DSC520 Week10 Exercise 11.2.1

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Project: Fit a Logistic Regression model to Binary Classifier Dataset

```
# Load the packages
library(caTools)
library(ggplot2)
setwd("/Users/Jagadeesh/Documents/GitHub/dsc520")
# Load Binary Classifier Dataset
binary_df <- read.csv("data/binary-classifier-data.csv")</pre>
# Check structure of binary_df
str(binary_df)
## 'data.frame':
                 1498 obs. of 3 variables:
## $ label: int 0000000000...
## $ x : num 70.9 75 73.8 66.4 69.1 ...
## $ y
          : num 83.2 87.9 92.2 81.1 84.5 ...
# Check sample rows of binary_df
head(binary_df)
##
    label
                 X
     0 70.88469 83.17702
## 2
       0 74.97176 87.92922
       0 73.78333 92.20325
## 4
       0 66.40747 81.10617
## 5
        0 69.07399 84.53739
## 6
       0 72.23616 86.38403
# Load the trinary classifier data set to dataframe
trinary_df <- read.csv("data/trinary-classifier-data.csv")</pre>
# Check structure of trinary_df
str(trinary_df)
## 'data.frame': 1568 obs. of 3 variables:
## $ label: int 0000000000...
## $ x : num 30.1 31.3 34.1 32.6 34.7 ...
## $ y : num 39.6 51.8 49.3 41.2 45.5 ...
```

Check sample rows head(trinary_df)

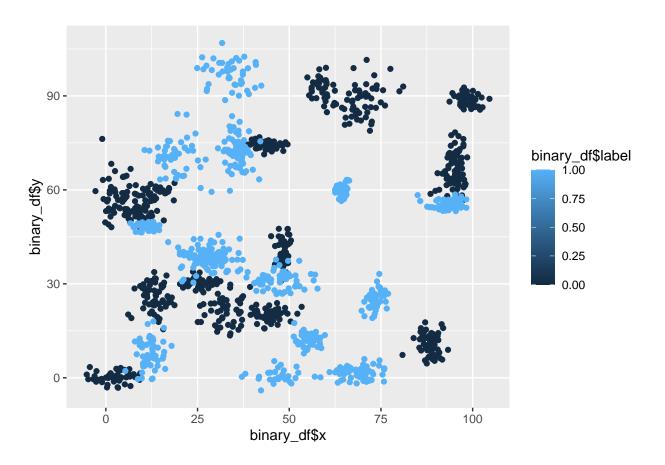
```
## 1 abel x y
## 1 0 30.08387 39.63094
## 2 0 31.27613 51.77511
## 3 0 34.12138 49.27575
## 4 0 32.58222 41.23300
## 5 0 34.65069 45.47956
## 6 0 33.80513 44.24656
```

i. Plot the data from each dataset using scatter plot ggplot(binary_df, aes(x=binary_df\$x, y=binary_df\$y)) + geom_point(aes(color = binary_df\$label))

Warning: Use of 'binary_df\$label' is discouraged. Use 'label' instead.

Warning: Use of 'binary_df\$x' is discouraged. Use 'x' instead.

Warning: Use of 'binary_df\$y' is discouraged. Use 'y' instead.

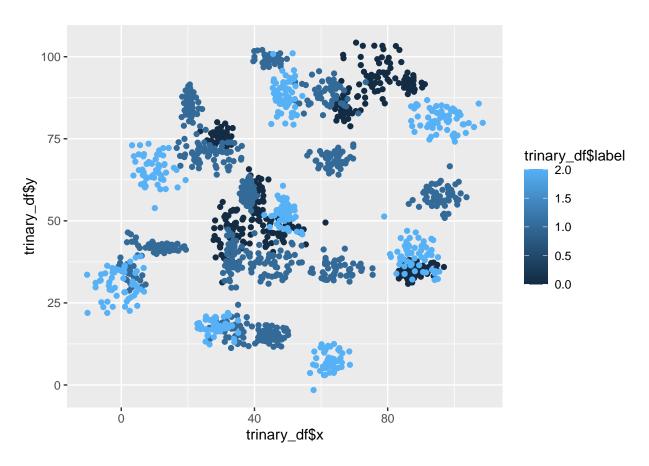


ggplot(trinary_df, aes(x=trinary_df\$x, y=trinary_df\$y)) + geom_point(aes(color = trinary_df\$label))

Warning: Use of 'trinary_df\$label' is discouraged. Use 'label' instead.

