

Heart Disease UCI

Dominik Wolff

3 6 2019

Detecting heart disease risks

Abstract

This work analyzes risk factors for heart disease based on the “Heart Disease UCI dataset.” The dataset is derived from Kaggle (<https://www.kaggle.com/ronitf/heart-disease-uci/downloads/heart-disease-uci.zip/1>). The dataset contains 13 features and the target variable. The “target” refers to the presence of heart disease in the patient. It is integer valued from 0 (no presence) to 1 (present). The 13 features are: 1. age 2. sex 3. chest pain type (4 values) 4. resting blood pressure 5. serum cholestoral in mg/dl 6. fasting blood sugar > 120 mg/dl 7. resting electrocardiographic results (values 0,1,2) 8. maximum heart rate achieved 9. exercise induced angina 10. oldpeak = ST depression induced by exercise relative to rest 11. the slope of the peak exercise ST segment 12. number of major vessels (0-3) colored by flourosopy 13. thal: 3 = normal; 6 = fixed defect; 7 = reversable defect

Load required packages

```
knitr::opts_chunk$set(echo = FALSE)
if(!require(tidyverse)) install.packages("tidyverse", repos = "http://cran.us.r-project.org")

## Loading required package: tidyverse
## Warning: package 'tidyverse' was built under R version 3.5.2
## -- Attaching packages ----- tidyverse 1.2.1 --
## v ggplot2 3.1.0      v purrr  0.2.5
## v tibble  1.4.2      v dplyr  0.7.8
## v tidyr   0.8.2      v stringr 1.3.1
## v readr   1.3.1      v forcats 0.3.0
## Warning: package 'readr' was built under R version 3.5.2
## Warning: package 'forcats' was built under R version 3.5.2
## -- Conflicts ----- tidyverse_conflicts() --
## x dplyr::filter() masks stats::filter()
## x dplyr::lag()    masks stats::lag()
if(!require(caret)) install.packages("caret", repos = "http://cran.us.r-project.org")

## Loading required package: caret
## Loading required package: lattice
##
## Attaching package: 'caret'
## The following object is masked from 'package:purrr':
##
## lift
```

```

if(!require(lubridate)) install.packages("lubridate", repos = "http://cran.us.r-project.org")

## Loading required package: lubridate
##
## Attaching package: 'lubridate'
## The following object is masked from 'package:base':
##
##     date
if(!require(e1071)) install.packages("e1071", repos = "http://cran.us.r-project.org")

## Loading required package: e1071
if(!require(naivebayes)) install.packages("naivebayes", repos = "http://cran.us.r-project.org")

## Loading required package: naivebayes
## Warning: package 'naivebayes' was built under R version 3.5.2
if(!require(rmarkdown)) install.packages("rmarkdown", repos = "http://cran.us.r-project.org")

## Loading required package: rmarkdown
## Warning: package 'rmarkdown' was built under R version 3.5.2
if(!require(caret)) install.packages("caret", repos = "http://cran.us.r-project.org")
if(!require(ranger)) install.packages("ranger", repos = "http://cran.us.r-project.org")

## Loading required package: ranger
if(!require(rpart)) install.packages("rpart", repos = "http://cran.us.r-project.org")

## Loading required package: rpart

```

Download heart disease dataset and prepare data

Source of the Data

<https://www.kaggle.com/ronitf/heart-disease-uci/downloads/heart-disease-uci.zip/1>. The data is downloaded from the web and unzipped. The csv file is saved to the working directory.

```

tmpdir <- "C:/Users/Dominik/Downloads/"
setwd(tmpdir)

url <- "https://www.kaggle.com/ronitf/heart-disease-uci/downloads/heart-disease-uci.zip/1"
temp <- tempfile(tmpdir=tmpdir, fileext=".zip")
download.file(url, temp)
unzip(temp)

## Warning in unzip(temp): Fehler 1 während des Extrahierens aus Zipfile
unlink(temp)

```

Prepare Data:

Load data from csv. Rename column names.

```
HeartDeaseaseData <- read.csv("C:/Users/Dominik/Downloads/heart.csv",header = TRUE, sep = ",",dec = ".")
class(HeartDeaseaseData)
```

```
## [1] "data.frame"
```

```
dim(HeartDeaseaseData)
```

```
## [1] 303 14
```

```
names <- c("age",
           "sex",
           "ChestPainType",
           "RestingBloodPressure",
           "SerumCholestoral",
           "FastingBloodSugar",
           "RestingElectrocardiographic",
           "MaximumHeartRate",
           "ExerciseAngina",
           "STDepressionExercise",
           "SlopePeakExercise",
           "NumberMajorVessels",
           "thal",
           "heartdesease")
```

```
names(HeartDeaseaseData) <- names
```

```
head(HeartDeaseaseData)
```

```
##   age sex ChestPainType RestingBloodPressure SerumCholestoral
## 1  63   1             3             145             233
## 2  37   1             2             130             250
## 3  41   0             1             130             204
## 4  56   1             1             120             236
## 5  57   0             0             120             354
## 6  57   1             0             140             192
##   FastingBloodSugar RestingElectrocardiographic MaximumHeartRate
## 1                 1                 0                 150
## 2                 0                 1                 187
## 3                 0                 0                 172
## 4                 0                 1                 178
## 5                 0                 1                 163
## 6                 0                 1                 148
##   ExerciseAngina STDepressionExercise SlopePeakExercise NumberMajorVessels
## 1              0                 2.3                 0              0
## 2              0                 3.5                 0              0
## 3              0                 1.4                 2              0
## 4              0                 0.8                 2              0
## 5              1                 0.6                 2              0
## 6              0                 0.4                 1              0
##   thal heartdesease
## 1    1            1
## 2    2            1
## 3    2            1
## 4    2            1
## 5    2            1
## 6    1            1
```

```
#Check for missing values  
sum(is.na(HeartDeaseaseData))
```

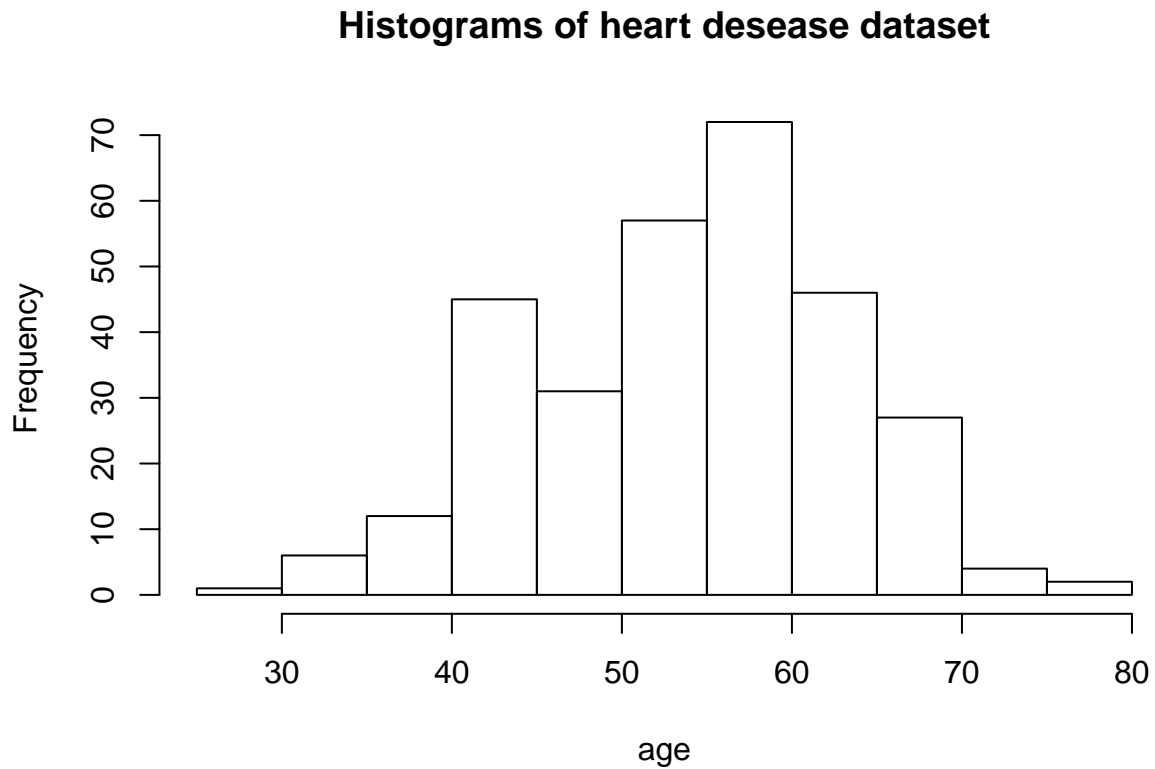
```
## [1] 0
```

There are no missing values in the dataset.

