Thoracic Surgery and Binary Classifier Assignment

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## Set the working directory to the root of my week 10 Assignment directory

setwd(“~/Documents/Bellevue University Classes/DSC520/Week 10 Assignment”)

## The ThoracicSurgery.csv file and a summary of the data

## I am importing readr from the library so I can use the read\_csv function to create my Thoracic Surgery data frame.  
library(readr)  
## Creating the Thoracic Surgery data frame by using the read\_csv function to pull my Thoracic Surgery data.   
ThoracicSurgery <- read\_csv("ThoracicSurgery.csv")  
## Creating the Thoracic Surgery data frame by using the read\_csv function to pull my Thoracic Surgery data.   
View(ThoracicSurgery)  
head(ThoracicSurgery)

## # A tibble: 6 x 17  
## Diagnosis FVC FEV1 Performance Pain Haemoptysis Dyspnoea Cough Weakness  
## <dbl> <dbl> <dbl> <dbl> <lgl> <lgl> <lgl> <lgl> <lgl>   
## 1 2 2.88 2.16 1 FALSE FALSE FALSE TRUE TRUE   
## 2 3 3.4 1.88 0 FALSE FALSE FALSE FALSE FALSE   
## 3 3 2.76 2.08 1 FALSE FALSE FALSE TRUE FALSE   
## 4 3 3.68 3.04 0 FALSE FALSE FALSE FALSE FALSE   
## 5 3 2.44 0.96 2 FALSE TRUE FALSE TRUE TRUE   
## 6 3 2.48 1.88 1 FALSE FALSE FALSE TRUE FALSE   
## # … with 8 more variables: Tumor\_Size <dbl>, Diabetes\_Mellitus <lgl>,  
## # MI\_6mo <lgl>, PAD <lgl>, Smoking <lgl>, Asthma <lgl>, Age <dbl>,  
## # Risk1Y <dbl>

## As seen below we can use the summary function to analyze the descriptive statistics for this data set. As I have updated the names of all the variables and taken out unneeded characters in the csv file before uploading the file to my Rmarkdown report.  
summary(ThoracicSurgery)

## Diagnosis FVC FEV1 Performance   
## Min. :1.000 Min. :1.440 Min. : 0.960 Min. :0.0000   
## 1st Qu.:3.000 1st Qu.:2.600 1st Qu.: 1.960 1st Qu.:0.0000   
## Median :3.000 Median :3.160 Median : 2.400 Median :1.0000   
## Mean :3.096 Mean :3.282 Mean : 4.569 Mean :0.7809   
## 3rd Qu.:3.000 3rd Qu.:3.808 3rd Qu.: 3.080 3rd Qu.:1.0000   
## Max. :8.000 Max. :6.300 Max. :86.300 Max. :2.0000   
## Pain Haemoptysis Dyspnoea Cough   
## Mode :logical Mode :logical Mode :logical Mode :logical   
## FALSE:439 FALSE:402 FALSE:439 FALSE:147   
## TRUE :31 TRUE :68 TRUE :31 TRUE :323   
##   
##   
##   
## Weakness Tumor\_Size Diabetes\_Mellitus MI\_6mo   
## Mode :logical Min. :11.00 Mode :logical Mode :logical   
## FALSE:392 1st Qu.:11.00 FALSE:435 FALSE:468   
## TRUE :78 Median :12.00 TRUE :35 TRUE :2   
## Mean :11.74   
## 3rd Qu.:12.00   
## Max. :14.00   
## PAD Smoking Asthma Age   
## Mode :logical Mode :logical Mode :logical Min. :21.00   
## FALSE:462 FALSE:84 FALSE:468 1st Qu.:57.00   
## TRUE :8 TRUE :386 TRUE :2 Median :62.00   
## Mean :62.53   
## 3rd Qu.:69.00   
## Max. :87.00   
## Risk1Y   
## Min. :0.0000   
## 1st Qu.:0.0000   
## Median :0.0000   
## Mean :0.1489   
## 3rd Qu.:0.0000   
## Max. :1.0000

## Fit a binary logistic regression model to the data set that predicts whether or not the patient survived for one year (the Risk1Y variable) after the surgery. Use the glm() function to perform the logistic regression. See Generalized Linear Models for an example. Include a summary using the summary() function in your results.

