Assignment_4

Tarun BT

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Imported necessary library files required for task

```r
library(ggplot2)
library(lattice)
library(caret)
library(e1071)
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
```

```r
library(pROC)
```

```
## Type 'citation("pROC")' for a citation.

##
## Attaching package: 'pROC'

## The following objects are masked from 'package:stats':
##
##     cov, smooth, var
```

```r
library(naivebayes)
```

```
## naivebayes 1.0.0 loaded

## For more information please visit:

## https://majkamichal.github.io/naivebayes/
```

Loading the data set

```r
Heart_disease <- read.csv("C:\\Users\\Tarun\\OneDrive\\Desktop\\R program\\4th Assignment\\Heart_diseas
```

Checking for duplicate value and removing record from the data-set

```r
duplicates <- Heart_disease[duplicated(Heart_disease), ]
cat("Number of duplicate record ",nrow(duplicates),"\n")
```

```
## Number of duplicate record  1
```

```r
print(duplicates)
```

```
##     Age Sex chest_pain_type Blood_Pressure Cholestrol Fasting_Blood_Sugar
## 165  38   1               1            138        175                   0
##     Rest_ECG MAX_HeartRate Exercise
## 165        1           173        0
```

```r
df_unique <- Heart_disease %>% distinct() #data-set after removing the duplicate value
nrow(df_unique)
```

```
## [1] 302
```

Creating dummy variables

```r
df_unique$Target <- ifelse(df_unique$MAX_HeartRate > 170, "Yes", "No")
df_unique$BP_New <- ifelse(df_unique$Blood_Pressure > 120, "Yes", "No")
```

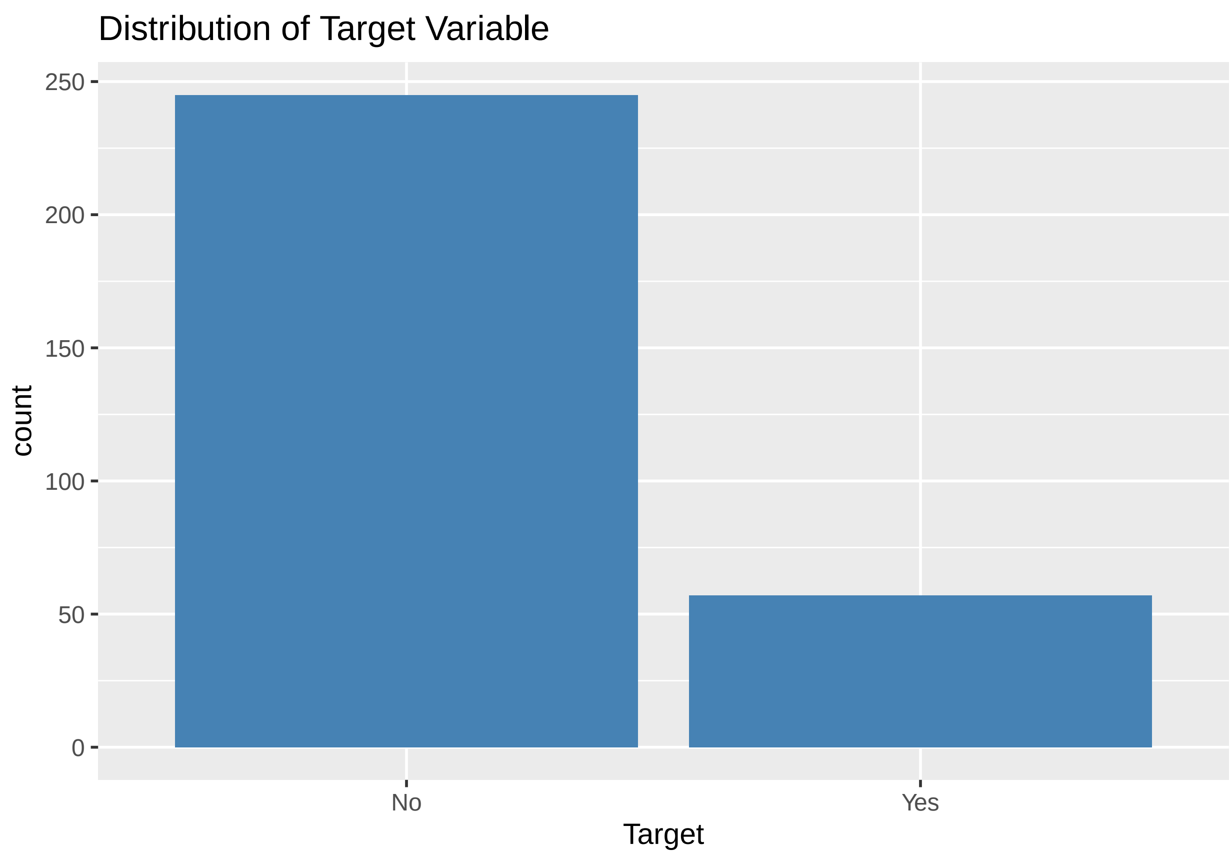
Q1: Initial Prediction Based on Target Distribution

```r
target_table <- table(df_unique$Target)
target_table
```

```
##
##  No Yes
## 245  57
```