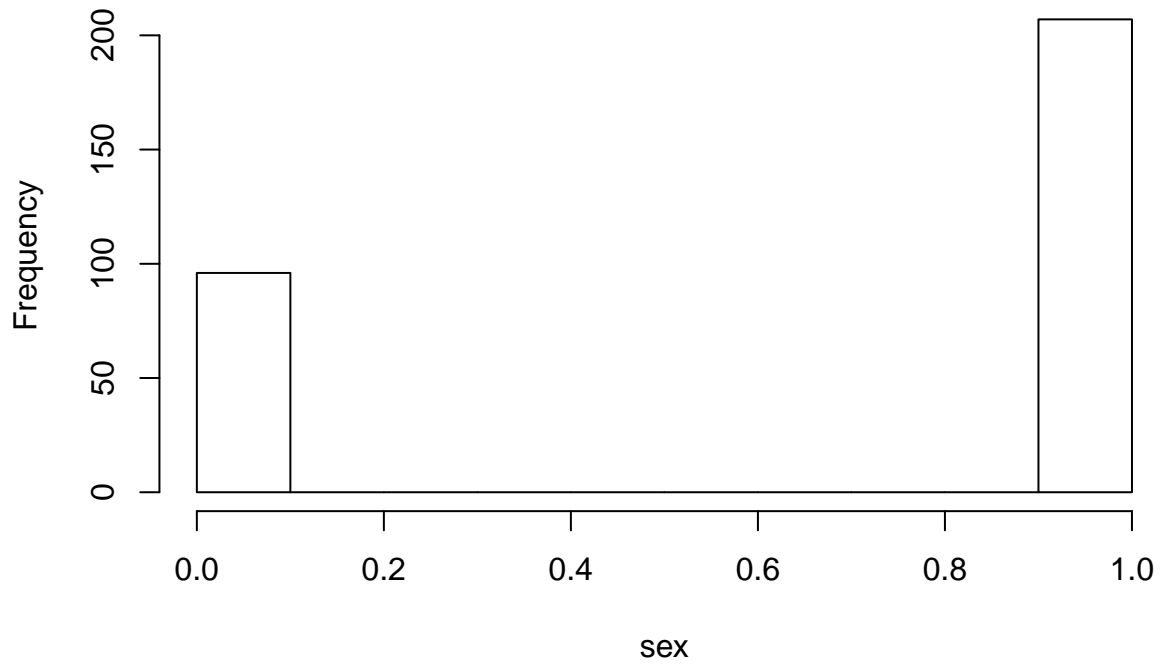
Explanatory Data Analysis

Plot histograms for all variables to analyze the distribution

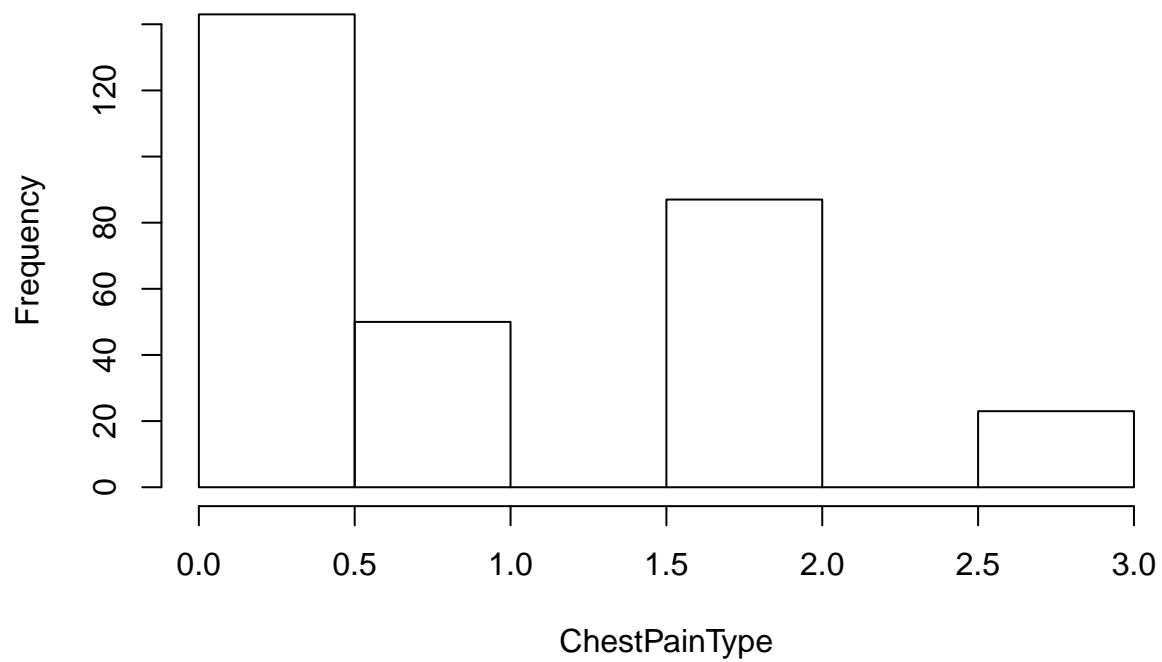
```
for (i in (1:ncol(HeartDeaseaseData))){  
  hist(HeartDeaseaseData[,i], xlab=names(HeartDeaseaseData[i]), main="Histograms of heart desease dataset"  
}
```