## I fit a binary logistic regression model to determine if the tumor size was 12 or above which will indicate a True.   
ThoracicSurgery$Patiet\_Predicts\_Survival <- with(ThoracicSurgery, Tumor\_Size >= 12 & Risk1Y >= 1)  
## to the data from the ThoracicSurgery data frame by using an glm() function to perform a logistic regression.  
patient\_surival\_regression <- glm(Patiet\_Predicts\_Survival ~ Age + Asthma + Smoking + PAD + MI\_6mo + Diabetes\_Mellitus + Tumor\_Size + Weakness + Cough + Dyspnoea + Haemoptysis + Pain + Performance + FEV1 + FVC + Diagnosis + Risk1Y, data = ThoracicSurgery, family = binomial(link = "logit"))  
  
## As seen below in the summary we see the Number of Fisher Scoring iterations being 25. While the Null deviance: 3.2698e+02 on 469 degrees of freedom which shows how well the response variable is predicted by a model that includes only the intercept.  
  
summary(patient\_surival\_regression)

##   
## Call:  
## glm(formula = Patiet\_Predicts\_Survival ~ Age + Asthma + Smoking +   
## PAD + MI\_6mo + Diabetes\_Mellitus + Tumor\_Size + Weakness +   
## Cough + Dyspnoea + Haemoptysis + Pain + Performance + FEV1 +   
## FVC + Diagnosis + Risk1Y, family = binomial(link = "logit"),   
## data = ThoracicSurgery)  
##   
## Deviance Residuals:   
## Min 1Q Median 3Q Max   
## -4.503e-05 -2.100e-08 -2.100e-08 -2.100e-08 4.573e-05   
##   
## Coefficients:  
## Estimate Std. Error z value Pr(>|z|)  
## (Intercept) -6.322e+02 1.744e+05 -0.004 0.997  
## Age 4.869e-02 8.099e+02 0.000 1.000  
## AsthmaTRUE 8.507e+01 2.237e+05 0.000 1.000  
## SmokingTRUE -4.307e+00 5.247e+04 0.000 1.000  
## PADTRUE -1.488e+00 2.667e+04 0.000 1.000  
## MI\_6moTRUE 8.563e+01 2.218e+05 0.000 1.000  
## Diabetes\_MellitusTRUE 4.437e-01 1.378e+04 0.000 1.000  
## Tumor\_Size 4.387e+01 1.112e+04 0.004 0.997  
## WeaknessTRUE -1.170e+00 1.301e+04 0.000 1.000  
## CoughTRUE 1.084e+00 2.254e+04 0.000 1.000  
## DyspnoeaTRUE 1.588e+00 2.373e+04 0.000 1.000  
## HaemoptysisTRUE -4.300e-01 1.265e+04 0.000 1.000  
## PainTRUE 2.566e-01 2.172e+04 0.000 1.000  
## Performance -2.475e-01 1.533e+04 0.000 1.000  
## FEV1 9.586e-01 1.556e+03 0.001 1.000  
## FVC -1.274e+00 8.571e+03 0.000 1.000  
## Diagnosis -5.902e-01 7.682e+03 0.000 1.000  
## Risk1Y 1.325e+02 3.052e+04 0.004 0.997  
##   
## (Dispersion parameter for binomial family taken to be 1)  
##   
## Null deviance: 3.2698e+02 on 469 degrees of freedom  
## Residual deviance: 3.2981e-08 on 452 degrees of freedom  
## AIC: 36  
##   
## Number of Fisher Scoring iterations: 25

## According to the summary, which variables had the greatest effect on the survival rate?

## As seen below we use the summary function to show a summary of our logistic regression.  
  
## In the summary function we see that the variables SmokingTRUE, HaemoptysisTRUE, and Diagnosis had the greatest negative effect while the variables Age, AsthmaTRUE, MI\_6moTRUE, Diabetes\_MellitusTRUE, Tumor\_Size, and FEV1 greatest possitive effect on the survival rate as seen in the estimate.  
  
summary(patient\_surival\_regression)

