STAT 6340 Mini Project 1 Report

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1 Answers

Experiment 1

Question 1.a

We have fitted KNN for both training and testing set for values of k ranging between 1, 5, ...,196 and additional values of 200, 225, 250,...,400.

Question 1.b

```
#Question 1.b

#Generating plot of training and testing error rates against k.

g=ggplot(data=Error_df, aes(x=kval, y=trn_Error))+
  geom_line(aes(y=trn_Error, color=graph_legend[1]), size=1,alpha = .8)+
  geom_point(color=error_colors[1], shape=19,alpha = .8)+
  geom_line(aes(y=tst_Error, color=graph_legend[2]), size=1,alpha=.6)+
  geom_point(x=Error_df$kval, y=Error_df$tst_Error, color=error_colors[2], shape=15,alpha=.6)+
  scale_color_manual("Legend",values=c("Training Set"=error_colors[1], "Testing Set"=error_colors[2]))+
  labs(title="Classification Error Rate", x="K", y="Error Rate")+
  theme(plot.title=element_text(hjust=0.5))
g
```

We present the training and testing error rates against the number of nearest neighbors on @ref(fig:graph1). We can appreciate that for small values of k we have a low error rate on the training set in contrast we obtained high error rates for the testing set. As the value of K increases we can appreciate how the error of the training set increases while the testing set start to decrease. Both training and testing sets stabilizes and then the testing set increases again. This is consistent with class discussion since the K-NN algorithm flexibility decreases as the value of K increases, leading to an increase in bias. For small values of K this algorithm tends to overfit due to high variance while for greater values of k the variance

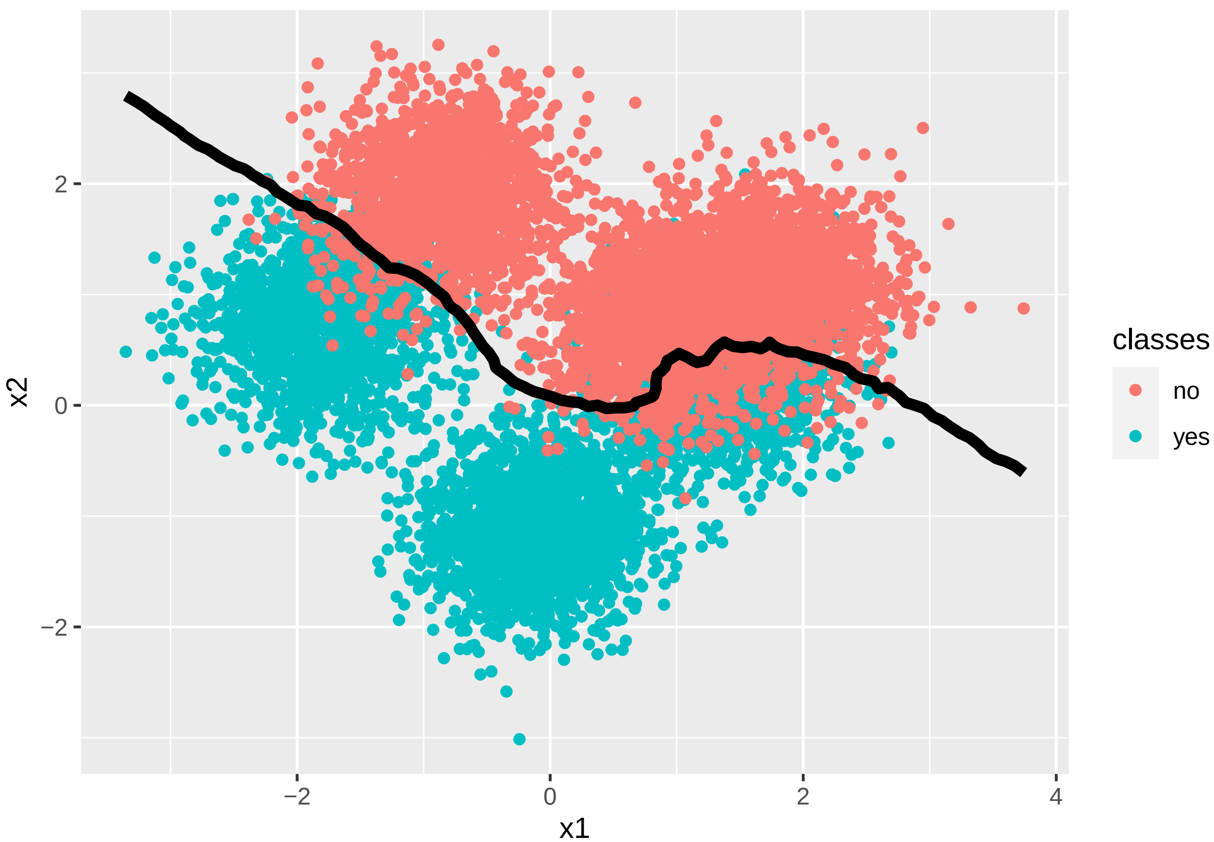
As K increases, flexibility decreases, implying that bias increases and variance decreases

