# Pima

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#### R Markdown

```
pima <- read.csv("https://pmatheson.people.amherst.edu/Pima.dat", header=FALSE) #Loading data colnames(pima) <- c("PRG", "PLASMA", "BP", "THICK", "INSULIN", "BODY", "PEDIGREE", "AGE", "RESPONSE") #
```

### Predict the probability that individual females have diabetes

```
tally(pima$RESPONSE)
## X
##
    0
## 500 268
268/(500+268)
## [1] 0.3489583
#Approximately 35% of the individual females in this sample have diabetes
filteredpima <- filter(pima, PLASMA>0, BP>0, THICK>0, BODY>0, INSULIN>0) #creates a dataset that does not ha
#Create a stepwise model
model <- glm(RESPONSE~., data=pima, family=binomial) %>%
 MASS::stepAIC(trace=FALSE)
summary(model)
##
## Call:
## glm(formula = RESPONSE ~ PRG + PLASMA + BP + INSULIN + BODY +
##
      PEDIGREE + AGE, family = binomial, data = pima)
##
## Deviance Residuals:
##
      Min
                    Median
                                3Q
               1Q
                                       Max
## -2.5617 -0.7286 -0.4156
                            0.7271
                                     2.9297
##
## Coefficients:
               Estimate Std. Error z value Pr(>|z|)
##
## (Intercept) -8.4051362 0.7167033 -11.727 < 2e-16 ***
              ## PRG
              0.0351123 0.0036625
## PLASMA
                                   9.587 < 2e-16 ***
## BP
             ## INSULIN
             -0.0011570 0.0008142 -1.421 0.155275
## BODY
              0.0900886 0.0144619 6.229 4.68e-10 ***
## PEDIGREE
              0.9475954 0.2980063 3.180 0.001474 **
## AGE
              0.0147888 0.0092897 1.592 0.111393
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
```

```
## (Dispersion parameter for binomial family taken to be 1)
##
##
      Null deviance: 993.48 on 767 degrees of freedom
## Residual deviance: 723.45 on 760 degrees of freedom
## AIC: 739.45
## Number of Fisher Scoring iterations: 5
#Stepwise model using the filtered dataset
filteredmodel <- glm(RESPONSE~., data=filteredpima, family=binomial) %>%
 MASS::stepAIC(trace=FALSE)
summary(filteredmodel)
##
## Call:
## glm(formula = RESPONSE ~ PRG + PLASMA + BODY + PEDIGREE + AGE,
      family = binomial, data = filteredpima)
##
## Deviance Residuals:
      Min
                1Q
                     Median
                                  3Q
                                          Max
## -2.8827 -0.6535 -0.3694
                              0.6521
                                       2.5814
##
## Coefficients:
               Estimate Std. Error z value Pr(>|z|)
## (Intercept) -9.992080 1.086866 -9.193 < 2e-16 ***
## PRG
               0.083953
                         0.055031
                                    1.526 0.127117
## PLASMA
               0.036458 0.004978
                                   7.324 2.41e-13 ***
## BODY
               0.078139 0.020605
                                   3.792 0.000149 ***
## PEDIGREE
              1.150913
                          0.424242
                                   2.713 0.006670 **
## AGE
               0.034360 0.017810 1.929 0.053692 .
## Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
## (Dispersion parameter for binomial family taken to be 1)
##
      Null deviance: 498.10 on 391 degrees of freedom
## Residual deviance: 344.89 on 386 degrees of freedom
## AIC: 356.89
##
## Number of Fisher Scoring iterations: 5
```

