

Risk Stratification

Risk stratification of diabetes patients with random forest

```
# Load the cleaned data
data <- read.csv("data/data_cleaned.csv", header=TRUE,
                na.strings = c("NA","na","", " ","?"), stringsAsFactors = FALSE)
# save the ID of patients
ID <- data$ID
# Remove the ID before analysis
data <- data[2:42]
table(data$readmitted)
```

```
##
##      NO      YES
## 53316 46176
```

```
data$readmitted <- as.factor(data$readmitted)
```

```
# sampling down the data
set.seed(123)
data_rf <- data[sample(nrow(data), nrow(data)*0.25, replace = F),]

set.seed(123)
indices <- sample(2, nrow(data_rf), replace = T, prob = c(0.75, 0.25))
train <- data_rf[indices == 1, ]
test <- data_rf[indices == 2, ]
```

```
set.seed(123)
rf.model <- randomForest(readmitted ~ ., data = train, do.trace = T)
```

```
## ntree      OOB      1      2
##      1:  44.50% 40.17% 49.41%
##      2:  45.20% 40.07% 51.04%
##      3:  44.84% 38.59% 52.00%
##      4:  44.82% 38.14% 52.46%
##      5:  44.76% 37.60% 53.00%
##      6:  44.73% 37.33% 53.19%
##      7:  44.57% 37.06% 53.12%
```

##	8:	44.32%	36.40%	53.37%
##	9:	44.14%	36.49%	52.91%
##	10:	44.22%	36.59%	52.98%
##	11:	43.89%	36.09%	52.84%
##	12:	43.50%	35.69%	52.48%
##	13:	43.36%	35.42%	52.48%
##	14:	42.82%	34.74%	52.13%
##	15:	42.32%	33.95%	51.95%
##	16:	42.45%	34.01%	52.15%
##	17:	42.11%	33.70%	51.78%
##	18:	42.14%	33.81%	51.72%
##	19:	42.01%	33.46%	51.84%
##	20:	41.74%	33.13%	51.66%
##	21:	41.83%	33.03%	51.97%
##	22:	41.40%	32.65%	51.48%
##	23:	41.31%	32.63%	51.30%
##	24:	41.26%	32.64%	51.19%
##	25:	41.12%	32.48%	51.06%
##	26:	41.07%	32.57%	50.85%
##	27:	40.65%	31.90%	50.72%
##	28:	40.90%	32.14%	50.98%
##	29:	40.73%	32.04%	50.74%
##	30:	40.61%	31.87%	50.66%
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##	32:	40.38%	31.72%	50.33%
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##	36:	40.28%	31.54%	50.35%
##	37:	40.19%	31.37%	50.33%
##	38:	40.08%	31.48%	49.98%
##	39:	40.22%	31.65%	50.08%
##	40:	40.11%	31.68%	49.82%
##	41:	39.97%	31.23%	50.03%
##	42:	40.05%	31.45%	49.95%
##	43:	40.19%	31.62%	50.05%
##	44:	40.03%	31.50%	49.85%
##	45:	39.89%	31.29%	49.78%
##	46:	39.94%	31.30%	49.87%
##	47:	40.09%	31.45%	50.03%
##	48:	39.81%	30.93%	50.02%
##	49:	39.77%	30.89%	50.00%
##	50:	39.87%	31.11%	49.94%
##	51:	39.79%	30.90%	50.02%
##	52:	39.88%	30.91%	50.20%
##	53:	39.79%	30.73%	50.21%
##	54:	39.82%	30.96%	50.01%
##	55:	39.84%	30.97%	50.05%
##	56:	39.67%	30.92%	49.75%
##	57:	39.91%	31.18%	49.97%
##	58:	39.94%	31.12%	50.09%