Question 1.c

The optimal K for our experiment is 116, dealing a training error rate of 0.1181 and a testing error rate of 0.1155.

Question 1.d

```
#Plotting the training set and decision boundary
g2=ggplot()+geom_point(aes(x=x1,y=x2,color=classes),data=df_trn)+
  geom_contour(aes(x=x,y=y,z=z),
               data=df_contour,size=2,colour="black",breaks = 0.5)
g2
```



We present the training data set along with the decision boundary obtained from the optimal value K(116) on @ref(fig:graph2). We appreciate how the decision boundary for a majority of the observations correctly separates the training set into two clear classes. There is misclassification close to the decision as expected, although the decision boundary tends to predict the correct class, therefore it is not as much sensible to new data. The classification error rate is around 12%, we can correctly clasified a point using the related decision boundary with 88%

without too much overfitting in the sense that the red dots that are "out of place" are reasonably classified as green but the boundary manages to correctly classify the set of green dots that are misclassified in the smoother boundary determined at k=50.

Experiment 2

Question 2.a

Question 2.b

Question 2.c

2 Code

```r
#Packages
library(ggplot2) #Used for graphics an visual representations
library(class) #Used for KNN models
library(data.table)
library(dplyr) #Data manipulation

rdseed=8467 #Seed to replicate results in case of a tie on KNN

#Helper function to calculate the classification error rate
classification_error_rate=function(ypred,ytrue)
{
  mean(ypred!=ytrue)
}


#Setting graphic options.
error_colors=c("blue","orange")
graph_legend=c("Training Set","Testing Set")


##########################


#Experiment 1

#Values of K for experiment 1
kvals=c(seq(1,200,5),seq(200,400,25))


#Reading training and testing data sets
trn=read.csv("1-training_data.csv", stringsAsFactors = TRUE)
tst=read.csv("1-test_data.csv", stringsAsFactors = TRUE)

#Exploring the data set
str(trn)
summary(trn)

str(tst)
summary(tst)
#We can appreciate that the class labels are equally distributed
#in both training and testing sets

#Saving training and testing labels
trn_y=trn$y
tst_y=tst$y

#Dropping the classes to use only the predictors on the knn function.
trn$y=NULL
tst$y=NULL

#Helper function to find KNN predictions and find the classification error rate
#This function is declared for dplyr manipulation purposes.
```

```r
fitKNN_Error=function(testing_set,true_labels,i)
{
  set.seed(rdseed)
  classification_error_rate(knn(trn,testing_set,cl=trn_y,k=i),true_labels)
}


#Dataframe to track the error rates
Error_df=data.frame(kval=kvals)

#Question 1.a

#Fitting KNN for different values of K (training data)
Error_df=Error_df%>%group_by(kval)%>%mutate(trn_Error=fitKNN_Error(trn,trn_y,kval))

#Fitting KNN for different values of K (testing data)
Error_df=Error_df%>%group_by(kval)%>%mutate(tst_Error=fitKNN_Error(tst,tst_y,kval))


#Question 1.b

#Generating plot of training and testing error rates against k.

g=ggplot(data=Error_df, aes(x=kval, y=trn_Error))+
  geom_line(aes(y=trn_Error, color=graph_legend[1]), size=1,alpha = .8)+