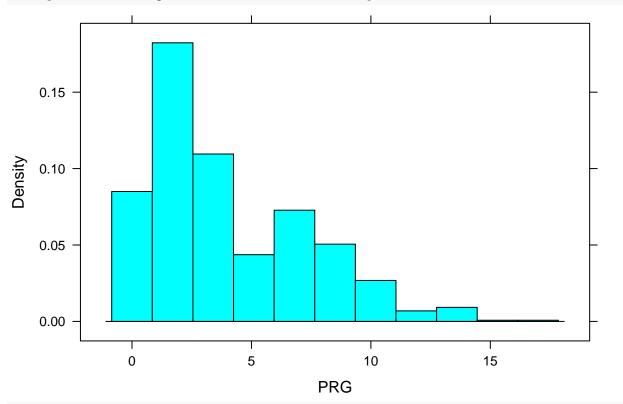
#### EDA

#### summary(pima)

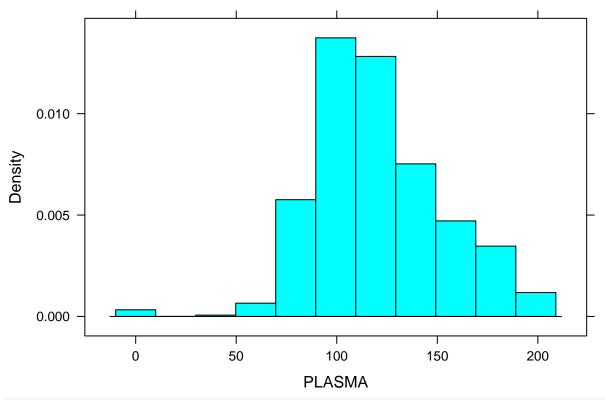
```
PRG
                       PLASMA
                                        BP
                                                      THICK
  Min.
         : 0.000
                   Min. : 0.0
                                  Min.
                                        : 0.00
                                                  Min.
                                                        : 0.00
  1st Qu.: 1.000
                                  1st Qu.: 62.00
                   1st Qu.: 99.0
                                                  1st Qu.: 0.00
## Median : 3.000
                   Median :117.0
                                  Median : 72.00
                                                  Median :23.00
## Mean : 3.845
                   Mean :120.9
                                  Mean : 69.11
                                                  Mean :20.54
## 3rd Qu.: 6.000
                   3rd Qu.:140.2
                                  3rd Qu.: 80.00
                                                  3rd Qu.:32.00
## Max.
         :17.000
                   Max. :199.0
                                 Max. :122.00
                                                  Max.
                                                        :99.00
##
      INSULIN
                       BODY
                                  PEDIGREE
                                                      AGE
```

```
Min. : 0.0
                   Min. : 0.00
                                   Min.
                                          :0.0780
                                                    Min.
                                                           :21.00
   1st Qu.: 0.0
                   1st Qu.:27.30
                                   1st Qu.:0.2437
                                                    1st Qu.:24.00
##
   Median: 30.5
                   Median :32.00
                                   Median :0.3725
                                                    Median :29.00
##
   Mean
         : 79.8
                   Mean
                          :31.99
                                   Mean
                                          :0.4719
                                                    Mean
                                                           :33.24
   3rd Qu.:127.2
                   3rd Qu.:36.60
                                   3rd Qu.:0.6262
                                                    3rd Qu.:41.00
##
##
   Max.
           :846.0
                   Max.
                          :67.10
                                   Max.
                                          :2.4200
                                                    Max.
                                                           :81.00
      RESPONSE
##
           :0.000
##
   Min.
   1st Qu.:0.000
##
  Median :0.000
##
  Mean
         :0.349
##
   3rd Qu.:1.000
## Max.
          :1.000
```

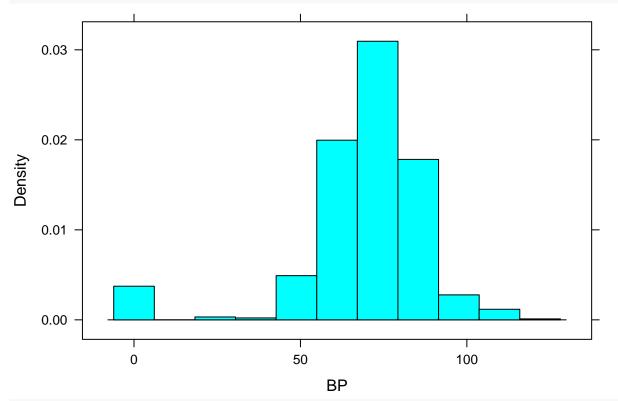
### histogram(~PRG, data=pima) #PRG is skewed to the right