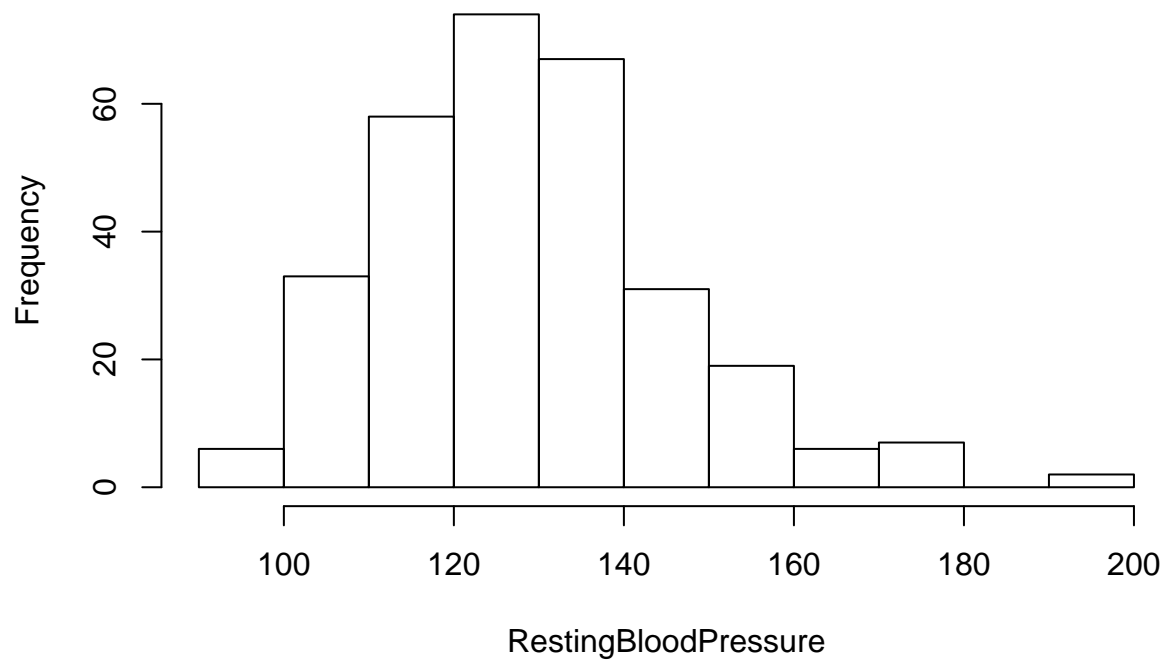
Histograms of heart disease dataset



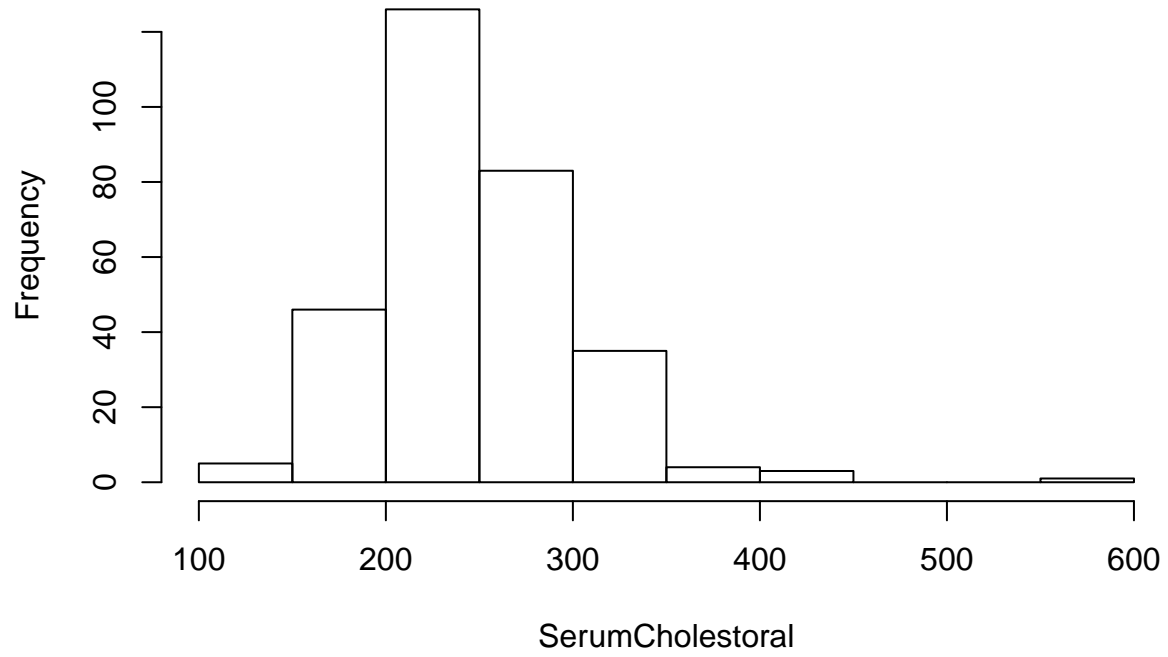
Histograms of heart disease dataset



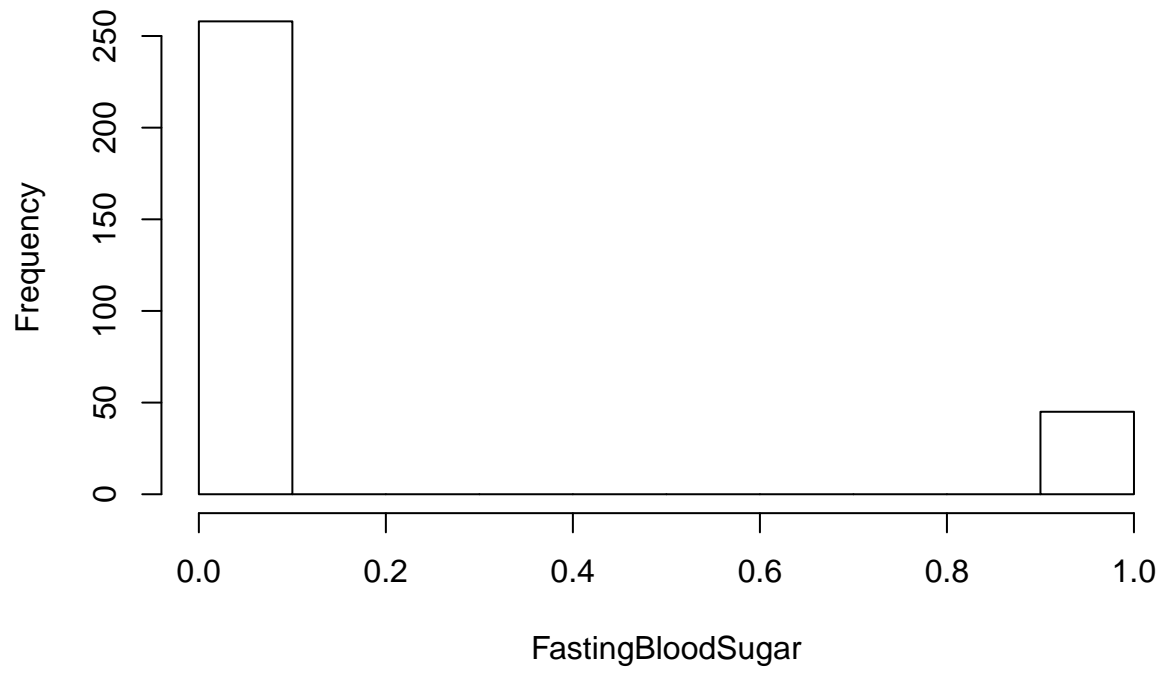
Histograms of heart disease dataset



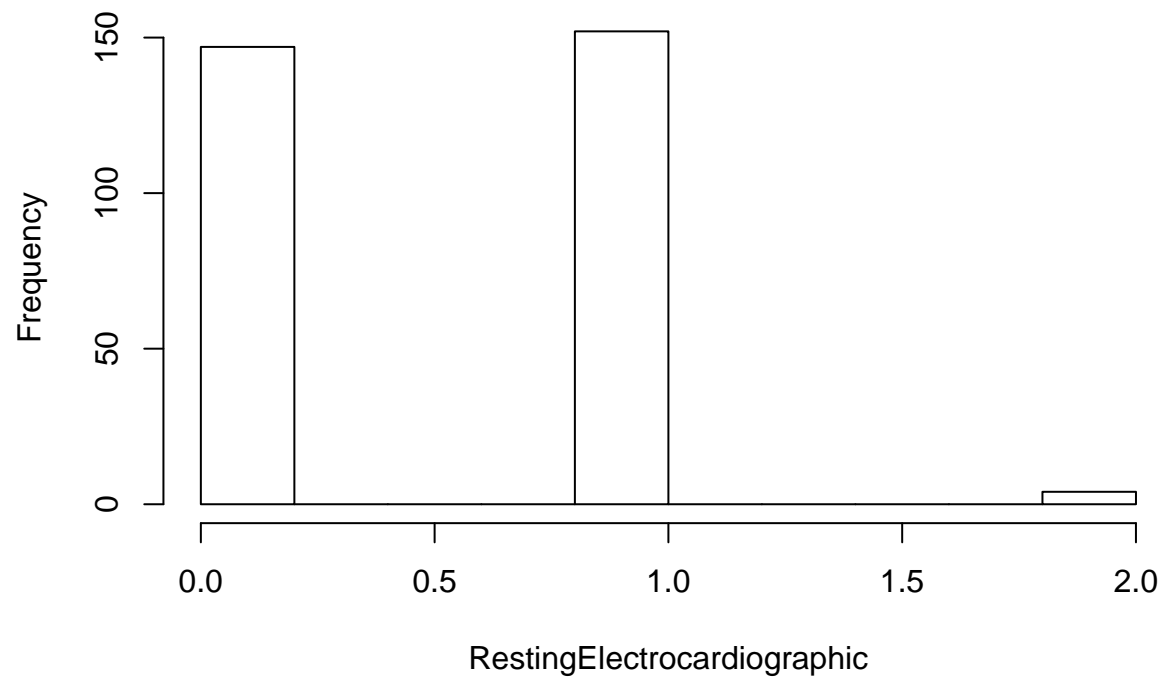
Histograms of heart disease dataset



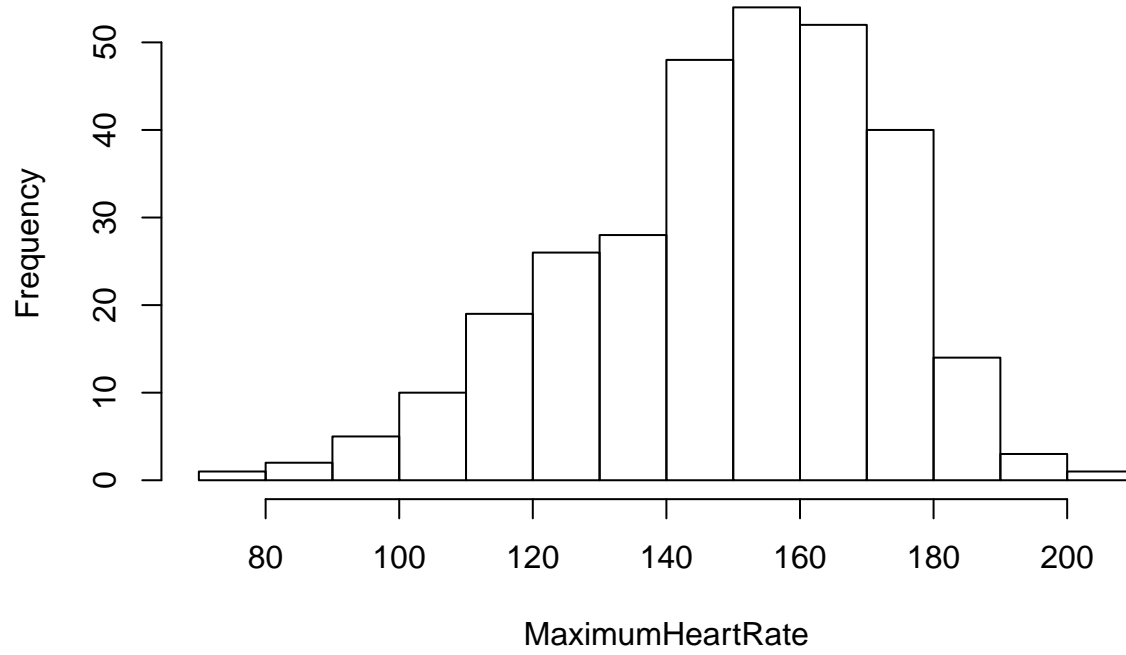
Histograms of heart disease dataset



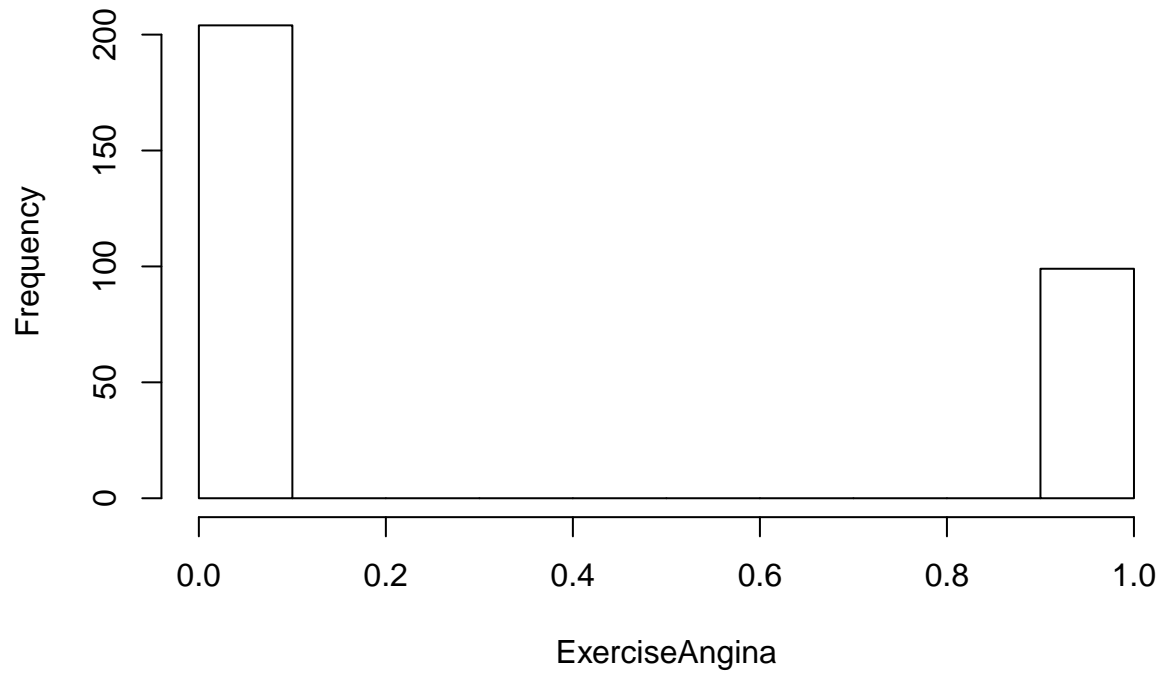
Histograms of heart disease dataset



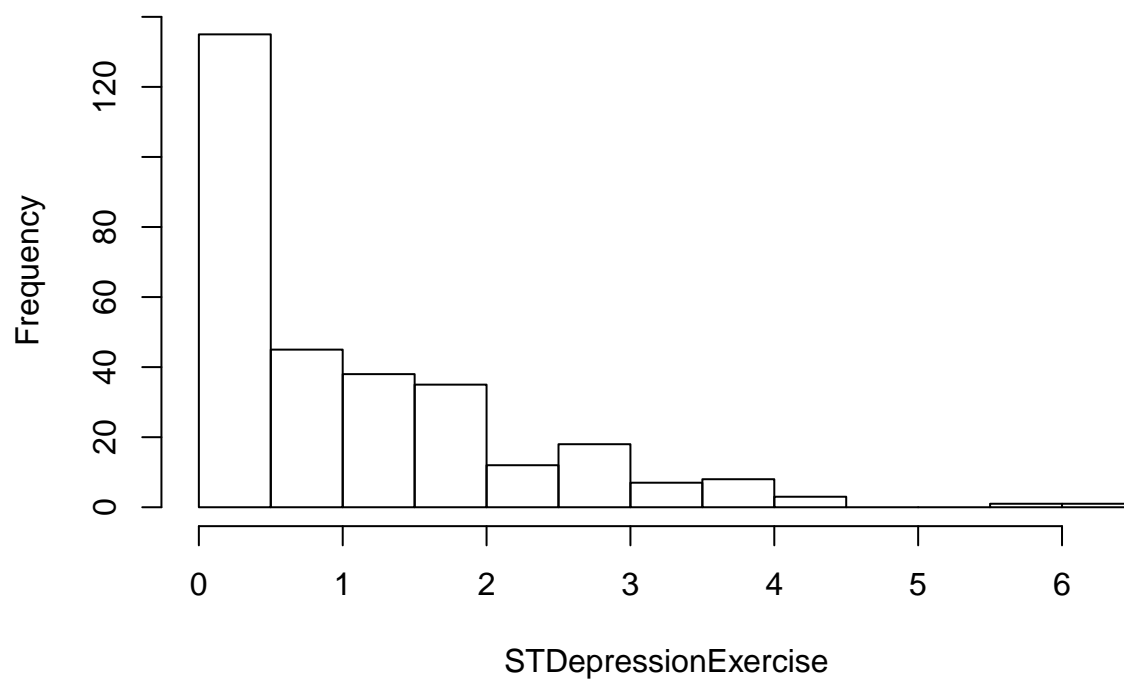
Histograms of heart disease dataset



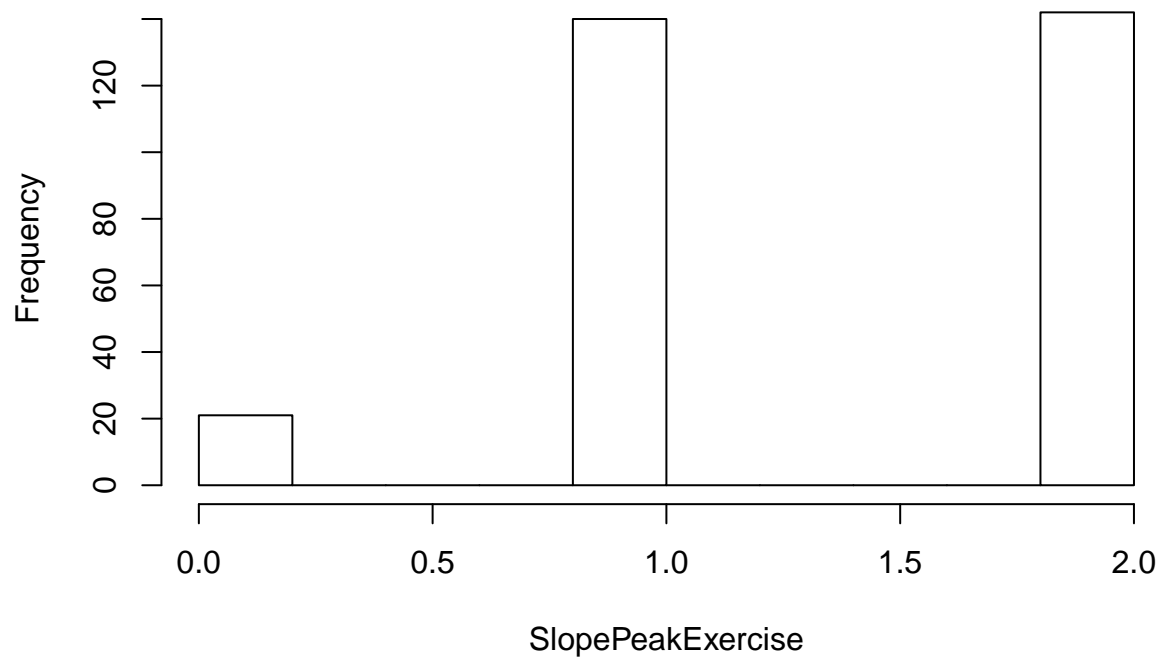
Histograms of heart disease dataset



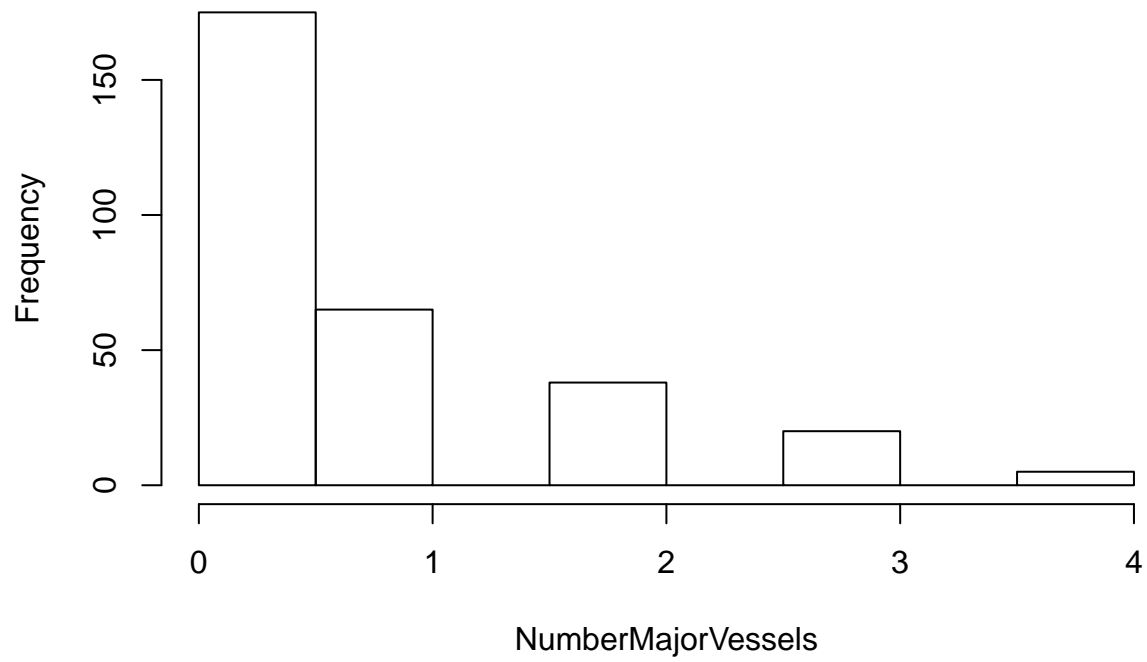
Histograms of heart disease dataset



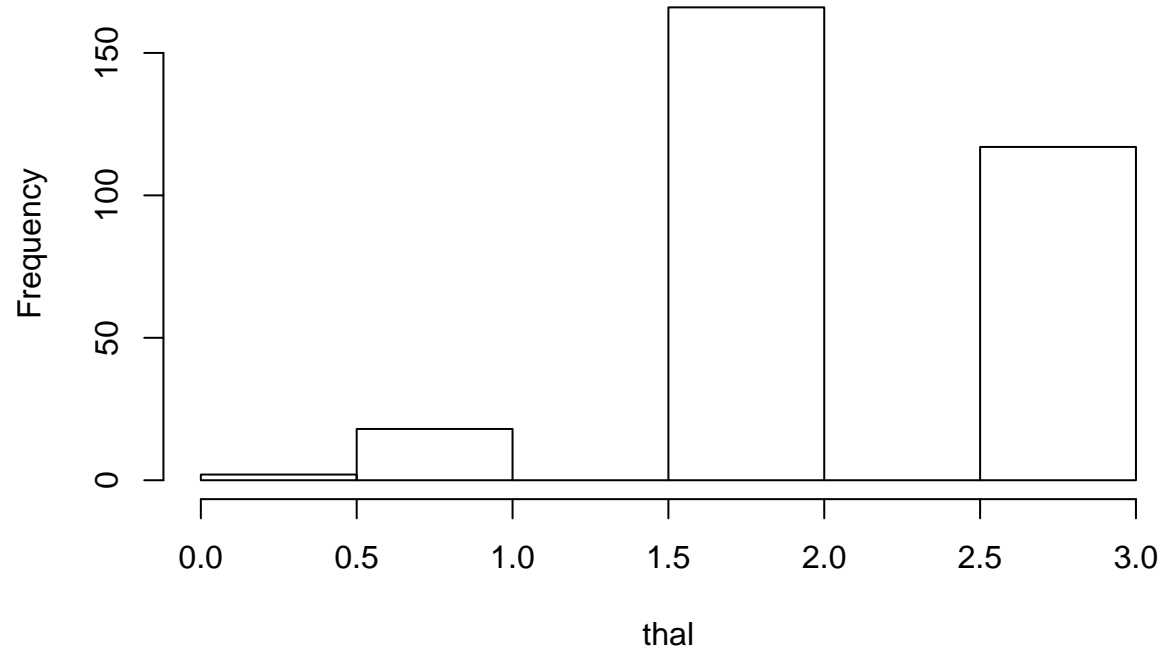
Histograms of heart disease dataset



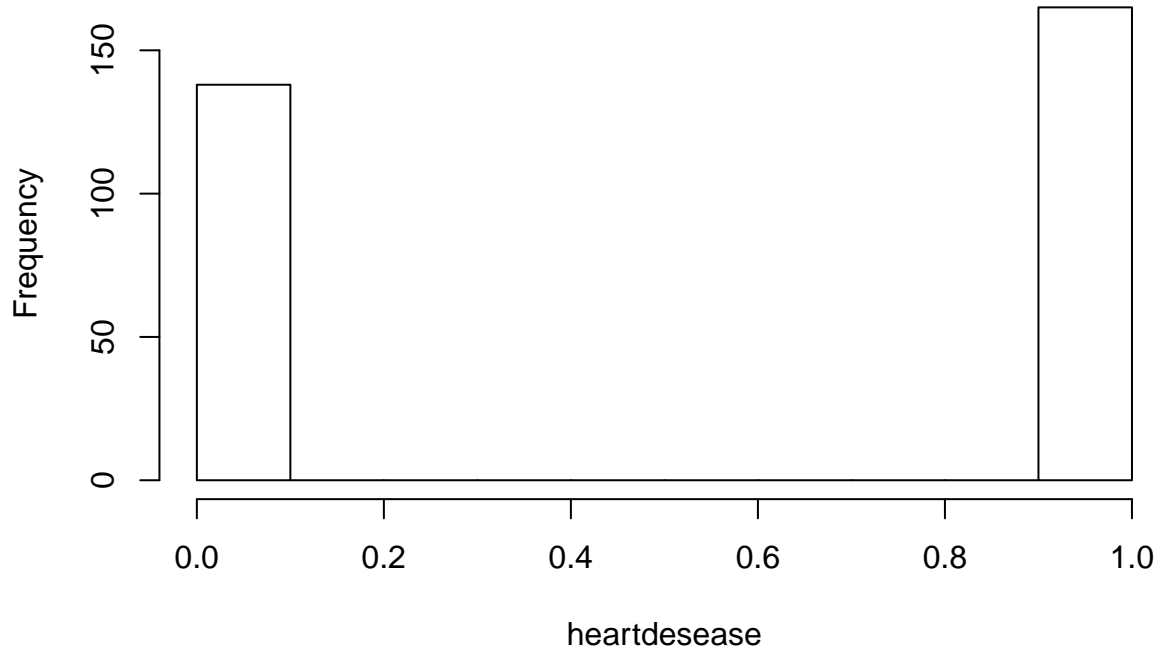
Histograms of heart disease dataset



Histograms of heart disease dataset



Histograms of heart disease dataset



Show a data summary

```
summary(HeartDeaseaseData)
```

```
##      age      sex ChestPainType RestingBloodPressure
## Min.   :29.00  Min.   :0.0000  Min.   :0.000  Min.   : 94.0
## 1st Qu.:47.50  1st Qu.:0.0000  1st Qu.:0.000  1st Qu.:120.0
## Median :55.00  Median :1.0000  Median :1.000  Median :130.0
## Mean   :54.37  Mean   :0.6832  Mean   :0.967  Mean   :131.6
## 3rd Qu.:61.00  3rd Qu.:1.0000  3rd Qu.:2.000  3rd Qu.:140.0
## Max.   :77.00  Max.   :1.0000  Max.   :3.000  Max.   :200.0
## SerumCholestoral FastingBloodSugar RestingElectrocardiographic
## Min.   :126.0  Min.   :0.0000  Min.   :0.0000
## 1st Qu.:211.0  1st Qu.:0.0000  1st Qu.:0.0000
## Median :240.0  Median :0.0000  Median :1.0000
## Mean   :246.3  Mean   :0.1485  Mean   :0.5281
## 3rd Qu.:274.5  3rd Qu.:0.0000  3rd Qu.:1.0000
## Max.   :564.0  Max.   :1.0000  Max.   :2.0000
## MaximumHeartRate ExerciseAngina STDepressionExercise SlopePeakExercise
## Min.   : 71.0  Min.   :0.0000  Min.   :0.00  Min.   :0.000
## 1st Qu.:133.5  1st Qu.:0.0000  1st Qu.:0.00  1st Qu.:1.000
## Median :153.0  Median :0.0000  Median :0.80  Median :1.000
## Mean   :149.6  Mean   :0.3267  Mean   :1.04  Mean   :1.399
## 3rd Qu.:166.0  3rd Qu.:1.0000  3rd Qu.:1.60  3rd Qu.:2.000
## Max.   :202.0  Max.   :1.0000  Max.   :6.20  Max.   :2.000
## NumberMajorVessels thal heartdesease
## Min.   :0.0000  Min.   :0.000  Min.   :0.0000
```

```
## 1st Qu.:0.0000    1st Qu.:2.000    1st Qu.:0.0000
## Median :0.0000    Median :2.000    Median :1.0000
## Mean   :0.7294    Mean   :2.314    Mean   :0.5446
## 3rd Qu.:1.0000    3rd Qu.:3.000    3rd Qu.:1.0000
## Max.   :4.0000    Max.   :3.000    Max.   :1.0000
```

Find risk factors for heart disease

Compute correlation coefficients with target variable for all features

```
correlations <- NULL
for (i in (1:(ncol(HeartDeseaseData)-1))){
  correlations[i] <- cor(HeartDeseaseData[,i],HeartDeseaseData$heartdesease)
}

names(correlations) <-names(HeartDeseaseData[-ncol(HeartDeseaseData)])
as.data.frame(correlations)
```

```
##               correlations
## age              -0.22543872
## sex              -0.28093658
## ChestPainType      0.43379826
## RestingBloodPressure -0.14493113
## SerumCholestoral  -0.08523911
## FastingBloodSugar -0.02804576
## RestingElectrocardiographic 0.13722950
## MaximumHeartRate   0.42174093
## ExerciseAngina     -0.43675708
## STDepressionExercise -0.43069600
## SlopePeakExercise   0.34587708
## NumberMajorVessels  -0.39172399
## thal              -0.34402927
```