Warning: Use of 'trinary_df\$x' is discouraged. Use 'x' instead.

Warning: Use of 'trinary_df\$y' is discouraged. Use 'y' instead.



```
# Normalization of binary_df
normalize <- function(x) { return ((x - min(x)) / (max(x) - min(x))) }
binary_df.n = as.data.frame(lapply(binary_df[,2:3], normalize))
binary_df.n = as.data.frame(lapply(binary_df[,2:3], normalize))
set.seed(123)

# Random sample of 70% of data
dat.d <- sample(1:nrow(binary_df.n), size = nrow(binary_df.n)*0.7, replace = FALSE)

# Create test and train datasets
train.binary_df <- binary_df[dat.d,]
test.binary_df <- binary_df[-dat.d,]

# Create separate dataframe for label feature
train.binary_df_label <- binary_df[dat.d,1]
test.binary_df_label <- binary_df[-dat.d,1]

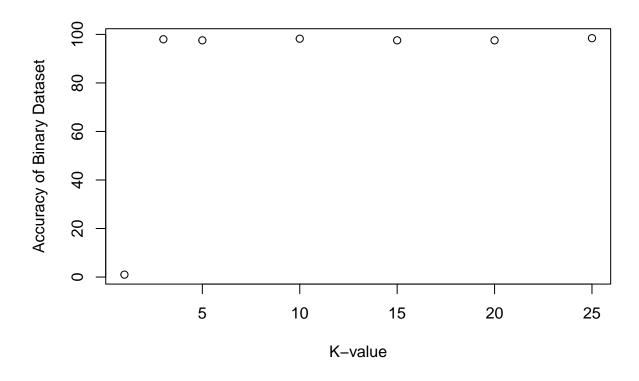
# Find no. of observations
NROW(train.binary_df)</pre>
```

[1] 1048

```
# From above, we have 700 observations in our training dataset. The square root of 700 is about 26.45.
# Therefore, we'll create 2 models. One with 'K' value 26 and other with 'K' value 27
library(class)
knn.binary_df.1 <- knn(train=train.binary_df, test=test.binary_df, cl=train.binary_df_label, k=1)
# Calculate accuracy of the models
\# Caculate the proportion of correct classification for k=32,33
ACC.binary_df.1 <- 100*sum(test.binary_df_label == knn.binary_df.1)/NROW(test.binary_df_label)
ACC.binary_df.1
## [1] 98.22222
# Accuracy is 98.22
# Check prediction against actual value in tabular form for k=32
table(knn.binary_df.1, test.binary_df_label)
##
                  test.binary_df_label
## knn.binary_df.1
                    0
                        1
##
                 0 227
                    4 215
##
                 1
# Use confusion matrix to calculate the accuracy.
library(caret)
## Loading required package: lattice
confusionMatrix(table(knn.binary_df.1, test.binary_df_label))
## Confusion Matrix and Statistics
##
##
                  test.binary_df_label
## knn.binary_df.1
                   0
                         1
##
                 0 227
##
                 1 4 215
##
##
                  Accuracy: 0.9822
##
                    95% CI: (0.9653, 0.9923)
##
      No Information Rate: 0.5133
##
       P-Value [Acc > NIR] : <2e-16
##
##
                     Kappa: 0.9644
##
   Mcnemar's Test P-Value : 1
##
##
               Sensitivity: 0.9827
##
##
               Specificity: 0.9817
           Pos Pred Value: 0.9827
##
##
            Neg Pred Value: 0.9817
                Prevalence: 0.5133
##
##
            Detection Rate: 0.5044
     Detection Prevalence: 0.5133
##
```

```
##
         Balanced Accuracy: 0.9822
##
          'Positive' Class: 0
##
##
# Normalization of trinary df
normalize \leftarrow function(x) { return ((x - min(x)) / (max(x) - min(x))) }
trinary_df.n = as.data.frame(lapply(trinary_df[,2:3], normalize))
trinary_df.n = as.data.frame(lapply(trinary_df[,2:3], normalize))
set.seed(123)
# Random sample of 70% of data
dat.d <- sample(1:nrow(trinary_df.n), size = nrow(trinary_df.n)*0.7, replace = FALSE)</pre>
# Create test and train datasets
train.trinary_df <- trinary_df[dat.d,]</pre>
test.trinary_df <- trinary_df[-dat.d,]</pre>
# Create separate dataframe for label feature
train.trinary_df_label <- trinary_df[dat.d,1]</pre>
test.trinary_df_label <- trinary_df[-dat.d,1]</pre>
# Find no. of observations
NROW(train.trinary_df)
## [1] 1097
library(class)
knn.trinary_df.1 <- knn(train=train.trinary_df, test=test.trinary_df, cl=train.trinary_df_label, k=1)
# Calculate accuracy of the models
# Caculate the proportion of correct classification for k=32,33
ACC.trinary_df.1 <- 100*sum(test.trinary_df_label == knn.trinary_df.1)/NROW(test.trinary_df_label)
ACC.trinary_df.1
## [1] 95.75372
# Accuracy is 95.75
# Check prediction against actual value in tabular form for k=32
table(knn.trinary_df.1, test.trinary_df_label)
##
                   test.trinary_df_label
## knn.trinary_df.1 0 1
##
                         7
                  0 131
                              1
##
                  1
                     3 185
                     0 2 135
##
# Use confusion matrix to calculate the accuracy.
library(caret)
confusionMatrix(table(knn.trinary_df.1, test.trinary_df_label))
## Confusion Matrix and Statistics
##
##
                   test.trinary_df_label
```