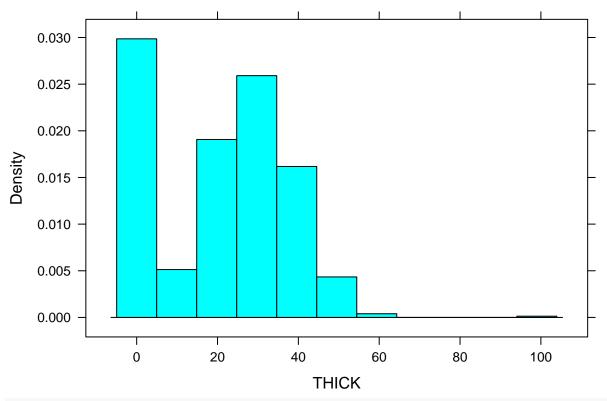
histogram(~PLASMA, data=pima) #rather bell-shaped



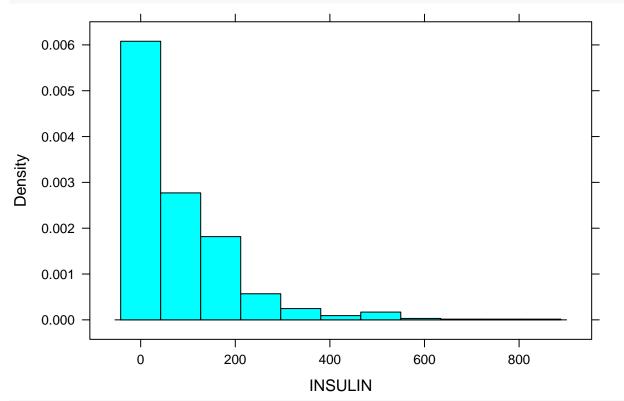
histogram(~BP, data=pima) #normal, but why are there so many Os???



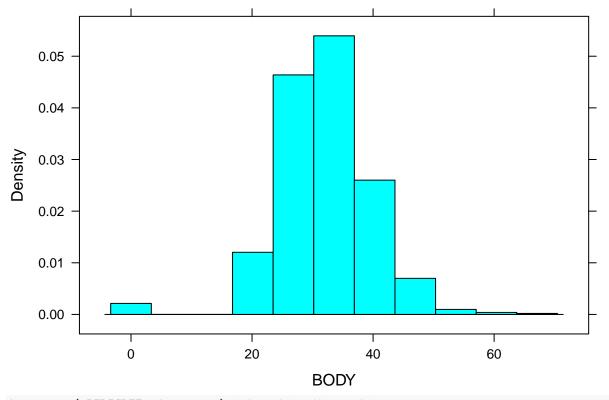
histogram(~THICK, data=pima) #many zeros, and one outlier at 99, but normal otherwise



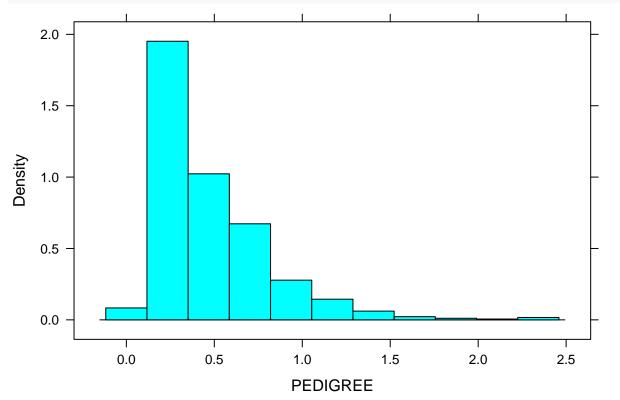
histogram(~INSULIN, data=pima) #skewed to the right