```
sort(correlations, decreasing=TRUE)
```

```
##           ChestPainType           MaximumHeartRate
##           0.43379826           0.42174093
##           SlopePeakExercise RestingElectrocardiographic
##           0.34587708           0.13722950
##           FastingBloodSugar           SerumCholestoral
##           -0.02804576           -0.08523911
##           RestingBloodPressure           age
##           -0.14493113           -0.22543872
##           sex           thal
##           -0.28093658           -0.34402927
##           NumberMajorVessels           STDepressionExercise
##           -0.39172399           -0.43069600
##           ExerciseAngina
##           -0.43675708
```

Findings from correlation analysis:

*The Chest Pain Type as well as the maximum heart rate are important risk factors for heart diseases

Setup Training and Testing Datasets

Covert target variable to factor Shuffle data Split into training data (70%) and test data (30%) check dimensions

```
ColsToFactors <- c(
  #"sex",
  #"ChestPainType",
  #"FastingBloodSugar",
  #"RestingElectrocardiographic",
  #"ExerciseAngina",
  #"SlopePeakExercise",
  #"NumberMajorVessels",
  #"thal",
  "heartdesease")

HeartDeaseaseData[,ColsToFactors] <- as.factor(HeartDeaseaseData[,ColsToFactors])

RowIndices <- sample((1:nrow(HeartDeaseaseData)))
HeartDeaseaseData <- HeartDeaseaseData[RowIndices,]
split <- floor(0.7*nrow(HeartDeaseaseData))
training <- HeartDeaseaseData[(1:split),]
