Assignment 11.2.1

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R Markdown

R Markdown

```
library(caTools)
```

```
## Warning: package 'caTools' was built under R version 4.2.3
```

```
library(ggplot2)
```

```
## Warning: package 'ggplot2' was built under R version 4.2.3
```

```
setwd("C:/Users/mghan/Documents/dsc520")


# Load the `data/binary-classifier-data.csv` to
binary_df <- read.csv("data/binary-classifier-data.csv")
# Examine the structure of `binary-classifier-data.csv` using `str()`
str(binary_df)
```

```
## 'data.frame':    1498 obs. of  3 variables:
##  $ label: int  0 0 0 0 0 0 0 0 0 0 ...
##  $ x    : num  70.9 75 73.8 66.4 69.1 ...
##  $ y    : num  83.2 87.9 92.2 81.1 84.5 ...
```

```
# Show the top rows of binary-classifier-data.csv
head(binary_df)
```

```
##   label        x        y
## 1     0 70.88469 83.17702
## 2     0 74.97176 87.92922
## 3     0 73.78333 92.20325
## 4     0 66.40747 81.10617
## 5     0 69.07399 84.53739
## 6     0 72.23616 86.38403
```

```r
# Load the `data/trinary-classifier-data.csv`
trinary_df <- read.csv("data/trinary-classifier-data.csv")
```

```r
# Examine the structure of `trinary-classifier-data.csv` using `str()`
str(trinary_df)
```

```
## 'data.frame':    1568 obs. of  3 variables:
##  $ label: int  0 0 0 0 0 0 0 0 0 0 ...
##  $ x    : num  30.1 31.3 34.1 32.6 34.7 ...
##  $ y    : num  39.6 51.8 49.3 41.2 45.5 ...
```

```r
# Show the top rows of trinary-classifier-data.csv
head(trinary_df)
```

```
##   label        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
```