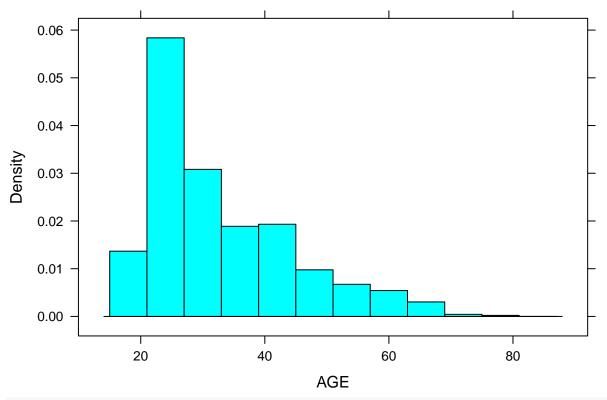
histogram(~BODY, data=pima) #kind of normal, slightly skewed to the right, many zeros



 $\verb|histogram(~PEDIGREE, data=pima)| \textit{\#skewed to the right}|$ 



histogram(~AGE, data=pima) #skewed to the right



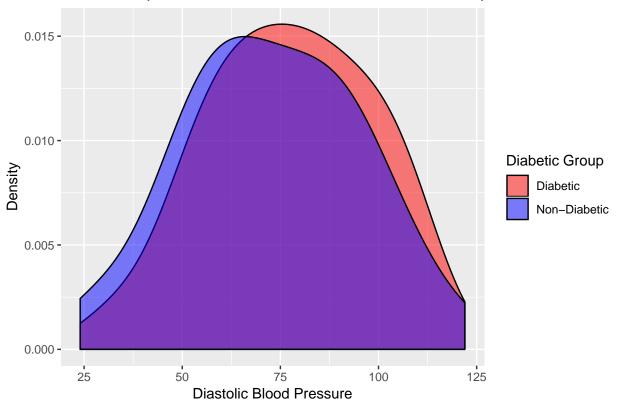
tally(~RESPONSE, data=pima) #500 no diabetes, 268 do have diabetes

```
## RESPONSE
## 0 1
## 500 268
```

### **Plots**

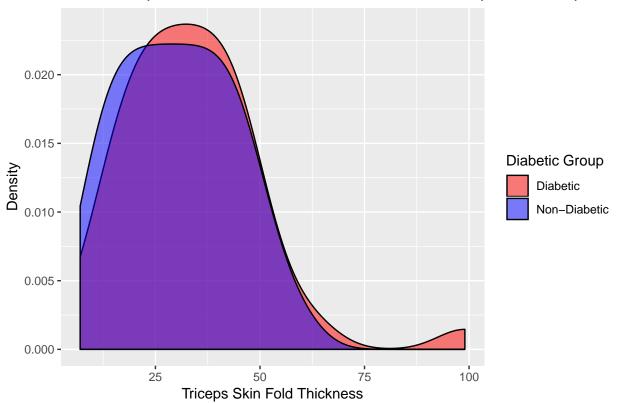
```
#Plot regarding blood pressure
pima_bp <- pima %>%
    mutate(RESPONSE = ifelse(RESPONSE == 0, "Non-Diabetic", "Diabetic"))%>%
    filter(BP > 0) %>%
    group_by(BP, RESPONSE) %>%
    summarize(response_total = n())
ggplot(pima_bp, aes(x=BP, fill=factor(RESPONSE))) +
    geom_density(alpha=0.5) +
    ylab("Density") +
    xlab("Diastolic Blood Pressure") +
    ggtitle("Relationship between Diabetic and Non-Diabetic Groups and Blood Pressure") +
    scale_fill_manual("Diabetic Group", values=c("Red","Blue"))
```

