## **Heart Desease**

Name: Austin Sampson

eMail: aws9t5@mst.edu

Course: CS 5402

**Date:** 02-24-2020

## **Concept Description:**

Train a system to draw a conection between biological metrics and Chronic Heat Desiease

### **Data Collection:**

Data has been provided from the client based off the observation of their feild agents. All data has been provided in the heart-disease.csv file ## Example Description:

### Age

Scalar to represent age of the patient. zero represents the absolute lowest age. zero years old

#### cigsPerDay

Scalar data to represent amount of cigerates consumed a day. zero represents no cigs being used.

#### totChol

Scalar data to represent amout of choleseterol in the patient. zero represents an absince of choleseterol.

## **sysBP**

systolic blood pressure is scalar data. zero represent no blood presure(in other words death/heart attack).

## diaBP

Diastolic Blood Pressure is scalar data. zero represent no blood presure(in other words death/heart attack).

#### **BMI**

body mass index is Scalar data representing expected body mass in respect to age group. zero means no body mass.

#### **Heart Rate**

Scalar Data, Zero represents the absince of a heart beat.

#### **Blood Glucose level**

Scalar Data, zero represnts an absince of Glucose in the body.

#### **CHD**

Chronic Heart Disease. This is our concept.

## **Data Import and Wrangling:**

```
#import data
data <- read.csv("heart-disease.csv")</pre>
#impute missing values (linear regression)
imp <- mice(data, method = "norm.predict", m = 1)</pre>
##
## iter imp variable
## 1 1 cigsPerDay totChol BMI heartRate glucose
## 2 1 cigsPerDay totChol BMI heartRate glucose
## 3 1 cigsPerDay totChol BMI heartRate glucose
   4 1 cigsPerDay totChol BMI heartRate glucose
##
##
    5 1 cigsPerDay totChol BMI heartRate glucose
#store data in graph form
data imp <- complete(imp)</pre>
#Partition data set to 70% train, 30% test.
smp size <- floor(0.70*nrow(data imp))</pre>
set.seed(123)
train_ind <- sample(seq_len(nrow(data_imp)), size = smp_size)</pre>
#create train and test tables
train <- data_imp[train_ind, ]</pre>
test <- data imp[-train ind, ]
```

# **Mining and Analytics:**

First I will begin with developing the Logistical Regression Model

```
#create Model
log_model <- glm(CHD ~., data = train, family = "binomial"(link="logit"))
#display model summary
summary(log_model)
##
## Call:
## glm(formula = CHD ~ ., family = binomial(link = "logit"), data = train)
##</pre>
```

```
## Deviance Residuals:
##
      Min
              10
                   Median
                              3Q
                                     Max
## -1.8311 -0.5971 -0.4299 -0.3008
                                   2.7798
## Coefficients:
##
              Estimate Std. Error z value Pr(>|z|)
## (Intercept) -8.4557408 0.6594270 -12.823 < 2e-16 ***
                                  9.074 < 2e-16 ***
## age
             0.0673678 0.0074243
                                  6.870 6.42e-12 ***
## cigsPerDay
             0.0304686 0.0044350
             0.0008665 0.0012579
## totChol
                                  0.689 0.490908
             ## sysBP
             0.0044515 0.0070517
## diaBP
                                  0.631 0.527868
             0.0003546 0.0136839 0.026 0.979327
## BMI
## heartRate
             0.0075786 0.0020030 3.784 0.000155 ***
## glucose
## Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
## (Dispersion parameter for binomial family taken to be 1)
##
##
      Null deviance: 2538.9 on 2965 degrees of freedom
## Residual deviance: 2251.4 on 2957
                                  degrees of freedom
## AIC: 2269.4
## Number of Fisher Scoring iterations: 5
```

The knn operator I am using directly returns the confusion matrix rather than a model. therofer I will be covering it in the next section.

```
#K-nearst Neighbor Function K=3
nn3 <- kNN(CHD ~ .,train,test,norm=TRUE,k=3)</pre>
#confusion Matrix
table(test[,'CHD'],nn3)
##
      nn3
##
                1
          0
##
     0 1017
               65
               25
##
     1 165
#K-nearst Neighbor Function K=1
nn2 <- kNN(CHD ~ .,train,test,norm=TRUE,k=5)</pre>
#confusion Matrix
table(test[,'CHD'],nn2)
##
      nn2
##
          0
                1
##
     0 1041
               41
##
     1 171
               19
```

## **Evaluation:**

## logistical Regression

First I will calculate the confusion matrix for the Logistic Regression Model

```
#calculate confusion matrix
pred_log <- predict(log_model, newdata = test,type="response")</pre>
#Code Testing
test$CHD <- as.factor(test$CHD)</pre>
temp <- as.numeric(pred_log>0.5)
temp <- as.factor(temp)</pre>
#code Testing
confusionMatrix(temp, test$CHD)
## Confusion Matrix and Statistics
##
             Reference
##
## Prediction
                 0
                      1
##
            0 1070 183
            1
                12
##
##
##
                  Accuracy : 0.8467
##
                    95% CI: (0.8257, 0.8661)
##
       No Information Rate: 0.8506
##
       P-Value [Acc > NIR] : 0.6701
##
##
                     Kappa: 0.0409
##
   Mcnemar's Test P-Value : <2e-16
##
##
##
               Sensitivity: 0.98891
##
               Specificity: 0.03684
##
            Pos Pred Value: 0.85395
            Neg Pred Value: 0.36842
##
##
                Prevalence: 0.85063
            Detection Rate: 0.84119
##
##
      Detection Prevalence: 0.98506
##
         Balanced Accuracy: 0.51288
##
          'Positive' Class: 0
##
##
```

K Nearest Neighbor

```
#K-nearst Neighbor Function K=3
nn3 <- kNN(CHD ~ .,train,test,norm=TRUE,k=3)</pre>
```

```
#confusion Matrix
table(test[,'CHD'],nn3)
##
      nn3
##
               1
              65
##
     0 1017
##
     1 165
              25
Error Rate = (65+165)/(1017+65+165+25)=0.1808
Accuracy = (1017+25)/(1017+65+165+25)=0.8192
Precission= (1017)/(1017+65)=0.9621
Recall=(1017)/(1017+165)=0.9399
F-measure=(20.93990.9621)/(0.8589+0.9621)=0.9075
```

Based off the results of the confusion matrices for the two model I would present the Logistical Regression model to the customer. I would do this because the logistical regressional model presents a slightly better accuraccy but more importantly the model produces significantly less false negatives. Due to the nature of what we are predicting being corolated to the risk of heart attack or stroke we should prioritize minimizing false negatives because they present an increased risk of death. False positives can be identified with further medical tests.

## **Referinces:**

https://cran.r-project.org/web/packages/mice/mice.pdf https://stats.stackexchange.com/questions/100841/imputation-by-regression-in-r https://stackoverflow.com/questions/17200114/how-to-split-data-into-training-testing-sets-using-sample-function

https://www.rdocumentation.org/packages/DMwR/versions/0.4.1/topics/kNN https://stats.idre.ucla.edu/r/dae/logit-regression/ https://stats.idre.ucla.edu/r/dae/logit-regression/ https://intellipaat.com/community/1546/error-in-confusion-matrix-the-data-and-reference-factors-must-have-the-same-number-of-levels