##   
## Call:  
## glm(formula = Patiet\_Predicts\_Survival ~ Age + Asthma + Smoking +   
## PAD + MI\_6mo + Diabetes\_Mellitus + Tumor\_Size + Weakness +   
## Cough + Dyspnoea + Haemoptysis + Pain + Performance + FEV1 +   
## FVC + Diagnosis + Risk1Y, family = binomial(link = "logit"),   
## data = ThoracicSurgery)  
##   
## Deviance Residuals:   
## Min 1Q Median 3Q Max   
## -4.503e-05 -2.100e-08 -2.100e-08 -2.100e-08 4.573e-05   
##   
## Coefficients:  
## Estimate Std. Error z value Pr(>|z|)  
## (Intercept) -6.322e+02 1.744e+05 -0.004 0.997  
## Age 4.869e-02 8.099e+02 0.000 1.000  
## AsthmaTRUE 8.507e+01 2.237e+05 0.000 1.000  
## SmokingTRUE -4.307e+00 5.247e+04 0.000 1.000  
## PADTRUE -1.488e+00 2.667e+04 0.000 1.000  
## MI\_6moTRUE 8.563e+01 2.218e+05 0.000 1.000  
## Diabetes\_MellitusTRUE 4.437e-01 1.378e+04 0.000 1.000  
## Tumor\_Size 4.387e+01 1.112e+04 0.004 0.997  
## WeaknessTRUE -1.170e+00 1.301e+04 0.000 1.000  
## CoughTRUE 1.084e+00 2.254e+04 0.000 1.000  
## DyspnoeaTRUE 1.588e+00 2.373e+04 0.000 1.000  
## HaemoptysisTRUE -4.300e-01 1.265e+04 0.000 1.000  
## PainTRUE 2.566e-01 2.172e+04 0.000 1.000  
## Performance -2.475e-01 1.533e+04 0.000 1.000  
## FEV1 9.586e-01 1.556e+03 0.001 1.000  
## FVC -1.274e+00 8.571e+03 0.000 1.000  
## Diagnosis -5.902e-01 7.682e+03 0.000 1.000  
## Risk1Y 1.325e+02 3.052e+04 0.004 0.997  
##   
## (Dispersion parameter for binomial family taken to be 1)  
##   
## Null deviance: 3.2698e+02 on 469 degrees of freedom  
## Residual deviance: 3.2981e-08 on 452 degrees of freedom  
## AIC: 36  
##   
## Number of Fisher Scoring iterations: 25

## To compute the accuracy of your model, use the dataset to predict the outcome variable. The percent of correct predictions is the accuracy of your model. What is the accuracy of your model?

## First I will pull up the summary of my updated ThoracicSurgery  
summary(ThoracicSurgery)

## Diagnosis FVC FEV1 Performance   
## Min. :1.000 Min. :1.440 Min. : 0.960 Min. :0.0000   
## 1st Qu.:3.000 1st Qu.:2.600 1st Qu.: 1.960 1st Qu.:0.0000   
## Median :3.000 Median :3.160 Median : 2.400 Median :1.0000   
## Mean :3.096 Mean :3.282 Mean : 4.569 Mean :0.7809   
## 3rd Qu.:3.000 3rd Qu.:3.808 3rd Qu.: 3.080 3rd Qu.:1.0000   
## Max. :8.000 Max. :6.300 Max. :86.300 Max. :2.0000   
## Pain Haemoptysis Dyspnoea Cough   
## Mode :logical Mode :logical Mode :logical Mode :logical   
## FALSE:439 FALSE:402 FALSE:439 FALSE:147   
## TRUE :31 TRUE :68 TRUE :31 TRUE :323   
##   
##   
##   
## Weakness Tumor\_Size Diabetes\_Mellitus MI\_6mo   
## Mode :logical Min. :11.00 Mode :logical Mode :logical   
## FALSE:392 1st Qu.:11.00 FALSE:435 FALSE:468   
## TRUE :78 Median :12.00 TRUE :35 TRUE :2   
## Mean :11.74   
## 3rd Qu.:12.00   
## Max. :14.00   
## PAD Smoking Asthma Age   
## Mode :logical Mode :logical Mode :logical Min. :21.00   
## FALSE:462 FALSE:84 FALSE:468 1st Qu.:57.00   
## TRUE :8 TRUE :386 TRUE :2 Median :62.00   
## Mean :62.53   
## 3rd Qu.:69.00   
## Max. :87.00   
## Risk1Y Patiet\_Predicts\_Survival  
## Min. :0.0000 Mode :logical   
## 1st Qu.:0.0000 FALSE:418   
## Median :0.0000 TRUE :52   
## Mean :0.1489   
## 3rd Qu.:0.0000   
## Max. :1.0000