# Relationship between Diabetic and Non-Diabetic Groups and Blood Press



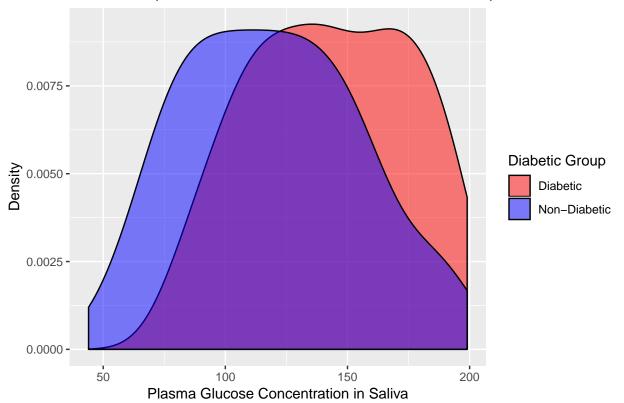
```
#Plot regarding skinfold thickness
pima_thick <- pima %>%
    mutate(RESPONSE = ifelse(RESPONSE == 0, "Non-Diabetic", "Diabetic"))%>%
    filter(THICK > 0) %>%
    group_by(THICK, RESPONSE) %>%
    summarize(response_total = n())
ggplot(pima_thick, aes(x=THICK, fill=factor(RESPONSE))) +
    geom_density(alpha=0.5) +
    ylab("Density") +
    xlab("Triceps Skin Fold Thickness") +
    ggtitle("Relationship between Diabetic and Non-Diabetic Groups and Triceps Skin Fold Thickness") +
    scale_fill_manual("Diabetic Group", values=c("Red", "Blue"))
```

## Relationship between Diabetic and Non-Diabetic Groups and Triceps Skii



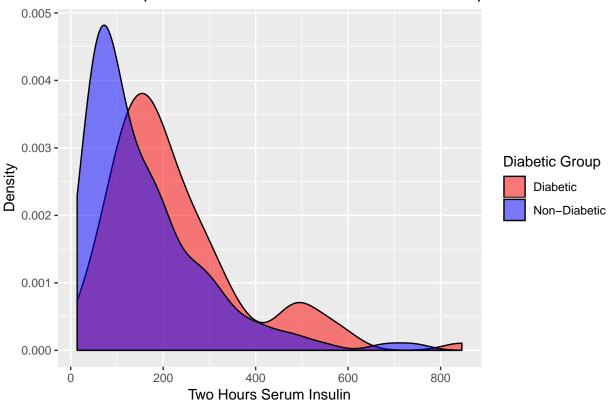
```
#Plot regarding plasma level
pima_plasma <- pima %>%
  mutate(RESPONSE = ifelse(RESPONSE == 0, "Non-Diabetic", "Diabetic"))%>%
  filter(PLASMA > 0) %>%
  group_by(PLASMA, RESPONSE) %>%
  summarize(response_total = n())
ggplot(pima_plasma, aes(x=PLASMA, fill=factor(RESPONSE))) +
  geom_density(alpha=0.5) +
  ylab("Density") +
  xlab("Plasma Glucose Concentration in Saliva") +
  ggtitle("Relationship between Diabetic and Non-Diabetic Groups and Plasma Glucose Concentration in Sa
  scale_fill_manual("Diabetic Group", values=c("Red", "Blue"))
```

# Relationship between Diabetic and Non-Diabetic Groups and Plasma GI



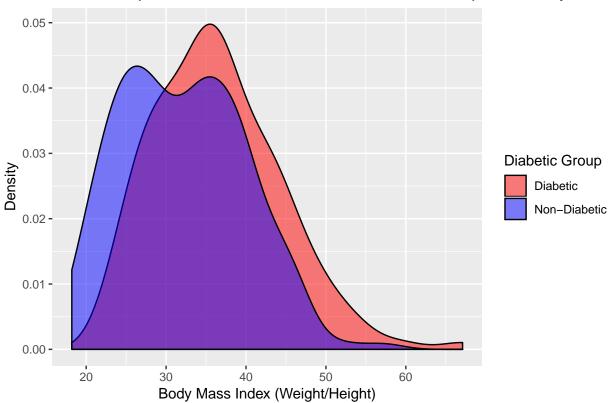
```
#Plot regarding insulin levels
pima_insulin <- pima %>%
    mutate(RESPONSE = ifelse(RESPONSE == 0, "Non-Diabetic", "Diabetic"))%>%
    filter(INSULIN > 0) %>%
    group_by(INSULIN, RESPONSE) %>%
    summarize(response_total = n())
ggplot(pima_insulin, aes(x=INSULIN, fill=factor(RESPONSE))) +
    geom_density(alpha=0.5) +
    ylab("Density") +
    xlab("Two Hours Serum Insulin") +
    ggtitle("Relationship between Diabetic and Non-Diabetic Groups and Two Hours Serum Insulin") +
    scale_fill_manual("Diabetic Group", values=c("Red","Blue"))
```