##	59:	39.80%	31.25%	49.64%
##	60:	39.81%	30.95%	50.01%
##	61:	39.92%	31.16%	50.01%
##	62:	39.67%	31.01%	49.63%
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425: 38.21% 28.68% 49.19%
426: 38.27% 28.77% 49.22%
427: 38.27% 28.86% 49.10%
428: 38.25% 28.69% 49.25%
429: 38.23% 28.70% 49.20%
430: 38.17% 28.66% 49.12%
431: 38.17% 28.68% 49.10%
432: 38.19% 28.69% 49.13%
433: 38.17% 28.68% 49.09%
434: 38.20% 28.63% 49.23%
435: 38.27% 28.67% 49.32%
436: 38.27% 28.69% 49.30%
437: 38.23% 28.71% 49.19%
438: 38.24% 28.62% 49.31%
439: 38.20% 28.62% 49.24%
440: 38.21% 28.56% 49.32%
441: 38.26% 28.68% 49.28%
442: 38.29% 28.71% 49.32%
443: 38.29% 28.71% 49.32%
444: 38.31% 28.73% 49.33%
445: 38.36% 28.74% 49.45%
446: 38.32% 28.66% 49.45%
447: 38.33% 28.72% 49.40%
448: 38.24% 28.59% 49.35%
449: 38.36% 28.68% 49.50%
450: 38.36% 28.74% 49.43%
451: 38.29% 28.61% 49.43%
452: 38.29% 28.73% 49.30%
453: 38.24% 28.60% 49.34%
454: 38.25% 28.60% 49.35%
455: 38.28% 28.57% 49.47%
456: 38.21% 28.55% 49.33%
457: 38.26% 28.58% 49.40%
458: 38.23% 28.63% 49.28%
459: 38.18% 28.61% 49.20%
460: 38.25% 28.59% 49.37%
461: 38.17% 28.47% 49.34%
462: 38.23% 28.51% 49.42%
463: 38.28% 28.69% 49.32%
464: 38.26% 28.55% 49.45%
465: 38.23% 28.54% 49.38%
466: 38.27% 28.59% 49.42%

```
## 467: 38.12% 28.41% 49.30%
## 468: 38.15% 28.43% 49.34%
## 469: 38.16% 28.52% 49.25%
## 470: 38.16% 28.44% 49.35%
## 471: 38.19% 28.53% 49.32%
## 472: 38.23% 28.53% 49.39%
## 473: 38.18% 28.52% 49.31%
## 474: 38.19% 28.55% 49.30%
## 475: 38.18% 28.57% 49.25%
## 476: 38.20% 28.58% 49.27%
## 477: 38.24% 28.57% 49.38%
## 478: 38.19% 28.57% 49.26%
## 479: 38.19% 28.54% 49.31%
## 480: 38.25% 28.56% 49.40%
## 481: 38.21% 28.60% 49.27%
## 482: 38.29% 28.61% 49.45%
## 483: 38.29% 28.60% 49.46%
## 484: 38.24% 28.57% 49.37%
## 485: 38.32% 28.67% 49.43%
## 486: 38.20% 28.55% 49.31%
## 487: 38.19% 28.51% 49.34%
## 488: 38.23% 28.56% 49.37%
## 489: 38.24% 28.57% 49.37%
## 490: 38.24% 28.60% 49.34%
## 491: 38.26% 28.58% 49.40%
## 492: 38.25% 28.50% 49.47%
## 493: 38.26% 28.56% 49.43%
## 494: 38.32% 28.53% 49.60%
## 495: 38.27% 28.54% 49.48%
## 496: 38.24% 28.54% 49.40%
## 497: 38.21% 28.53% 49.35%
## 498: 38.29% 28.65% 49.40%
## 499: 38.21% 28.56% 49.33%
## 500: 38.23% 28.58% 49.33%
```

```
rf.predict <- predict(rf.model, test[,-1], type = "class")
confusionMatrix(rf.predict, test$readmitted)
```

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

```
##
```

```
##           Reference
```

```
## Prediction  NO  YES
```

```
##           NO  2138 1093
```

```
##           YES 1249 1743
```

```
##
```

```
##           Accuracy : 0.6237
```

```
##           95% CI : (0.6115, 0.6357)
```

```
##           No Information Rate : 0.5443
```

```
##           P-Value [Acc > NTR] : < 2.2e-16
```

```
##      F-value [ACC / NIN] :  \ 2.2E-10
##
##      Kappa : 0.2447
##  McNemar's Test P-Value : 0.001361
##
##      Sensitivity : 0.6312
##      Specificity : 0.6146
##      Pos Pred Value : 0.6617
##      Neg Pred Value : 0.5826
##      Prevalence : 0.5443
##      Detection Rate : 0.3436
##      Detection Prevalence : 0.5192
##      Balanced Accuracy : 0.6229
##
##      'Positive' Class : NO
##
```