Bar Plot for Target Distribution

```r
ggplot(df_unique, aes(x = Target)) + geom_bar(fill = "steelblue") + ggtitle("Distribution of Target Vari
```



Interpretation: No appeared 245 counts Yes appeared 57 counts Since No is the majority class - No Heart Disease

Q2: Analysis of the First 30 Records

```
Heart_disease30 <- df_unique[1:30, c("Target", "BP_New", "chest_pain_type")]
Object1 <- ftable(Heart_disease30)
Object1
```

```
##                 chest_pain_type 0 1
## Target BP_New
## No     No                       2 2
##        Yes                      7 8
## Yes    No                       0 3
##        Yes                      3 5
```

```
head(Heart_disease30)
```

```
##   Target BP_New chest_pain_type
## 1     No    Yes               0
## 2    Yes    Yes               1
## 3    Yes    Yes               1
## 4    Yes     No               1
## 5     No     No               0
## 6     No    Yes               0
```

pivot table without target column

```r
Object2 <- ftable(Heart_disease30[ ,-1])
Object2
```

```
##         chest_pain_type  0  1
## BP_New
## No                       2  5
## Yes                     10 13
```

2a. Computing Bayes Conditional Probabilities

```r
p1 <- Object1[3,1]/Object2[1,1] #Target=yes , BP_New=No & chest_pain_type=0
p2 <- Object1[3,2]/Object2[1,2] #Target=yes , BP_New=No & Chest_pain_type=1
p3 <- Object1[4,1]/Object2[2,1] #Target=yes , BP_New=Yes & Chest_pain_type=0
p4 <- Object1[4,2]/Object2[2,2] #Target=yes , BP_New=Yes & Chest_pain_type=1
```

Conditional probabilities values

```r
cat("The conditional probability of having heart disease with no BP and No chest Pain:",p1,"\n")
```

```
## The conditional probability of having heart disease with no BP and No chest Pain: 0
```

```r
cat("The conditional probability of having heart disease with high BP and chest Pain:", p2,"\n")
```

```
## The conditional probability of having heart disease with high BP and chest Pain: 0.6
```

```r
cat("The conditional probability of having heart disease with BP and No chest Pain:", p3 ,"\n")
```

```
## The conditional probability of having heart disease with BP and No chest Pain: 0.3
```

```r
cat("The conditional probability of having heart disease with BP and chest Pain:", p4 ,"\n")
```

```
## The conditional probability of having heart disease with BP and chest Pain: 0.3846154
```

2b. Classification using a cutoff of 0.5

```r
Probability_Target <- rep(0, 30)

for (i in 1:30) {
  BP_New <- Heart_disease30$BP_New[i]  # Getting BP_New value for row i
  chest_pain <- Heart_disease30$chest_pain_type[i]  # Getting chest_pain for row i

  # Matching the probability from pre-computed values (p1, p2, p3, p4)
  if (BP_New == "No" & chest_pain == 0) {
    Probability_Target[i] <- p1
  } else if (BP_New == "Yes" & chest_pain == 1) {
    Probability_Target[i] <- p2
  } else if (BP_New == "Yes" & chest_pain == 0) {
```

```
    Probability_Target[i] <- p3
  } else if (BP_New == "No" & chest_pain == 1) {
    Probability_Target[i] <- p4
  }
}

Heart_disease30$Probability_Target <- Probability_Target
Heart_disease30$Pred_Probability <- ifelse(Heart_disease30$Probability_Target > 0.5, "Yes", "No")
Heart_disease30
```

```
##    Target BP_New chest_pain_type Probability_Target Pred_Probability
## 1      No    Yes               0          0.3000000               No
## 2     Yes    Yes               1          0.6000000              Yes
## 3     Yes    Yes               1          0.6000000              Yes
## 4     Yes     No               1          0.3846154               No
## 5      No     No               0          0.0000000               No
## 6      No    Yes               0          0.3000000               No
## 7      No    Yes               1          0.6000000              Yes
## 8     Yes     No               1          0.3846154               No
## 9      No    Yes               1          0.6000000              Yes
## 10    Yes    Yes               1          0.6000000              Yes
## 11     No    Yes               0          0.3000000               No
## 12     No    Yes               1          0.6000000              Yes
## 13    Yes    Yes               1          0.6000000              Yes
## 14     No     No               0          0.0000000               No
## 15     No    Yes               0          0.3000000               No
## 16     No     No               1          0.3846154               No
## 17    Yes     No               1          0.3846154               No
## 18     No    Yes               0          0.3000000               No
## 19    Yes    Yes               0          0.3000000               No
## 20     No    Yes               0          0.3000000               No
## 21     No    Yes               0          0.3000000               No
## 22    Yes    Yes               1          0.6000000              Yes
## 23    Yes    Yes               0          0.3000000               No
## 24     No    Yes               1          0.6000000              Yes
## 25    Yes    Yes               0          0.3000000               No
## 26     No    Yes               1          0.6000000              Yes
## 27     No    Yes               1          0.6000000              Yes
## 28     No     No               1          0.3846154               No
## 29     No    Yes               1          0.6000000              Yes
## 30     No    Yes               1          0.6000000              Yes
```