## Relationship between Diabetic and Non-Diabetic Groups and Two Hours



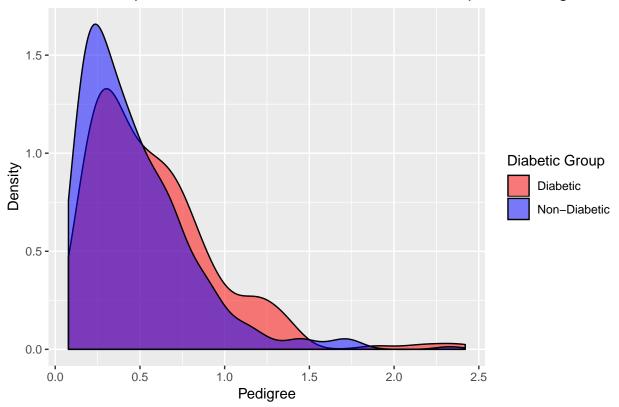
```
#Plot regarding BMI
pima_body <- pima %>%
    mutate(RESPONSE = ifelse(RESPONSE == 0, "Non-Diabetic", "Diabetic"))%>%
    filter(BODY > 0) %>%
    group_by(BODY, RESPONSE) %>%
    summarize(response_total = n())
ggplot(pima_body, aes(x=BODY, fill=factor(RESPONSE))) +
    geom_density(alpha=0.5) +
    ylab("Density") +
    xlab("Body Mass Index (Weight/Height)") +
    ggtitle("Relationship between Diabetic and Non-Diabetic Groups and Body Mass Index (Weight/Height)")
    scale_fill_manual("Diabetic Group", values=c("Red", "Blue"))
```

# Relationship between Diabetic and Non-Diabetic Groups and Body Mass I



```
#Plot regarding pedigree
pima_pedigree <- pima %>%
  mutate(RESPONSE = ifelse(RESPONSE == 0, "Non-Diabetic", "Diabetic"))%>%
  filter(PEDIGREE > 0) %>%
  group_by(PEDIGREE, RESPONSE) %>%
  summarize(response_total = n())
ggplot(pima_pedigree, aes(x=PEDIGREE, fill=factor(RESPONSE))) +
  geom_density(alpha=0.5) +
  ylab("Density") +
  xlab("Pedigree") +
  ggtitle("Relationship between Diabetic and Non-Diabetic Groups and Pedigree") +
  scale_fill_manual("Diabetic Group", values=c("Red","Blue"))
```

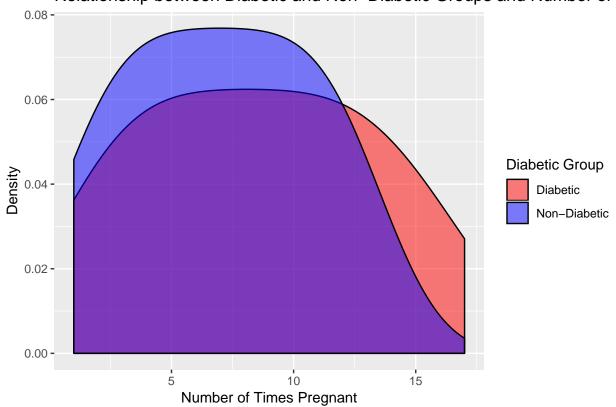
## Relationship between Diabetic and Non-Diabetic Groups and Pedigree



#Pedigree may not be overly important; however, it does seem that there may be a slight relationship