Random forest gives better accuracy. Find out the optimal probability cutoff. Create a function to find the accuracy, sensitivity and specificity for a given cutoff.

```
rf_predict <- data.frame(predict(rf.model, test[, -1], type = "prob"))
predicted_readmission <- factor(ifelse(rf_predict$YES >= 0.5, "YES", "NO"))
perform_fn <- function(cutoff)
{
  predicted_readmission <- factor(ifelse(rf_predict$YES >= cutoff, "YES", "NO"))
  conf <- confusionMatrix(predicted_readmission, test$readmitted, positive = "YES")
  acc <- conf$overall[1]
  sens <- conf$byClass[1]
  spec <- conf$byClass[2]
  out <- t(as.matrix(c(sens, spec, acc)))
  colnames(out) <- c("sensitivity", "specificity", "accuracy")
  return(out)
}
summary(rf_predict$YES)
```

```
##      Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##  0.0400  0.3860  0.4920  0.4905  0.5980  0.9280
```

```
summary(rf_predict$NO)
```

```
##      Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##  0.0720  0.4020  0.5080  0.5095  0.6140  0.9600
```

```
# Creating cutoff values from 0.01 to 0.95 for plotting and initiallizing a matrix of
s = seq(.01,.95,length=100)
OUT = matrix(0,100,3)
for(i in 1:100){
  OUT[i,] = perform_fn(s[i])
}
```

```
## Warning in confusionMatrix.default(predicted_readmission,
## test$readmitted, : Levels are not in the same order for reference and data.
## Refactoring data to match.
```

```
## Warning in confusionMatrix.default(predicted_readmission,
## test$readmitted, : Levels are not in the same order for reference and data.
## Refactoring data to match.
```

```
## Warning in confusionMatrix.default(predicted_readmission,
## test$readmitted, : Levels are not in the same order for reference and data.
## Refactoring data to match.
```