test <- HeartDeaseaseData[((split+1):nrow(HeartDeaseaseData)),]

dim(training)

## [1] 212 14

dim(test)

## [1] 91 14
```

Apply Machine Learning Models on dataset

- Logistic Regression
- PCA Regression
- Ridge, LASSO and Elastic Net Regression
- Random Forest Model

Logistic regression

```
LogReg_model <- train(as.factor(heartdesease)~., data=training, method="glm")

# Out-of-Sample predictions
LogReg_predictions <-
  predict(
    LogReg_model,
    newdata = test, type="prob")

# Out-of-sample forecast error:
confusionMatrix(
  as.factor(as.numeric(LogReg_predictions[,2]>0.5)),
  as.factor(test$heartdesease))
```

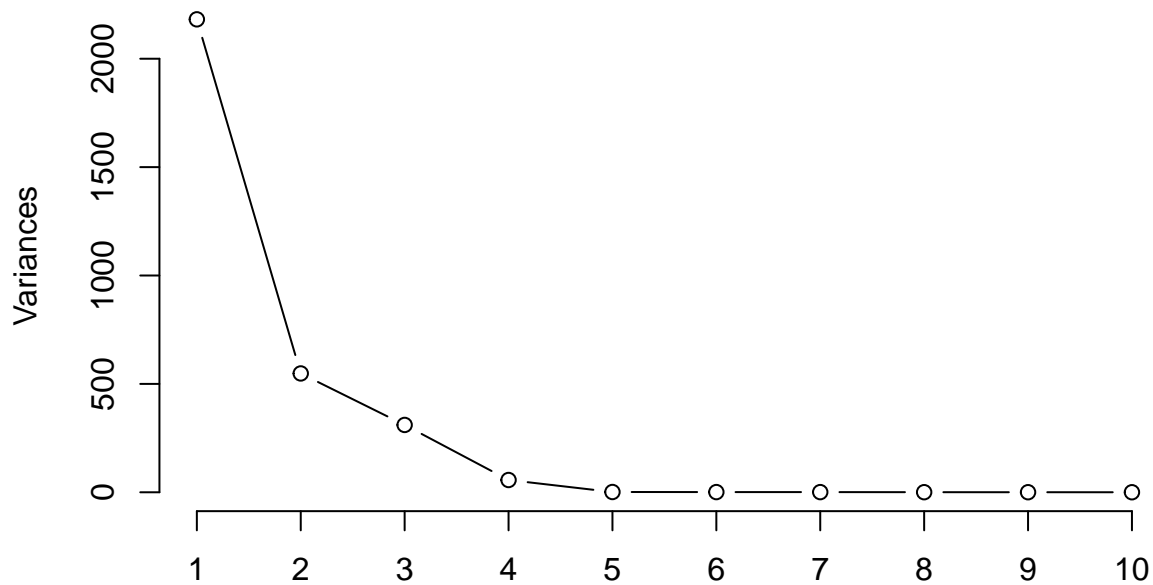
```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction  0   1
##           0 27   6
##           1   9 49
##
##           Accuracy : 0.8352
##           95% CI : (0.7427, 0.9047)
##           No Information Rate : 0.6044
##           P-Value [Acc > NIR] : 1.684e-06
##
##           Kappa : 0.6503
##           Mcnemar's Test P-Value : 0.6056
##
##           Sensitivity : 0.7500
##           Specificity : 0.8909
##           Pos Pred Value : 0.8182
##           Neg Pred Value : 0.8448
##           Prevalence : 0.3956
##           Detection Rate : 0.2967
##           Detection Prevalence : 0.3626
##           Balanced Accuracy : 0.8205
##
##           'Positive' Class : 0
##
```

Logistic PCA regression

```
training.pca <- prcomp(training[, -ncol(training)])

# Scree-Plot to determine number of PCA factors
plot(training.pca , type="l", main="Scree Plot")
```

Scree Plot



steep decline of the slope until the 5th PCA factor -> Include 5 PCA factors in PCA regression model