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

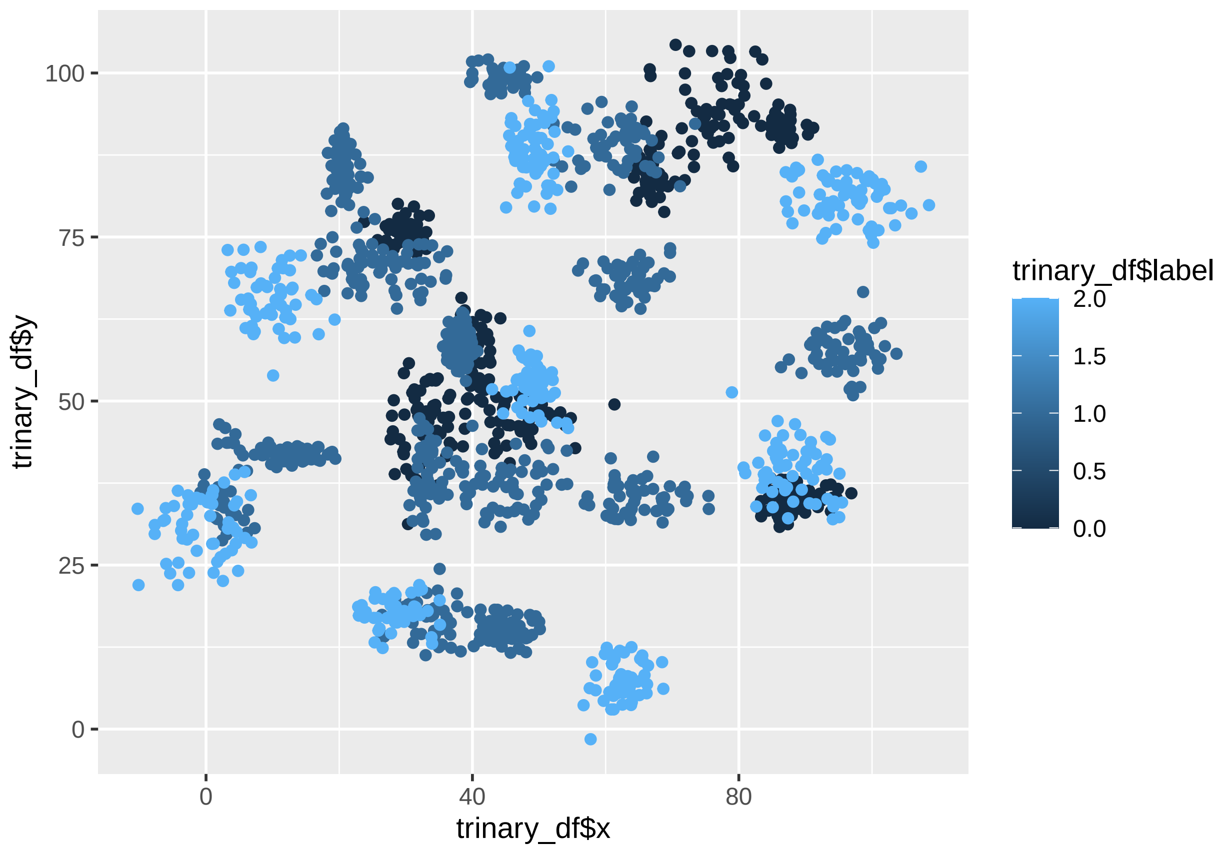
```
## Warning: Use of `binary_df$label` is discouraged.
## i Use `label` instead.

## Warning: Use of `binary_df$x` is discouraged.
## i Use `x` instead.

## Warning: Use of `binary_df$y` is discouraged.
## i Use `y` instead.
```


```
#scatter plot - trinary_df
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.
## i Use `label` instead.
```

```
## Warning: Use of `trinary_df$x` is discouraged.
## i Use `x` instead.
```

```
## Warning: Use of `trinary_df$y` is discouraged.
## i 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))
trinary_df.n=as.data.frame(lapply(trinary_df[,2:3], normalize))
set.seed(123)
dat.d <- sample(1:nrow(binary_df.n),size=nrow(binary_df.n)*0.7,replace = FALSE)
#random selection of 70% data.
train.binary_df <- binary_df[dat.d,] # 70% training data
test.binary_df <- binary_df[-dat.d,] # remaining 30% test data
#Creating seperate dataframe for 'label' feature which is our target.
train.binary_df_label <- binary_df[dat.d,1]
test.binary_df_label <-binary_df[-dat.d,1]
#Find the number of observation
NROW(train.binary_df)
```

```
## [1] 1048
```

```
#So, we have 700 observations in our training data set. The square root of
# 700 is around 26.45, therefore we'll create two models. One with 'K' value as
# 26 and the other model with a 'K' value as 27.
```

```
library(class)
knn.binary_df.1 <- knn(train=train.binary_df, test=test.binary_df, cl=train.binary_df_label, k=1)
#After building the model, it is time to calculate the accuracy of the created models:
#Calculate the proportion of correct classification for k = 32, 33
```

```r
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
```

```r
#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
##                1   4 215
```

```r
#use the confusion matrix to calculate the accuracy

library(caret)
```

```
## Warning: package 'caret' was built under R version 4.2.3
```

```
## Loading required package: lattice
```

```r
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   4
##                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
##
```

```r
#Normalization of trinary_df
normalize <- 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)
dat.d <- sample(1:nrow(trinary_df.n),size=nrow(trinary_df.n)*0.7,replace =
                  FALSE)
#random selection of 70% data.
train.trinary_df <- trinary_df[dat.d,] # 70% training data
test.trinary_df <- trinary_df[-dat.d,] # remaining 30% test data
#Creating seperate dataframe for 'label' feature which is our target.
train.trinary_df_label <- trinary_df[dat.d,1]
test.trinary_df_label <-trinary_df[-dat.d,1]
#Find the number of observation
NROW(train.trinary_df)
```

```
## [1] 1097
```

```r
library(class)
knn.trinary_df.1 <- knn(train=train.trinary_df, test=test.trinary_df, cl=train.trinary_df_label, k=1)
#After building the model, it is time to calculate the accuracy of the created models:
# Calculate 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
```

```r
#Accuracy is 95.75
```

```r
# 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   2
##                 0 131   7   1
##                 1   3 185   7
##                 2   0   2 135
```

```r
#use the confusion matrix to calculate the accuracy
library(caret)
confusionMatrix(table(knn.trinary_df.1 ,test.trinary_df_label))
```