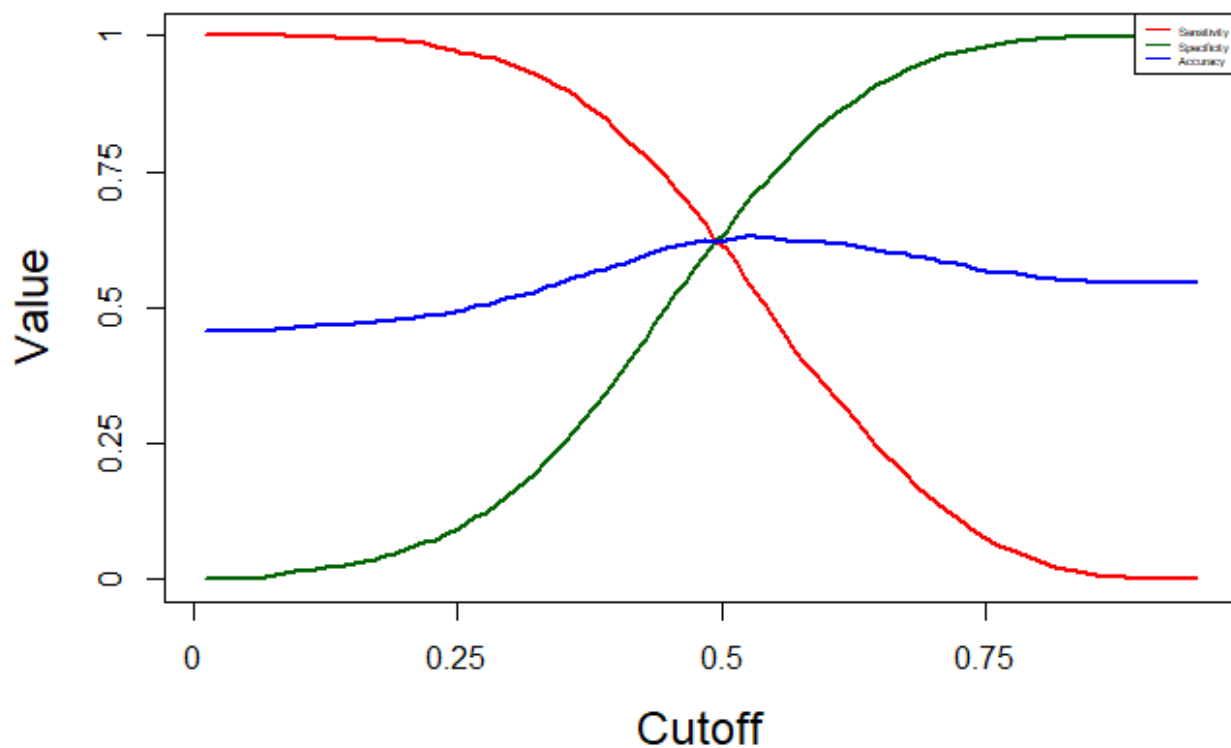
```
## Warning in confusionMatrix.default(predicted_readmission,
## test$readmitted, : Levels are not in the same order for reference and data.
## Refactoring data to match.
```

```
## Warning in confusionMatrix.default(predicted_readmission,
## test$readmitted, : Levels are not in the same order for reference and data.
## Refactoring data to match.
```

```
## Warning in confusionMatrix.default(predicted_readmission,
## test$readmitted, : Levels are not in the same order for reference and data.
## Refactoring data to match.
```

```
## Warning in confusionMatrix.default(predicted_readmission,
## test$readmitted, : Levels are not in the same order for reference and data.
## Refactoring data to match.
```

```
plot(s, OUT[,1],xlab="Cutoff",ylab="Value",cex.lab=1.5,cex.axis=1.5,ylim=c(0,1),type=
      lwd=2,axes=FALSE,col=2)
axis(1,seq(0,1,length=5),seq(0,1,length=5),cex.lab=1.5)
axis(2,seq(0,1,length=5),seq(0,1,length=5),cex.lab=1.5)
lines(s,OUT[,2],col="darkgreen",lwd=2)
lines(s,OUT[,3],col=4,lwd=2)
box()
legend("topright",col=c(2,"darkgreen",4),lwd=c(1,1,1),
      c("Sensitivity","Specificity","Accuracy"), cex=0.4)
```



```
cutoff <- s[which.min(abs(OUT[,1]-OUT[,2]))]
cutoff
```

```
## [1] 0.4942424
```

Confusion matrix for the cutoff value

```
test_cutoff_readmission <- factor(ifelse(rf_predict$YES >= cutoff, "YES", "NO"))
conf_final <- confusionMatrix(test_cutoff_readmission, test$readmitted, positive = "Y")
acc <- conf_final$overall[1]
sens <- conf_final$byClass[1]
spec <- conf_final$byClass[2]
acc
```

```
## Accuracy
## 0.6223686
```