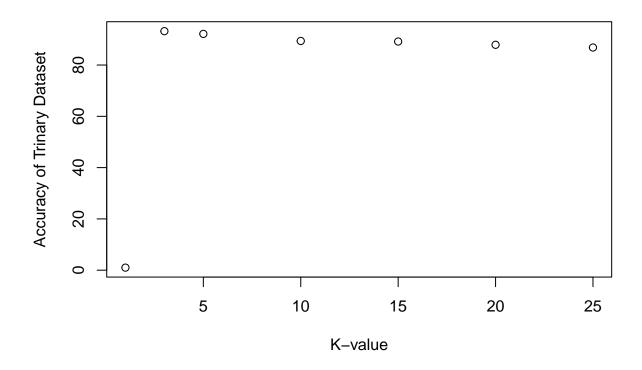
```
## knn.trinary_df.1
                      0
                  0 131
##
                          7
                              1
##
                  1
                      3 185
                              7
##
                  2
                      0
                          2 135
##
## Overall Statistics
##
##
                  Accuracy: 0.9575
                    95% CI : (0.9352, 0.9739)
##
       No Information Rate: 0.4119
##
##
       P-Value [Acc > NIR] : <2e-16
##
##
                     Kappa: 0.9354
##
##
   Mcnemar's Test P-Value: 0.1461
##
## Statistics by Class:
##
##
                        Class: 0 Class: 1 Class: 2
## Sensitivity
                          0.9776 0.9536
                                            0.9441
## Specificity
                          0.9763
                                  0.9639
                                            0.9939
## Pos Pred Value
                          0.9424
                                  0.9487
                                            0.9854
## Neg Pred Value
                                  0.9674
                                            0.9760
                          0.9910
## Prevalence
                          0.2845
                                  0.4119
                                            0.3036
## Detection Rate
                          0.2781
                                 0.3928
                                            0.2866
## Detection Prevalence
                          0.2951
                                   0.4140
                                            0.2909
## Balanced Accuracy
                          0.9769
                                   0.9588
                                            0.9690
# ii Fit a k nearest neighbors' model for each dataset for k=3, k=5, k=10, k=15, k=20, and k=25. Comput
# Accuracy level of binary dataset
j <- 1
k.optm <- 1
for (i in c(3,5,10,15,20,25)){
  knn.mod <- knn(train=train.binary_df, test=test.binary_df, cl=train.binary_df_label, k=i)
  k.optm[i] <- 100 * sum(test.binary_df_label == knn.mod)/NROW(test.binary_df_label)
  k <- i
  j <- j + 1
  cat(k,'=',k.optm[i],'')}
## 3 = 98 5 = 97.55556 10 = 98.22222 15 = 97.55556 20 = 97.55556 25 = 98.44444
# Accuracy Plot
plot(k.optm, type="b",xlab="K-value",ylab="Accuracy of Binary Dataset")
```