*# Set Training Parameter: Cross Validation & number of PCA Factors
for PCA Regression*

```
fitControlPCA <-  
  trainControl(method="none",  
    preProcOptions=list(pcaComp=5),  
    verboseIter = TRUE,  
    allowParallel = TRUE)
```

Logistic PCA Regression with 5 PCA Factors

```
PCR_model <-  
  train(  
    as.factor(heartdesease)~.,  
    data=training,  
    method="glm",  
    trControl = fitControlPCA,  
    preProcess="pca",  
    weights = NULL  
  )
```

Fitting parameter = none on full training set

Out-of-Sample predictions

```
PCR_predictions <-  
  predict(  
    PCR_model,
```

```

newdata = test, type="prob")

# Out-of-sample forecast error:
confusionMatrix(
  as.factor(as.numeric(PCR_predictions[,2]>0.5)),
  as.factor(test$heartdesease))

## Confusion Matrix and Statistics
##
##              Reference
## Prediction  0    1
##           0 28   6
##           1   8 49
##
##              Accuracy : 0.8462
##              95% CI : (0.7554, 0.9133)
##    No Information Rate : 0.6044
##    P-Value [Acc > NIR] : 4.859e-07
##
##              Kappa : 0.6752
##  Mcnemar's Test P-Value : 0.7893
##
##              Sensitivity : 0.7778
##              Specificity : 0.8909
##              Pos Pred Value : 0.8235
##              Neg Pred Value : 0.8596
##              Prevalence : 0.3956
##              Detection Rate : 0.3077
##    Detection Prevalence : 0.3736
##              Balanced Accuracy : 0.8343
##
##              'Positive' Class : 0
##

```

Logistic, Ridge-, LASSO- and Elastic Net Regression

```

# set Parameters -----
set.seed(1234)
# Initialize Parameters
Elastic_NetParameter <- data.frame(alpha=NaN, lambda=NaN)
LASSO_Parameter      <- data.frame(alpha=NaN, lambda=NaN)
RidgeReg_Parameter   <- data.frame(alpha=NaN, lambda=NaN)

# Set Grids for hyperparameters
Ridge_Grid <-
  expand.grid(alpha = 0,
             lambda = exp(seq(-9.21034,9.21034,length.out = 100)))
LASSO_Grid <-
  expand.grid(alpha = 1,
             lambda = exp(seq(-9.21034,9.21034,length.out = 100)))
Elastic_Grid <-

```

```

    expand.grid(alpha = seq(0,1,length.out = 100),
                lambda = exp(seq(-9.21034,9.21034,length.out = 100)))

# Set Training Parameter: Cross Validation
fitControl <- trainControl(method="cv",
                           number=5,
                           verboseIter = TRUE,
                           allowParallel = TRUE)

# Logistic Ridge regression -----
RidgeReg_model <-
  train(as.factor(heartdesease)~.,
        data=training,
        method="glmnet",
        trControl = fitControl,
        tuneGrid = Ridge_Grid,
        preProcess = NULL,
        weights = NULL)

## + Fold1: alpha=0, lambda=10000
## - Fold1: alpha=0, lambda=10000
## + Fold2: alpha=0, lambda=10000
## - Fold2: alpha=0, lambda=10000
## + Fold3: alpha=0, lambda=10000
## - Fold3: alpha=0, lambda=10000
## + Fold4: alpha=0, lambda=10000
## - Fold4: alpha=0, lambda=10000
## + Fold5: alpha=0, lambda=10000
## - Fold5: alpha=0, lambda=10000
## Aggregating results
## Selecting tuning parameters
## Fitting alpha = 0, lambda = 0.0673 on full training set

# Parameter of the best Ridge-Model (in cross-valuation)
RidgeReg_Parameter <- RidgeReg_model$bestTune
RidgeReg_Parameter

##      alpha      lambda
## 36      0 0.06734151

# Ridge Regression Prediction
# Out-of-sample-Sample predictions
RidgeReg_predictions <-
  predict(RidgeReg_model, test, type="prob")
# Out-of-sample forecast error:
# Out-of-sample forecast error:
confusionMatrix(
  as.factor(as.numeric(RidgeReg_predictions[,2]>0.5)),
  as.factor(test$heartdesease))

## Confusion Matrix and Statistics
##
##              Reference

```

```
## Prediction 0 1
##           0 26 5
##           1 10 50
##
##           Accuracy : 0.8352
##           95% CI : (0.7427, 0.9047)
##           No Information Rate : 0.6044
##           P-Value [Acc > NIR] : 1.684e-06
##
##           Kappa : 0.6468
##           McNemar's Test P-Value : 0.3017
##
##           Sensitivity : 0.7222
##           Specificity : 0.9091
##           Pos Pred Value : 0.8387
##           Neg Pred Value : 0.8333
##           Prevalence : 0.3956
##           Detection Rate : 0.2857
##           Detection Prevalence : 0.3407
##           Balanced Accuracy : 0.8157
##
##           'Positive' Class : 0
##
```

```
# Logistic LASSO regression -----
LASSO_model <- train(
  as.factor(heartdesease)~.,
  data=training,
  method="glmnet",
  trControl=fitControl,
  tuneGrid=LASSO_Grid,
  preProcess=NULL,weights=NULL
)
```

```
## + Fold1: alpha=1, lambda=10000
## - Fold1: alpha=1, lambda=10000
## + Fold2: alpha=1, lambda=10000
## - Fold2: alpha=1, lambda=10000
## + Fold3: alpha=1, lambda=10000
## - Fold3: alpha=1, lambda=10000
## + Fold4: alpha=1, lambda=10000
## - Fold4: alpha=1, lambda=10000
## + Fold5: alpha=1, lambda=10000
## - Fold5: alpha=1, lambda=10000
## Aggregating results
## Selecting tuning parameters
## Fitting alpha = 1, lambda = 0.00413 on full training set
```

```
# Parameter of the best LASSO-Model (in cross-validation)
LASSO_Parameter <- LASSO_model$bestTune
LASSO_Parameter
```

```
##      alpha      lambda
## 21      1 0.004132013
```



```

# Out-of-sample-Sample predictions
LASSO_predictions <-
  predict(LASSO_model, test, type="prob")
# Out-of-sample forecast error:
confusionMatrix(
  as.factor(as.numeric(LASSO_predictions[,2]>0.5)),
  as.factor(test$heartdesease))

```

```

## Confusion Matrix and Statistics
##
##           Reference
## Prediction  0   1
##           0 27  5
##           1  9 50
##
##           Accuracy : 0.8462
##           95% CI : (0.7554, 0.9133)
##       No Information Rate : 0.6044
##       P-Value [Acc > NIR] : 4.859e-07
##
##           Kappa : 0.672
##  Mcnemar's Test P-Value : 0.4227
##
##           Sensitivity : 0.7500
##           Specificity : 0.9091
##       Pos Pred Value : 0.8437
##       Neg Pred Value : 0.8475
##           Prevalence : 0.3956
##       Detection Rate : 0.2967
##       Detection Prevalence : 0.3516
##       Balanced Accuracy : 0.8295
##
##       'Positive' Class : 0
##

```

```

# Logistic Elastic Net regression -----
Elastic_Net_model <- train(
  as.factor(heartdesease)~.,
  data=training,
  method="glmnet",
  trControl=fitControl(preProcess=NULL,weights=NULL
)

```

```

## + Fold1: alpha=0.10, lambda=0.04376
## - Fold1: alpha=0.10, lambda=0.04376
## + Fold1: alpha=0.55, lambda=0.04376
## - Fold1: alpha=0.55, lambda=0.04376
## + Fold1: alpha=1.00, lambda=0.04376
## - Fold1: alpha=1.00, lambda=0.04376
## + Fold2: alpha=0.10, lambda=0.04376
## - Fold2: alpha=0.10, lambda=0.04376
## + Fold2: alpha=0.55, lambda=0.04376
## - Fold2: alpha=0.55, lambda=0.04376
## + Fold2: alpha=1.00, lambda=0.04376
## - Fold2: alpha=1.00, lambda=0.04376