2c. Manual Calculation of Naive Bayes Probability

```
# Compute total instances
total_count <- nrow(Heart_disease30)

# Compute P(Target = Yes)
p_target_yes <- sum(Heart_disease30$Target == "Yes") / total_count

# Compute P(BP_New = Yes, chest_pain_type = 1 | Target = Yes)
p_given_yes <- sum(Heart_disease30$BP_New == "Yes" & Heart_disease30$chest_pain_type == 1 & Heart_diseas
```

```r
# Compute P(BP_New = Yes, chest_pain_type = 1)
p_denominator <- sum(Heart_disease30$BP_New == "Yes" & Heart_disease30$chest_pain_type == 1) / total_co

# Compute the final probability using Bayes' Theorem
p_yes_given_bp_chest <- (p_given_yes * p_target_yes) / p_denominator

# Print result
cat("Manually compute the naive  Bayes conditional probability of an injury given that BP_New is Yes and
```

```
## Manually compute the naive  Bayes conditional probability of an injury given that BP_New is Yes and
```

Q3: Full Data set Analysis - Splitting into Training and Validation Sets

```r
set.seed(123)

train.index <- sample(row.names(df_unique),0.6 * nrow(df_unique))
valid.index <- setdiff(row.names(df_unique),train.index)

train.df <- df_unique[train.index, ]
valid.df <- df_unique[valid.index, ]

nrow(train.df)
```

```
## [1] 181
```

```r
nrow(valid.df)
```

```
## [1] 121
```

```r
train.df <- train.df[,-9]
valid.df <- valid.df[,-9]
```

Running Naive Bayes Classifier

```r
nb_model <- naiveBayes(Target ~ chest_pain_type + BP_New, data = train.df,1)
valid_pred <- predict(nb_model, valid.df)

# Convert predictions and actual target variable to factors with the same levels
valid.df$Target <- factor(valid.df$Target)
valid_pred <- factor(valid_pred, levels = levels(valid.df$Target))

# Compute confusion matrix
conf_matrix1 <- confusionMatrix(valid_pred, valid.df$Target)
```

```r
conf_matrix1
```

```
## Confusion Matrix and Statistics
##
##             Reference
## Prediction No Yes
```

```
##        No  96  25
##        Yes  0   0
##
##                Accuracy : 0.7934
##                  95% CI : (0.7103, 0.8616)
##     No Information Rate : 0.7934
##     P-Value [Acc > NIR] : 0.5533
##
##                   Kappa : 0
##
##  Mcnemar's Test P-Value : 1.587e-06
##
##             Sensitivity : 1.0000
##             Specificity : 0.0000
##          Pos Pred Value : 0.7934
##          Neg Pred Value :    NaN
##              Prevalence : 0.7934
##          Detection Rate : 0.7934
##    Detection Prevalence : 1.0000
##       Balanced Accuracy : 0.5000
##
##        'Positive' Class : No
##
```