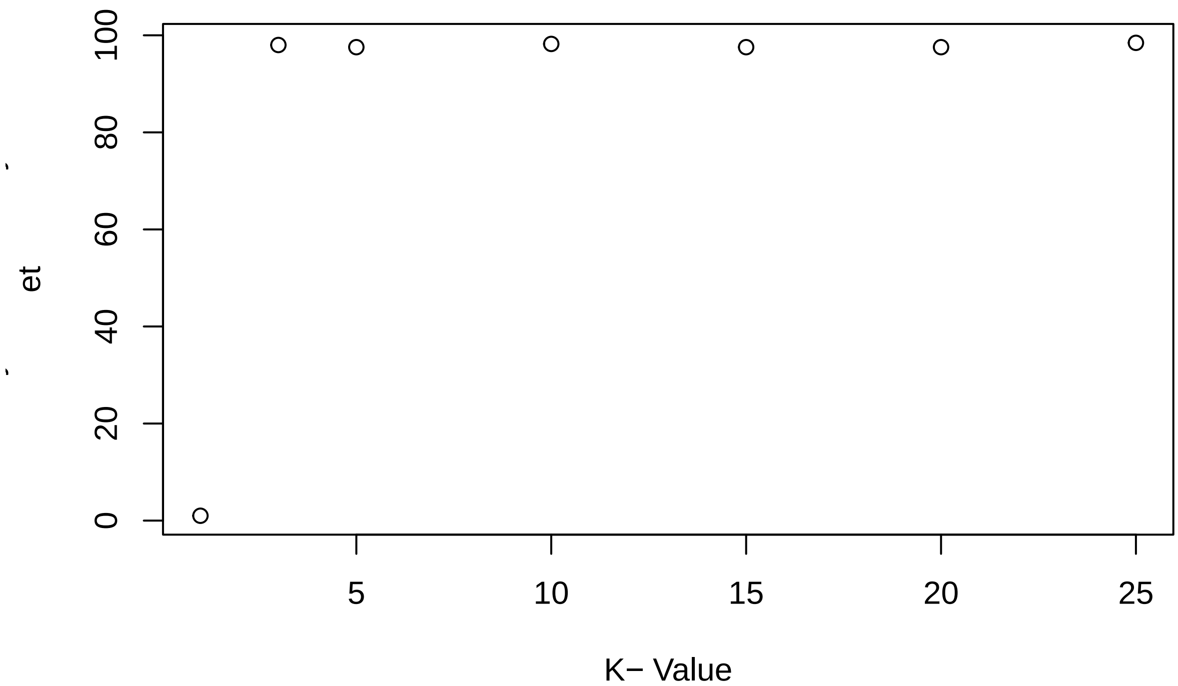
```
## Confusion Matrix and Statistics
##
##                   test.trinary_df_label
## knn.trinary_df.1   0   1   2
##                 0 131   7   1
##                 1   3 185   7
##                 2   0   2 135
##
```

```
## 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         0.9910   0.9674   0.9760
## 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
```

```r
#ii.Fit a k nearest neighbors' model for each dataset for k=3, k=5, k=10,
# k=15, k=20, and k=25. Compute the accuracy of the resulting models for
# each value of k. Plot the results in a graph where the x-axis is the
# different values of k and the y-axis is the accuracy of the model.
#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
```