sens

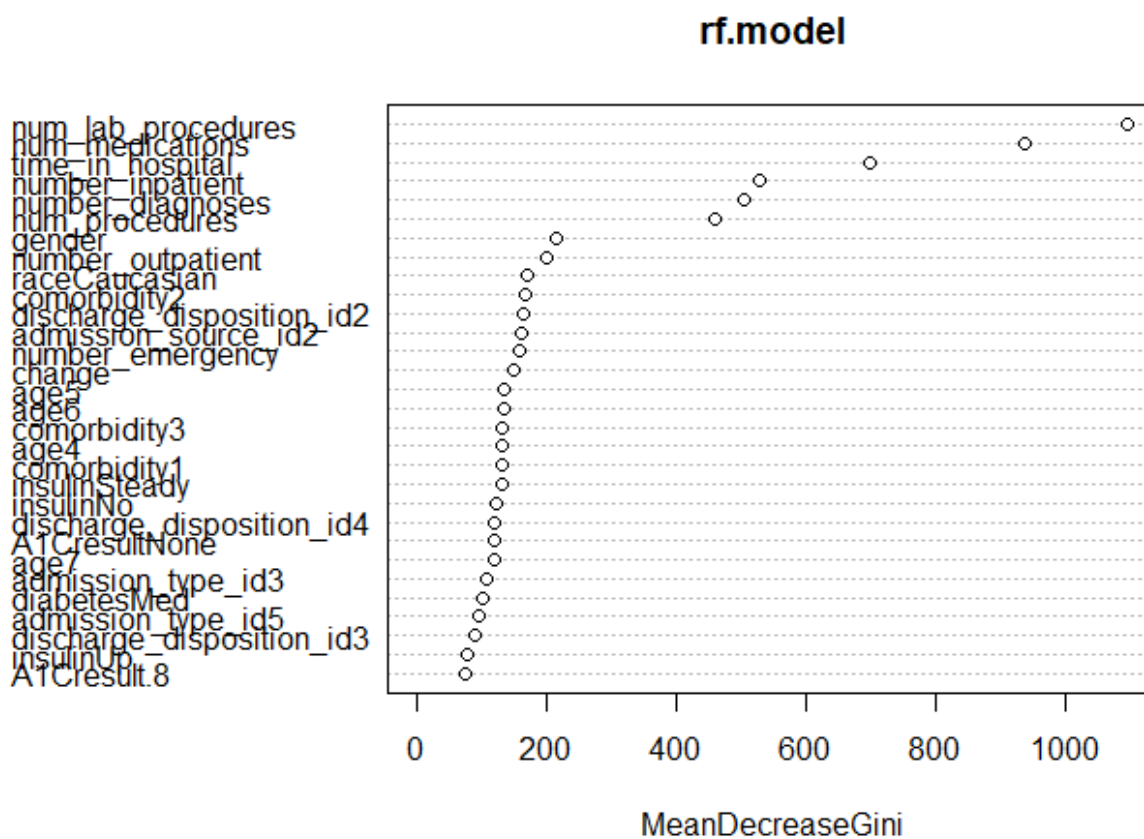
```
## Sensitivity
## 0.6255289
```

spec

```
## Specificity
## 0.6197225
```

Checking important variables

```
varImpPlot(rf.model)
```



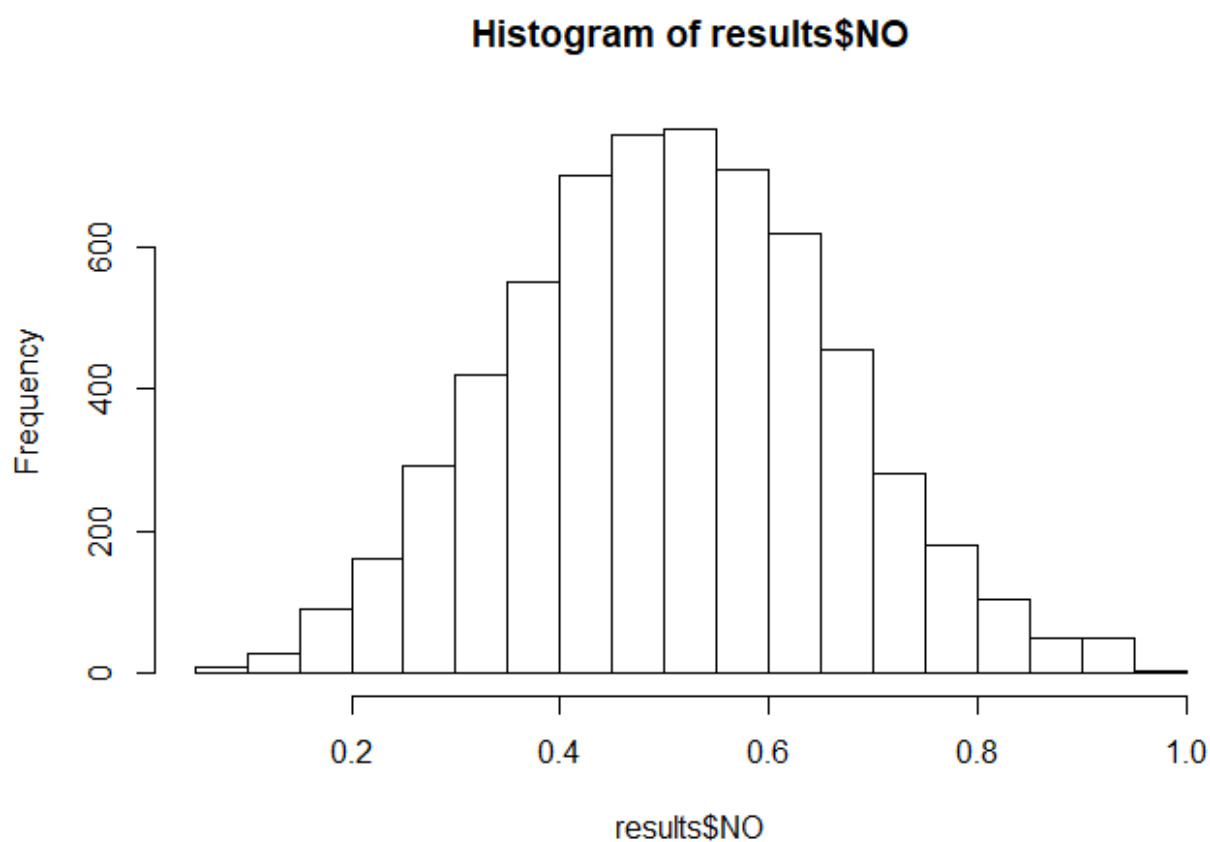
```
#Checking distribution of yeses and nos
Id_index <- as.numeric(row.names(test))
PATIENT_ID <- ID[Id_index]
```

```
results <- data.frame(PATIENT_ID, rf_predict)