Running Naive Bayes Classifier including all the attributes. (Validation set)

```
nb_model_1 <- naiveBayes(Target ~., data = train.df)
train_pred_1 <- predict(nb_model_1, valid.df)

# Convert predictions and actual target variable to factors with the same levels
valid.df$Target <- factor(valid.df$Target)
train_pred_1 <- factor(train_pred_1, levels = levels(valid.df$Target))

# Compute confusion matrix
conf_matrix1_1 <- confusionMatrix(train_pred_1, valid.df$Target)
conf_matrix1_1
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction No Yes
##        No  90   8
##        Yes  6  17
##
##                Accuracy : 0.8843
##                  95% CI : (0.8135, 0.9353)
##     No Information Rate : 0.7934
##     P-Value [Acc > NIR] : 0.006446
##
##                   Kappa : 0.6363
##
##  Mcnemar's Test P-Value : 0.789268
##
```

```
##              Sensitivity : 0.9375
##              Specificity : 0.6800
##           Pos Pred Value : 0.9184
##           Neg Pred Value : 0.7391
##               Prevalence : 0.7934
##           Detection Rate : 0.7438
##     Detection Prevalence : 0.8099
##        Balanced Accuracy : 0.8088
##
##         'Positive' Class : No
##
```

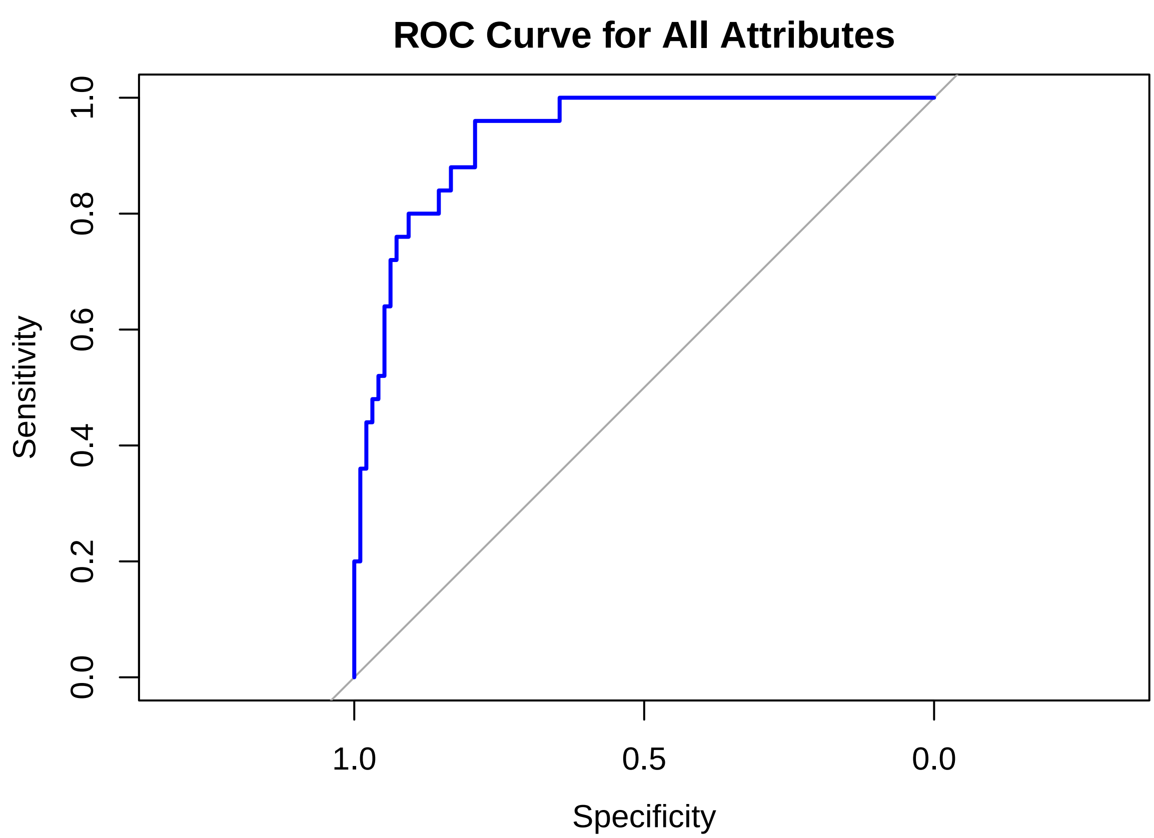
ROC Curve

```r
pred_probs_full <- predict(nb_model_1, valid.df, type = "raw")
prob_yes_full <- pred_probs_full[, "Yes"]
roc_full <- roc(valid.df$Target, prob_yes_full)
```

```
## Setting levels: control = No, case = Yes
```

```
## Setting direction: controls < cases
```

```r
plot(roc_full, col = "blue", main = "ROC Curve for All Attributes")
```



```r
auc_value <- auc(roc_full)
auc_value
```

```
## Area under the curve: 0.9325
```