## Next we can calculate the amount of Risk1Y that was a 1 for died within a year. This is calculated by taking the 470 amount of lines and multiply it by the mean 0.1489 which is seen as 470 \* 0.1489 = 69.983. Which we see 70.  
data\_set\_deaths <- 470\*0.1489  
data\_set\_deaths

## [1] 69.983

## While the predicted amount from our Patiet\_Predicts\_Survival shows 52 deaths s seen as the TRUE amount from our summary.  
Patiet\_Predicts\_Survival\_amount <- 52  
Patiet\_Predicts\_Survival\_amount

## [1] 52

## Finally we will take the Patiet\_Predicts\_Survival\_amount and divide by the data\_set\_deaths which will give us the percent of accuracy of the model.  
percent\_of\_accuracy <- Patiet\_Predicts\_Survival\_amount/data\_set\_deaths  
percent\_of\_accuracy

## [1] 0.7430376

## The binary-classifier-data.csv file and a summary of the data

## I am importing readr from the library so I can use the read\_csv function to create my binary-classifier data frame.  
library(readr)  
## Creating the binary-classifier data frame by using the read\_csv function to pull my binary-classifier data.   
binary\_classifier\_data <- read\_csv("data/binary-classifier-data.csv")  
## Creating the binary-classifier data frame by using the read\_csv function to pull my binary-classifier data.   
View(binary\_classifier\_data)  
head(binary\_classifier\_data)

## # A tibble: 6 x 3  
## label x y  
## <dbl> <dbl> <dbl>  
## 1 0 70.9 83.2  
## 2 0 75.0 87.9  
## 3 0 73.8 92.2  
## 4 0 66.4 81.1  
## 5 0 69.1 84.5  
## 6 0 72.2 86.4

## Fit a logistic regression model to the binary-classifier-data.csv dataset

## I fit a logistic regression model to determine if the x variable is greater than or equal to 32 and y variable is greater than or equal to 45 which will show as true.  
binary\_classifier\_data$label\_regression <- with(binary\_classifier\_data, x >= 32 & y >= 45)  
  
## I am going to use the glm() function to fit a logistic regression model with my new label regression variable.  
binary\_classifier\_regression <- glm(label\_regression ~ label + x + y, data = binary\_classifier\_data, family = binomial())  
  
## As seen in our logistic regression model we see that the AIC is 292.94 and we have a Null Deviance of 1913.40 on 1497 degrees of freedom.  
summary(binary\_classifier\_regression)

##   
## Call:  
## glm(formula = label\_regression ~ label + x + y, family = binomial(),   
## data = binary\_classifier\_data)  
##   
## Deviance Residuals:   
## Min 1Q Median 3Q Max   
## -3.6378 -0.0647 -0.0237 0.0159 2.1631   
##   
## Coefficients:  
## Estimate Std. Error z value Pr(>|z|)   
## (Intercept) -17.01254 1.29728 -13.114 <2e-16 \*\*\*  
## label -0.60551 0.39479 -1.534 0.125   
## x 0.14295 0.01303 10.970 <2e-16 \*\*\*  
## y 0.18431 0.01364 13.513 <2e-16 \*\*\*  
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
## (Dispersion parameter for binomial family taken to be 1)  
##   
## Null deviance: 1913.40 on 1497 degrees of freedom  
## Residual deviance: 284.94 on 1494 degrees of freedom  
## AIC: 292.94  
##   
## Number of Fisher Scoring iterations: 8

## What is the accuracy of the logistic regression classifier?

summary(binary\_classifier\_data)

## label x y label\_regression  
## Min. :0.000 Min. : -5.20 Min. : -4.019 Mode :logical   
## 1st Qu.:0.000 1st Qu.: 19.77 1st Qu.: 21.207 FALSE:994   
## Median :0.000 Median : 41.76 Median : 44.632 TRUE :504   
## Mean :0.488 Mean : 45.07 Mean : 45.011   
## 3rd Qu.:1.000 3rd Qu.: 66.39 3rd Qu.: 68.698   
## Max. :1.000 Max. :104.58 Max. :106.896

## I am going to view the summary of the binary\_classifier\_data and compare the mean of our labels to the percentage of true in the label regression.  
number\_of\_values\_in\_label\_regression <- 504 +994  
percentage\_of\_true\_label\_regression <- 504/1498  
percentage\_of\_true\_label\_regression

## [1] 0.3364486

## This shows us that our accuracy in comparison to our label variable is less due to the label being 0.488 while the label\_regression percent is 0.3364.