```

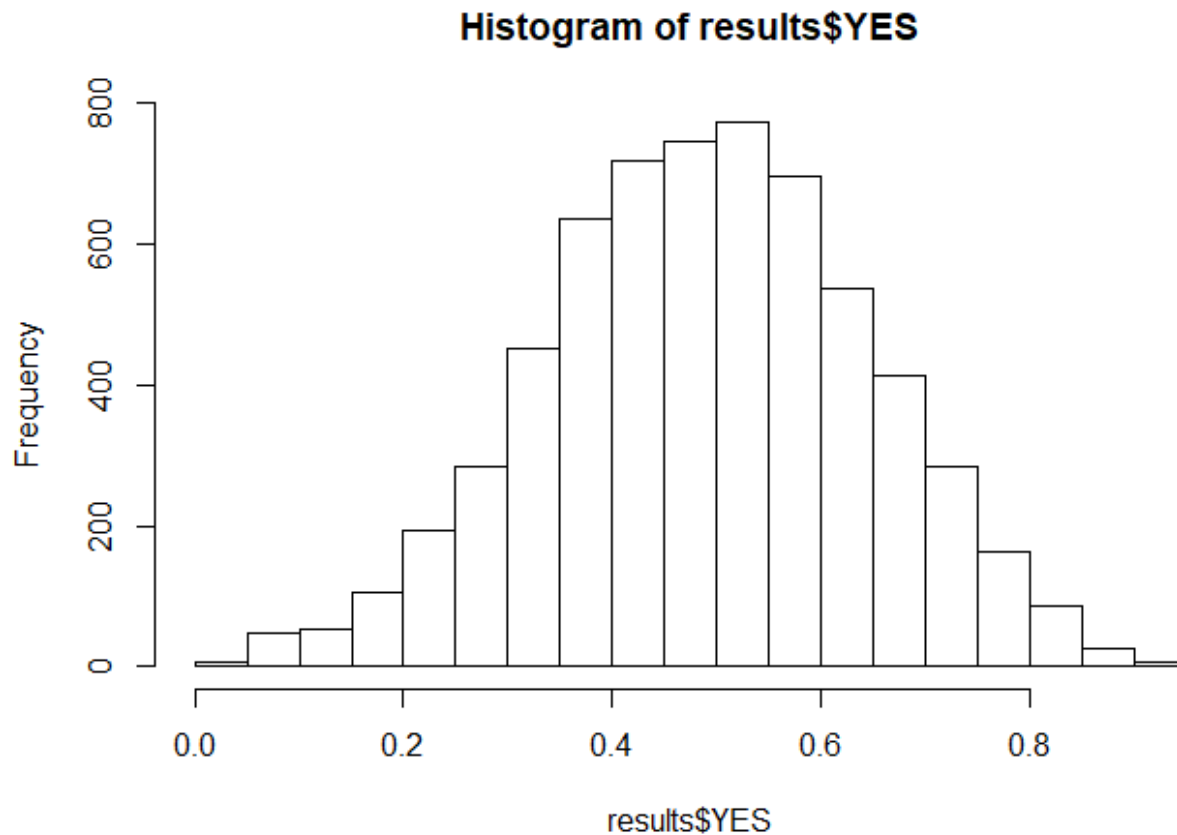
```
head(results)
```

```
##      PATIENT_ID    NO    YES
## 78430   41464089 0.518 0.482
## 87851  105071256 0.688 0.312
## 93566   90416916 0.586 0.414
## 88783  137757875 0.364 0.636
## 95188  103127940 0.494 0.506
## 89512   88498926 0.502 0.498
```

```
hist(results$NO)
```



```
hist(results$YES)
```