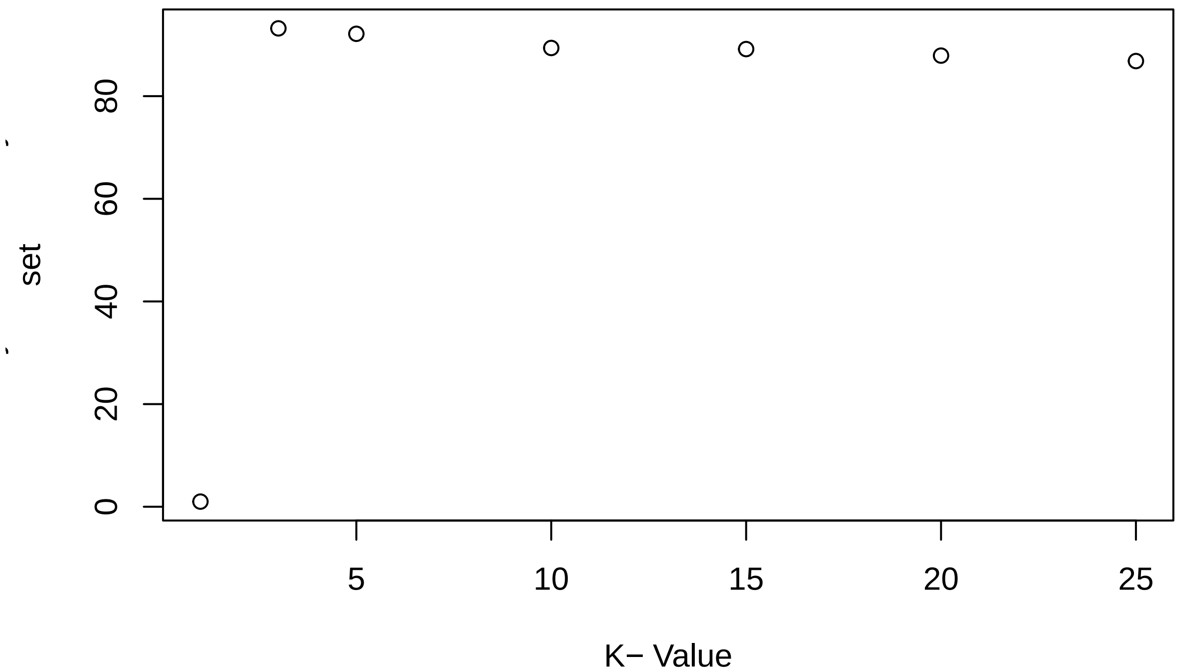
```r
#Accuracy plot
plot(k.optm, type="b", xlab="K- Value",ylab="Accuracy level of binary datas
et")
```




```r
#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
```

