter  20 value 136.057195
## iter  30 value 106.315123
## iter  40 value 91.581530
## iter  50 value 82.924591
## iter  60 value 78.376898
## iter  70 value 74.405124
## iter  80 value 71.121894
## iter  90 value 69.045569
```

```
## iter 100 value 67.352874
## final  value 67.352874
## stopped after 100 iterations
## # weights:  501
## initial  value 548.970825
## iter  10 value 240.274156
## iter  20 value 152.699492
## iter  30 value 116.226528
## iter  40 value 100.112875
## iter  50 value 90.408266
## iter  60 value 85.523246
## iter  70 value 80.677037
## iter  80 value 77.988379
## iter  90 value 75.460147
## iter 100 value 73.248058
## final  value 73.248058
## stopped after 100 iterations
## # weights:  501
## initial  value 408.709785
## iter  10 value 223.489350
## iter  20 value 137.293482
## iter  30 value 99.448567
## iter  40 value 82.276306
## iter  50 value 73.986803
## iter  60 value 71.077440
## iter  70 value 68.775037
## iter  80 value 67.107895
## iter  90 value 65.340468
## iter 100 value 64.557698
## final  value 64.557698
## stopped after 100 iterations
## # weights:  501
## initial  value 525.060046
## iter  10 value 235.861842
## iter  20 value 139.450955
## iter  30 value 93.920575
## iter  40 value 77.324171
## iter  50 value 70.690617
## iter  60 value 66.814938
## iter  70 value 64.728801
## iter  80 value 63.246874
## iter  90 value 62.454986
## iter 100 value 61.497749
## final  value 61.497749
## stopped after 100 iterations
## # weights:  501
## initial  value 488.565700
## iter  10 value 251.615467
## iter  20 value 164.827677
## iter  30 value 129.921785
```

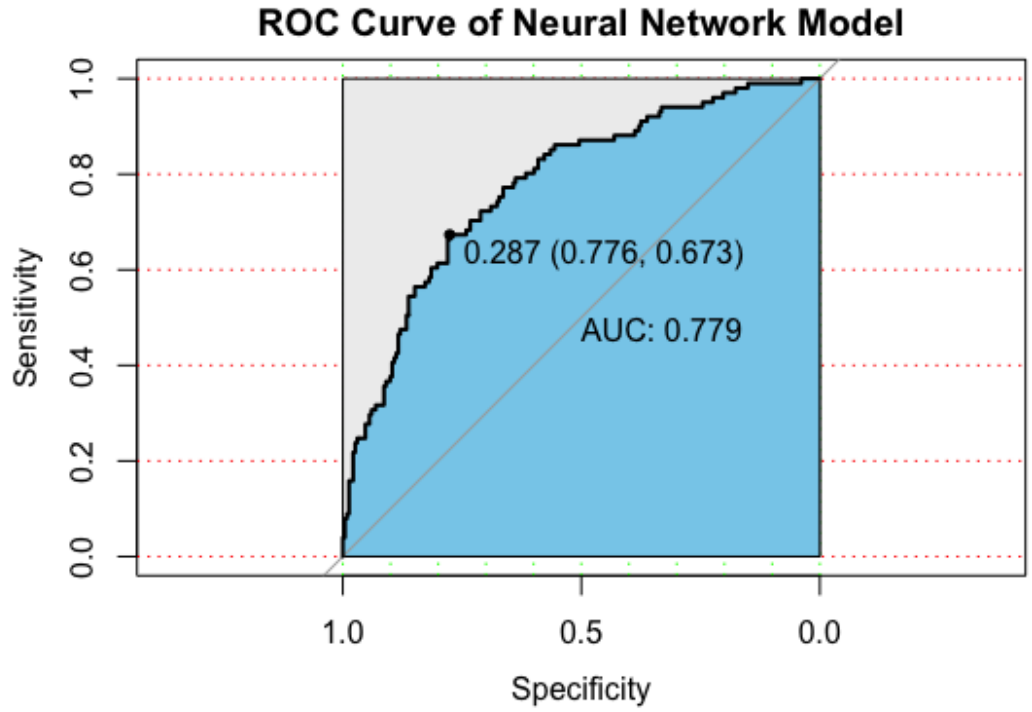
```
## iter  40 value 108.266790
## iter  50 value 95.254008
## iter  60 value 87.155702
## iter  70 value 82.276184
## iter  80 value 78.902746
## iter  90 value 76.602232
## iter 100 value 74.727299
## final  value 74.727299
## stopped after 100 iterations
```

```
nnPredict <- predict(nn_fit,newdata = test_set )
#Get the confusion matrix to see accuracy value and other parameter values
confusionMatrix(nnPredict, test_set$Y )
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction   1   2
##          1 197  46
##          2  35  55
##
##                Accuracy : 0.7568
##                  95% CI : (0.707, 0.8019)
##     No Information Rate : 0.6967
##     P-Value [Acc > NIR] : 0.009043
##
##                   Kappa : 0.4062
##
##  Mcnemar's Test P-Value : 0.266521
##
##             Sensitivity : 0.8491
##             Specificity : 0.5446
##          Pos Pred Value : 0.8107
##          Neg Pred Value : 0.6111
##              Prevalence : 0.6967
##          Detection Rate : 0.5916
##    Detection Prevalence : 0.7297
##       Balanced Accuracy : 0.6968
##
##        'Positive' Class : 1
##
```

```
t1<-table(nnPredict, test_set$Y)
nn_acc<-(t1[1,1]+t1[2,2])/(t1[1,1]+t1[2,2]+t1[1,2]+t1[2,1])
nn_spec<-t1[2,2]/(t1[1,2]+t1[2,2])

# Neural Network ROC curve
nn.predd <- predict(nn_fit, type='prob',test_set, probability = TRUE)

modelroc <- roc(test_set$Y,nn.predd[,2])
plot(modelroc, type="S",print.auc=TRUE, auc.polygon=TRUE, grid=c(0.1, 0.2),
```

```
     grid.col=c("green", "red"), max.auc.polygon=TRUE,
     auc.polygon.col="skyblue", print.thres=TRUE, main="ROC Curve of Neural N
etwork Model")
```




```
# Comparison and Conclusions
cat("\n")

cat(" Logistic regression model's accuracy: ", log_acc,
    "; Specificity: ",log_spec ,"\n",
    "kNN model's accuracy: ", knn_acc,
    "; Specificity: ",knn_spec ,"\n",
    "Decision tree model's accuracy: ", dt_acc,
    "; Specificity: ",dt_spec ,"\n",
    "Naive Bayes model's accuracy: ", nb_acc,
    "; Specificity: ",nb_spec ,"\n",
    "Support vector machine model's accuracy: ", svm_acc,
    "; Specificity: ",svm_spec ,"\n",
     "Neural Network model's accuracy: ", nn_acc,
    "; Specificity: ",nn_spec ,"\n")
```

```
##  Logistic regression model's accuracy:  0.7507508 ; Specificity:  0.465346
5
##  kNN model's accuracy:  0.7537538 ; Specificity:  0.2673267
##  Decision tree model's accuracy:  0.7297297 ; Specificity:  0.4752475
##  Naive Bayes model's accuracy:  0.7477477 ; Specificity:  0.4554455
##  Support vector machine model's accuracy:  0.7207207 ; Specificity:  0.118
8119
##  Neural Network model's accuracy:  0.7567568 ; Specificity:  0.5445545
```