Stratification

```

low_threshold <- 0.3
high_threshold <- 0.7
results$risk_bucket <- character(length = nrow(results))
results$risk_bucket <- apply(results, 1, function(x){
  if(x[3] < low_threshold)
    x[4] <- "LOW"
  else if(x[3] > high_threshold)
    x[4] <- "HIGH"
  else
    x[4] <- "MEDIUM"
})
head(results)

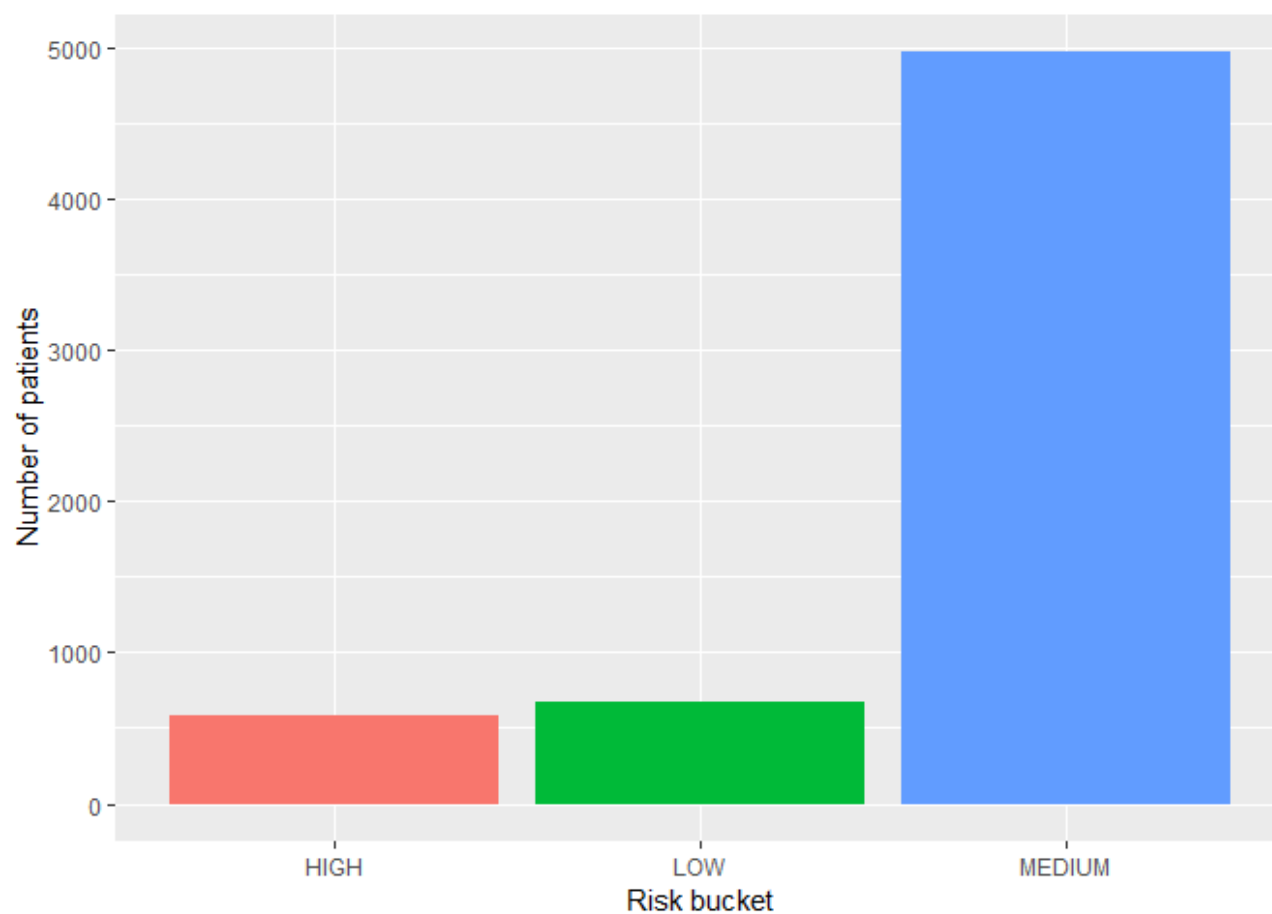
```

```

##      PATIENT_ID   NO   YES risk_bucket
## 78430   41464089 0.518 0.482      MEDIUM
## 87851  105071256 0.688 0.312      MEDIUM
## 93566   90416916 0.586 0.414      MEDIUM
## 88783  137757875 0.364 0.636      MEDIUM
## 95188  103127940 0.494 0.506      MEDIUM
## 89512   88498926 0.502 0.498      MEDIUM