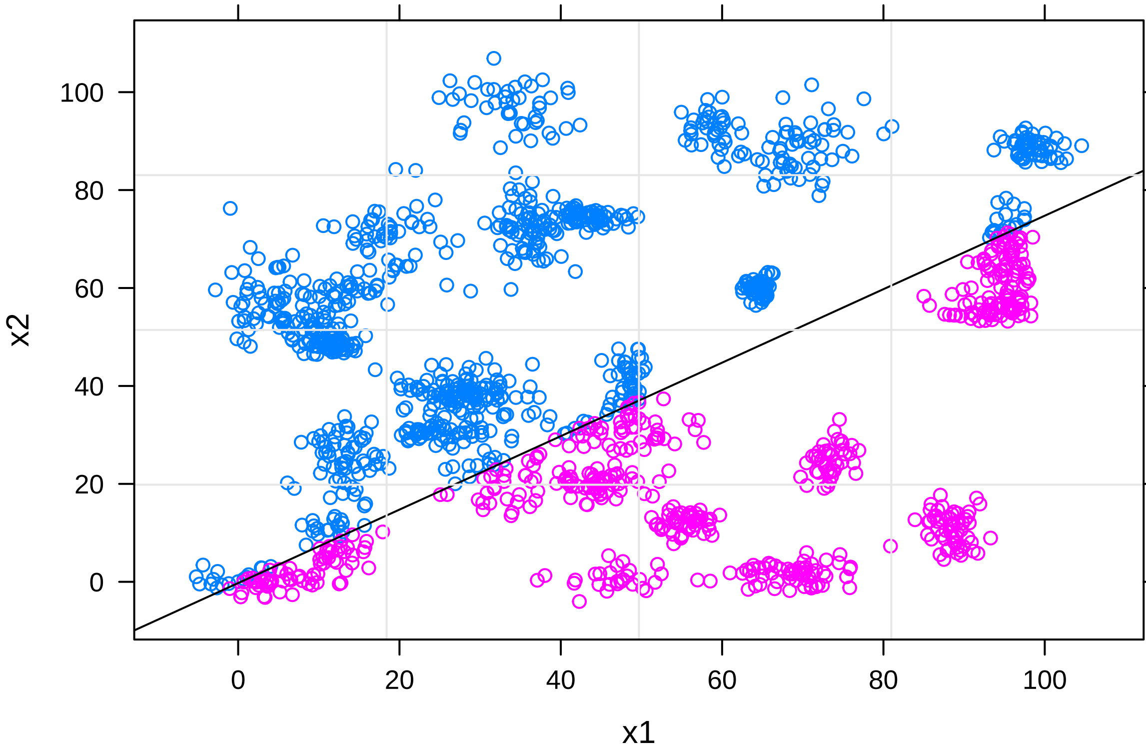
```r
#Accuracy plot
plot(k.optm, type="b", xlab="K- Value",ylab="Accuracy level of trinary data
set")
```




```r
#i.Looking back at the plots of the data, do you think a linear classifier
# would work well on these datasets?

x1=binary_df[2]
x2=binary_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)
```

```
## Warning: glm.fit: algorithm did not converge

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

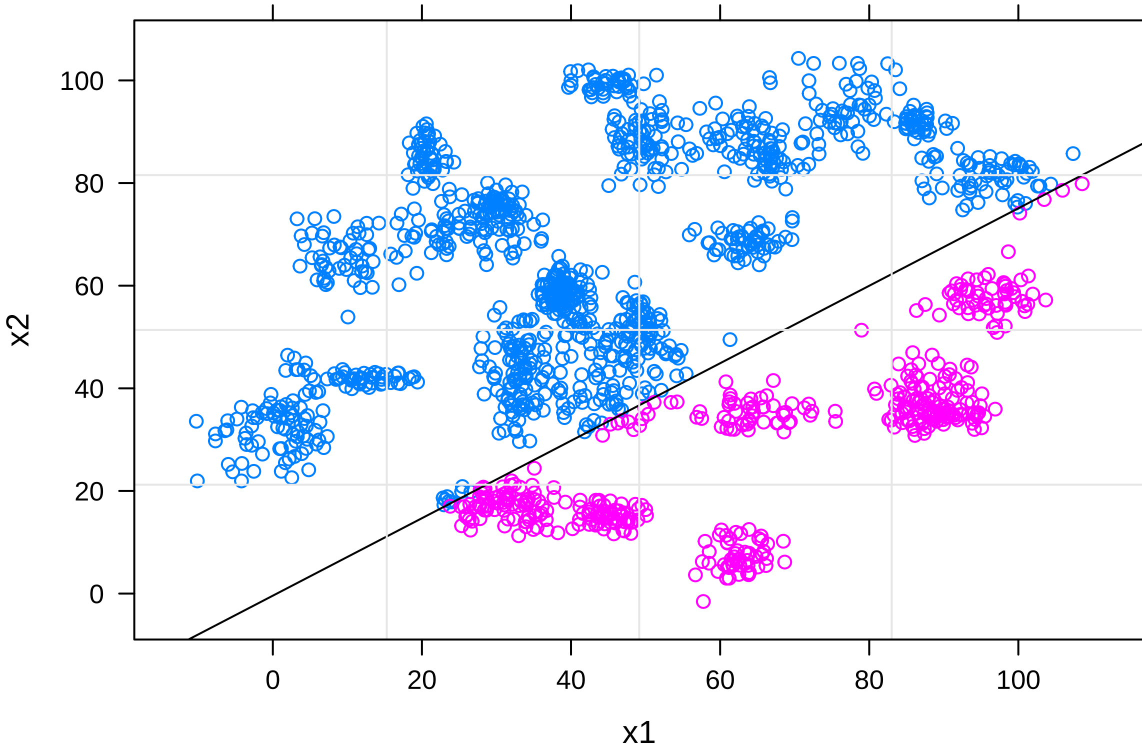
```r
slope <- coef(mdl)[2]/(-coef(mdl)[3])
intercept <- coef(mdl)[1]/(-coef(mdl)[3])
library(lattice)
xyplot( x2 ~ x1 , data = df, groups = y,
        panel=function(...){
          panel.xyplot(...)
          panel.abline(intercept , slope)
          panel.grid(...)
        })
```




```
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)
```

```
## 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(...)
        })
```




```
# By looking at the plots I think that the linear classfier would work well
# on binary dataset but not on trinary dataset.
# ii.How does the accuracy of your logistic regression classifier from last
# week compare? Why is the accuracy different between these two methods?
# The accuracy of logistic regression model was 67% but the accuracy of knn
# model is 98% for binary dataset
# 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 is more suitable model
# in our case.
```