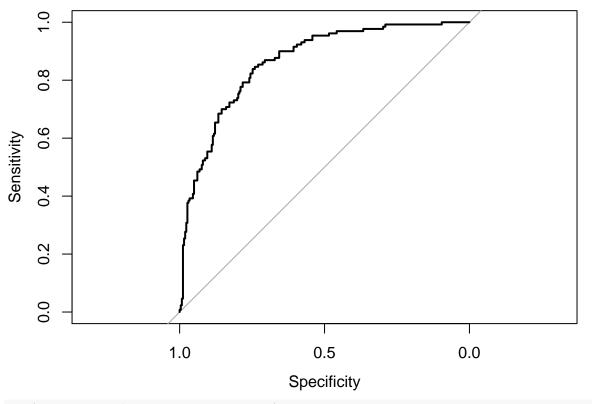
```
#plot regarding number of pregnancy
pima_prg <- pima %>%
   mutate(RESPONSE = ifelse(RESPONSE == 0, "Non-Diabetic", "Diabetic"))%>%
   filter(PRG > 0) %>%
   group_by(PRG, RESPONSE) %>%
   summarize(response_total = n())
ggplot(pima_prg, aes(x=PRG, fill=factor(RESPONSE))) +
   geom_density(alpha=0.5) +
   ylab("Density") +
   xlab("Number of Times Pregnant") +
   ggtitle("Relationship between Diabetic and Non-Diabetic Groups and Number of Times Pregnant") +
   scale_fill_manual("Diabetic Group", values=c("Red", "Blue"))
```

# Relationship between Diabetic and Non-Diabetic Groups and Number of T



## **ROC** Curve

#Creates a ROC Curve and prints out the area under the curve which suggests this model is pretty strong
predictions <- predict(filteredmodel, data=filteredpima)
plot.roc(filteredpima\$RESPONSE, predictions)</pre>



auc(filteredpima\$RESPONSE, predictions)

5

## Area under the curve: 0.8631

#### Classification Tree

## 4 0.044501

## 5 0.021167

## 6 0.013939

```
\# Creates a classification tree that denotes the thresholds: defines no diabetes, pre-diabetes, and diabetes
filteredmodelpart <- rpart(RESPONSE ~ ., data = filteredpima)</pre>
printcp(filteredmodelpart)
##
## Regression tree:
## rpart(formula = RESPONSE ~ ., data = filteredpima)
## Variables actually used in tree construction:
## [1] AGE
                BODY
                         ΒP
                                   INSULIN PEDIGREE PLASMA
##
## Root node error: 86.888/392 = 0.22165
##
## n= 392
##
##
           CP nsplit rel error xerror
## 1 0.239181
                       1.00000 1.00511 0.036346
                       0.76082 0.76797 0.049483
## 2 0.055005
                   1
## 3 0.054577
                       0.70581 0.81835 0.056061
```

3 0.65124 0.80197 0.057682

0.56223 0.76046 0.058999 0.54107 0.77132 0.063177

```
## 7 0.013933
                 8 0.51319 0.77281 0.066506
## 8 0.012276
                 12 0.45746 0.78618 0.067418
## 9 0.010000
                13 0.44518 0.80443 0.068277
pdf("diabetes.pdf", width = 25, height = 10)
plot(as.party(filteredmodelpart))
dev.off()
## pdf
##
    2
diabetes <- mutate(filteredpima, fittedtree = predict(filteredmodelpart))</pre>
#Removes age and pedigree from the classication tree (see pdf in the folder)
filteredmodelpart <- rpart(RESPONSE ~ . - AGE - PEDIGREE, data = filteredpima)
printcp(filteredmodelpart)
##
## Regression tree:
## rpart(formula = RESPONSE ~ . - AGE - PEDIGREE, data = filteredpima)
## Variables actually used in tree construction:
## [1] INSULIN PLASMA PRG
                              THICK
##
## Root node error: 86.888/392 = 0.22165
##
## n= 392
##
          CP nsplit rel error xerror
##
## 1 0.239181 0 1.00000 1.00446 0.036315
## 2 0.055005
                  1 0.76082 0.77091 0.049641
## 3 0.035786
                 2 0.70581 0.74793 0.053488
## 4 0.031114
                 3 0.67003 0.75900 0.057239
## 5 0.021753
                 4 0.63891 0.75356 0.056017
## 6 0.018444
                  6 0.59541 0.76175 0.058570
## 7 0.010000
                  7
                     0.57696 0.77484 0.062781
pdf("diabetes1.pdf", width = 25, height = 12)
plot(as.party(filteredmodelpart))
dev.off()
## pdf
##
diabetes <- mutate(filteredpima, fittedtree = predict(filteredmodelpart))</pre>
```