```

```
ggplot(data = results, aes(risk_bucket, fill=risk_bucket)) +
  geom_bar() +
  theme(legend.position = "none") +
  labs(x="Risk bucket", y="Number of patients")
```



```
prop.table(table(results$risk_bucket))
```

```
##
##      HIGH      LOW      MEDIUM
## 0.09336333 0.10782581 0.79881086
```

```
# low risk patients
low_risk <- subset(results, results$risk_bucket == "LOW")
low_risk <- low_risk %>% arrange(YES)
head(low_risk)
```

```
##  PATIENT_ID    NO  YES risk_bucket
## 1  141426248 0.960 0.040          LOW
## 2   66877713 0.958 0.042          LOW
```

```
## 3 41582448 0.958 0.042 LOW
## 4 95460858 0.954 0.046 LOW
## 5 102158460 0.954 0.046 LOW
## 6 76084191 0.950 0.050 LOW
```

```
# high risk patients
high_risk <- subset(results, results$risk_bucket == "HIGH")
high_risk <- high_risk %>% arrange(desc(YES))
head(high_risk)
```

```
## PATIENT_ID NO YES risk_bucket
## 1 40881753 0.072 0.928 HIGH
## 2 90052641 0.074 0.926 HIGH
## 3 88227540 0.086 0.914 HIGH
## 4 88479036 0.090 0.910 HIGH
## 5 50293827 0.094 0.906 HIGH
## 6 113805873 0.094 0.906 HIGH
```

```
# medium risk
medium_risk <- subset(results, results$risk_bucket == "MEDIUM")
medium_risk <- medium_risk %>% arrange(desc(YES))
head(medium_risk)
```

```
## PATIENT_ID NO YES risk_bucket
## 1 38169090 0.302 0.698 MEDIUM
## 2 101788749 0.302 0.698 MEDIUM
## 3 42629220 0.302 0.698 MEDIUM
## 4 94073715 0.302 0.698 MEDIUM
## 5 45403434 0.302 0.698 MEDIUM
## 6 38989440 0.302 0.698 MEDIUM
```