```

```
## + Fold3: alpha=0.10, lambda=0.04376
## - Fold3: alpha=0.10, lambda=0.04376
## + Fold3: alpha=0.55, lambda=0.04376
## - Fold3: alpha=0.55, lambda=0.04376
## + Fold3: alpha=1.00, lambda=0.04376
## - Fold3: alpha=1.00, lambda=0.04376
## + Fold4: alpha=0.10, lambda=0.04376
## - Fold4: alpha=0.10, lambda=0.04376
## + Fold4: alpha=0.55, lambda=0.04376
## - Fold4: alpha=0.55, lambda=0.04376
## + Fold4: alpha=1.00, lambda=0.04376
## - Fold4: alpha=1.00, lambda=0.04376
## + Fold5: alpha=0.10, lambda=0.04376
## - Fold5: alpha=0.10, lambda=0.04376
## + Fold5: alpha=0.55, lambda=0.04376
## - Fold5: alpha=0.55, lambda=0.04376
## + Fold5: alpha=1.00, lambda=0.04376
## - Fold5: alpha=1.00, lambda=0.04376
## Aggregating results
## Selecting tuning parameters
## Fitting alpha = 0.1, lambda = 0.00438 on full training set
```

```
# Parameter of the best Elastic-Net-Model (in cross-validation)
Elastic_Net_Parameter <- Elastic_Net_model$bestTune
```

```
# Out-of-sample-Sample predictions
Elastic_Net_predictions <-
  predict(Elastic_Net_model, test, type="prob")
# Out-of-sample forecast error:
confusionMatrix(
  as.factor(as.numeric(Elastic_Net_predictions[,2]>0.5)),
  as.factor(test$heartdisease))
```

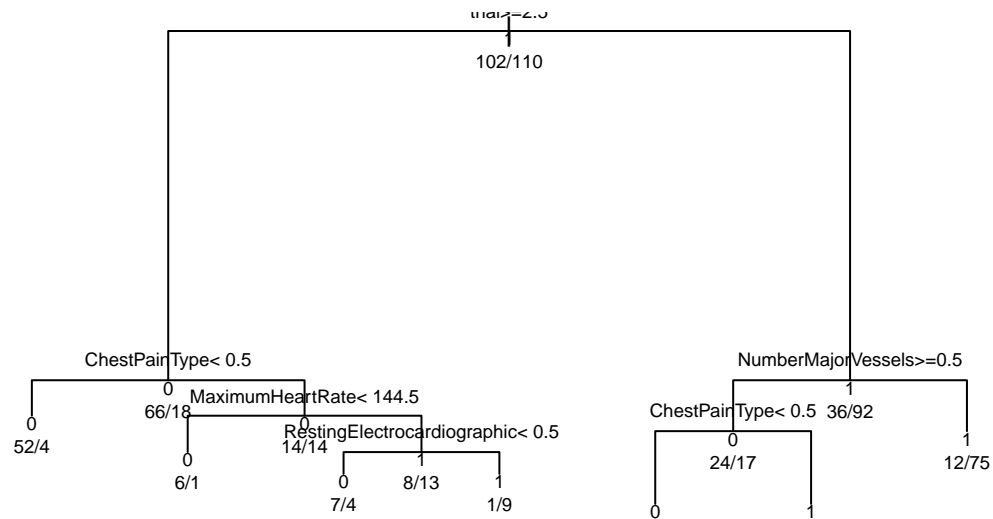
```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction  0  1
##           0 27  5
##           1  9 50
##
##           Accuracy : 0.8462
##           95% CI : (0.7554, 0.9133)
##           No Information Rate : 0.6044
##           P-Value [Acc > NIR] : 4.859e-07
##
##           Kappa : 0.672
##           McNemar's Test P-Value : 0.4227
##
##           Sensitivity : 0.7500
##           Specificity : 0.9091
##           Pos Pred Value : 0.8437
##           Neg Pred Value : 0.8475
##           Prevalence : 0.3956
##           Detection Rate : 0.2967
```

```
## Detection Prevalence : 0.3516
## Balanced Accuracy : 0.8295
##
## 'Positive' Class : 0
##
```

Random Forest

```
# Decision Tree -----
# grow tree
tree <- rpart(as.factor(heartdesease)~.,
              data=training)

# Plot decision tree as example
plot(tree)
text(tree, use.n=TRUE, all=TRUE, cex=.6)
```



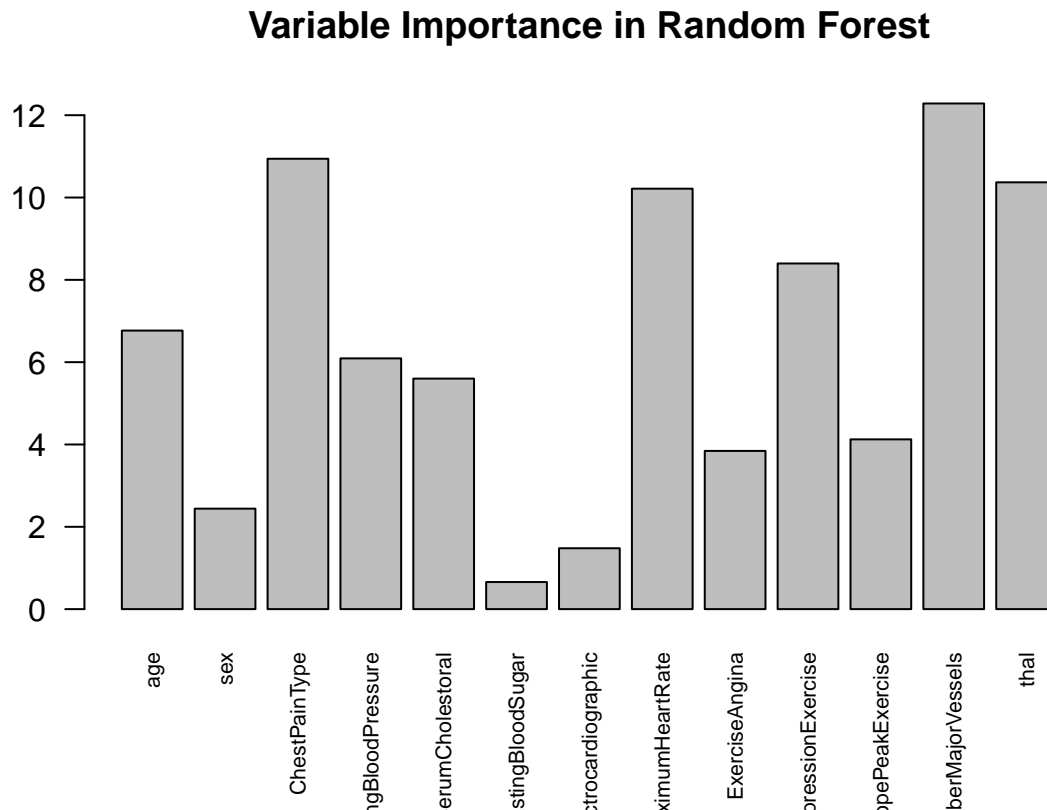
```
# Random Forest -----
set.seed(1234)
rf_model <-
  ranger (as.factor(heartdesease)~.,
          data=training,
          probability = TRUE,
          num.trees = 150,
          splitrule="gini",
          importance="impurity",
```

```

mtry=sqrt(ncol(training)-1),
verbose = TRUE)

barplot(rf_model$variable.importance, cex.names=0.7, horiz=FALSE, las=2,
main="Variable Importance in Random Forest")

```



```

# Out-of-sample predictions
rf_predictions <- predict(rf_model,test)
rf_predictions <- rf_predictions$predictions
# Out-of-sample forecast error:
confusionMatrix(
  as.factor(as.numeric(rf_predictions[,2]>0.5)),
  as.factor(test$heartdesease))

```

```

## Confusion Matrix and Statistics
##
##           Reference
## Prediction  0    1
##           0 28   8
##           1   8 47
##
##           Accuracy : 0.8242
##           95% CI : (0.7302, 0.896)
##           No Information Rate : 0.6044
##           P-Value [Acc > NIR] : 5.408e-06
##

```

```

##                Kappa : 0.6323
## Mcnemar's Test P-Value : 1
##
##                Sensitivity : 0.7778
##                Specificity : 0.8545
##                Pos Pred Value : 0.7778
##                Neg Pred Value : 0.8545
##                Prevalence : 0.3956
##                Detection Rate : 0.3077
##                Detection Prevalence : 0.3956
##                Balanced Accuracy : 0.8162
##
##                'Positive' Class : 0
##

```

Conclusion:

- The random forest model achieves a similar performance compared to the regression models on the test set.
- The variable importance plot shows that the most important variables in the random forest model are:
 1. Number of Major Vessels
 2. MaximumHeartRate (Feature 8: maximum heart rate achieved)
 3. ChestPainType (Feature 3: chest pain type (4 values))
 4. DepressionExercise (Feature 10. oldpeak = ST depression induced by exercise relative to rest)
- The Ridge Regression Model achieves the best accuracy on the test set, slightly better than the PCA Regression, LASSO, ELastic Net and Random Forest