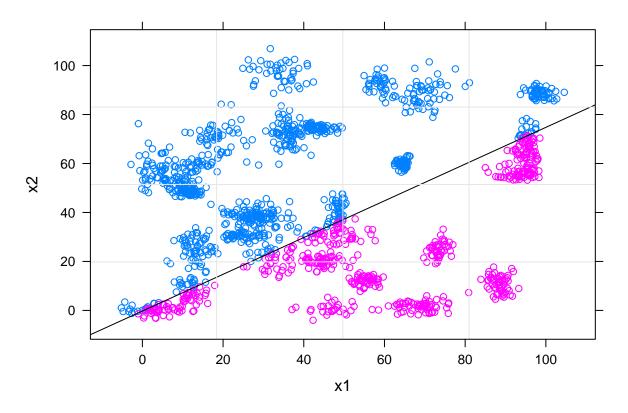
```
# Accuracy level of trinary dataset
j <- 1
k.optm <- 1
for (i in c(3,5,10,15,20,25)){
   knn.mod <- knn(train=train.trinary_df, test=test.trinary_df, cl=train.trinary_df_label, k=i)
   k.optm[i] <- 100 * sum(test.trinary_df_label == knn.mod)/NROW(test.trinary_df_label)
   k <- i
   j <- j + 1
   cat(k,'=',k.optm[i],'')}

## 3 = 93.20594 5 = 92.14437 10 = 89.38429 15 = 89.17197 20 = 87.89809 25 = 86.83652

# Accuracy Plot
plot(k.optm, type="b",xlab="K-value",ylab="Accuracy of Trinary Dataset")</pre>
```



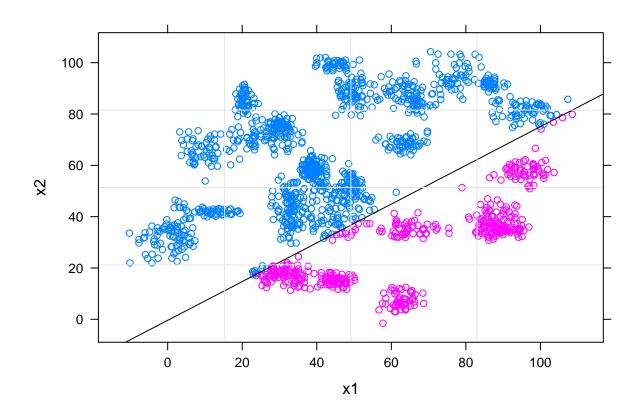
```
# i. Looking back at the plots of the data, do you think a linear classifier would work well on these d
x1=binary_df[2]
x2=binary_df[3]
y \leftarrow sign(3 * x1 - 4 * x2 - 1)
y[y == -1] \leftarrow 0
df <- cbind.data.frame(y,x1,x2)</pre>
names(df)[1] \leftarrow 'y'
names(df)[2] \leftarrow 'x1'
names(df)[3] \leftarrow 'x2'
mdl \leftarrow glm(y \sim ., data=df,family = binomial)
## Warning: glm.fit: algorithm did not converge
## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred
slope <- coef(mdl)[2]/(-coef(mdl)[3])</pre>
intercept <- coef(mdl)[1]/(-coef(mdl)[3])</pre>
library(lattice)
xyplot(x2 ~ x1,data=df, groups=y,panel=function(...){
  panel.xyplot(...)
  panel.abline(intercept, slope)
  panel.grid(...)
})
```



```
x1= trinary_df[2]
x2= trinary_df[3]
y <- sign(3 * x1 - 4 * x2 - 1)
y[y == -1] <- 0
df <- cbind.data.frame(y,x1,x2)
names(df)[1] <- 'y'
names(df)[2] <- 'x1'
names(df)[3] <- 'x2'
mdl <- glm(y ~ . , data=df,family = binomial)</pre>
## Warning: glm.fit: algorithm did not converge
```

Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred

```
slope <- coef(mdl)[2]/(-coef(mdl)[3])
intercept <- coef(mdl)[1]/(-coef(mdl)[3])
library(lattice)
xyplot(x2 ~ x1,data=df, groups=y,panel=function(...){
  panel.xyplot(...)
  panel.abline(intercept, slope)
  panel.grid(...)
})</pre>
```



Looking at the plots, I think that the linear classifier would work well on binary data set but not o
data set
ii. How does the accuracy of your logistic regression classifier from last week compare? Why is the

ii. How does the accuracy of your logistic regression classifier from last week compare? Why is the ## The accuracy of logistic regression model was 67% but the accuracy of knn model is 98% of binary dat

The difference in accuracy is due to the non-linearness of the data in the input datasets.

KNN fits good for the non-linear dataset and hence it is more suitable model in our case.