  geom_point(color=error_colors[1], shape=19,alpha = .8)+
  geom_line(aes(y=tst_Error, color=graph_legend[2]), size=1,alpha=.6)+
  geom_point(x=Error_df$kval, y=Error_df$tst_Error, color=error_colors[2], shape=15,alpha=.6)+
  scale_color_manual("Legend",values=c("Training Set"=error_colors[1], "Testing Set"=error_colors[2]))+
  labs(title="Classification Error Rate", x="K", y="Error Rate")+
  theme(plot.title=element_text(hjust=0.5))

print(g)


#Question 1.c

#Finding the index of the optimal K, this is the index of the least test error rate
ind_optimalK=which.min(Error_df$tst_Error)

Error_df[ind_optimalK,] #The row of the optimal k contains the associated errors for training and testi

optimalK=Error_df$kval[ind_optimalK]


#Question 1.d

#Creating grid
x1=seq(min(trn[,1]),max(trn[,1]),length.out=100)
x2=seq(min(trn[,2]),max(trn[,2]),length.out=100)
grid <- expand.grid(x=x1, y=x2)

#Classifying the grid
```

```r
bestK=knn(trn,grid,cl=trn_y,k=optimalK,prob = TRUE ) #Fitting with optimal K
prob = attr(bestK, "prob")
prob = ifelse(bestK=="yes", prob, 1-prob)

#Data Frame to generate the surface for the contour
df_contour=data.frame(x=grid[,1],y=grid[,2],z=prob)

#Data Frame to plot the training set
df_trn=data.frame(x1=trn[,1],x2=trn[,2],classes=trn_y)

#Plotting the training set
g2=ggplot()+geom_point(aes(x=x1,y=x2,color=classes),data=df_trn)

#Plotting the decision boundary
g2=g2+geom_contour(aes(x=x,y=y,z=z),
               data=df_contour,size=2,colour="black",breaks = 0.5)

print(g2)

##########################

#Experiment 2

##Preprocessing
library(keras)
cifar <- dataset_cifar10()
str(cifar)

x.train <- cifar$train$x
y.train <- cifar$train$y
x.test <- cifar$test$x
y.test <- cifar$test$y

# reshape the images as vectors (column-wise)
# (aka flatten or convert into wide format)
# (for row-wise reshaping, see ?array_reshape)
dim(x.train) <- c(nrow(x.train), 32*32*3) # 50000 x 3072
dim(x.test) <- c(nrow(x.test), 32*32*3) # 50000 x 3072

# rescale the x to lie between 0 and 1
x.train <- x.train/255
x.test <- x.test/255

# categorize the response
y.train <- as.factor(y.train)
y.test <- as.factor(y.test)

# randomly sample 1/100 of test data to reduce computing time

set.seed(2021)
id.test <- sample(1:10000, 100)

x.test <- x.test[id.test,]
```

```r
y.test <- y.test[id.test]

#Helper function to find KNN predictions and the classification error rate
#This function is declared for dplyr manipulation purposes.
fitKNN_Error_cifar=function(i)
{
  set.seed(rdseed)
  classification_error_rate(knn(x.train,x.test,cl=y.train,k=i),y.test)
}

#Values of K for experiment 2
kvals2=c(50, 100, 200, 300, 400)

#Dataframe to track the test error rates
Cifar_Error=data.frame(kval=kvals2)

##Experiment 2 questions

#Question 2.a

#Fitting KNN for different values of K
Cifar_Error=Cifar_Error%>%group_by(kval)%>%mutate(tst_Error=fitKNN_Error_cifar(kval))


#Question 2.b

ind_optimalK=which.min(Cifar_Error$tst_Error) #Finding optimal K

#Fitting KNN with the optimal K
set.seed(rdseed)
cifar_pred=knn(x.train,x.test,cl=y.train,k=ind_optimalK)

#Displaying confusion matrix
table(cifar_pred ,y.test,dnn=c("predicted","actual"))
```