LGM VIP Data Science Internship
Beginner Task-1: Iris Flowers Classification ML Project

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Description:

The iris flowers dataset contains numeric attributes. We have the attributes as:

1. sepal length in cm
2. sepal width in cm
3. petal length in cm
4. petal width in cm
5. class:
   (a) -- Iris Setosa
   (b) -- Iris Versicolour
   (c) -- Iris Virginica

We have to classify them into different categories using ML.

Importing libraries and visualising the data

We first load the libraries required for our work and then we read the dataset

```
library(class)#for the KNN function
set.seed(200)#setting the seed
df<-read.table('D:\\Important Documents\\Internship\\LGM-VIP Aug21\\Task-1\\iris.data',
                                sep=',',header=F)#reading the file
head(df)#a sneak peek into the dataset
```

```
##    V1  V2  V3  V4          V5
## 1 5.1 3.5 1.4 0.2 Iris-setosa
## 2 4.9 3.0 1.4 0.2 Iris-setosa
## 3 4.7 3.2 1.3 0.2 Iris-setosa
## 4 4.6 3.1 1.5 0.2 Iris-setosa
## 5 5.0 3.6 1.4 0.2 Iris-setosa
## 6 5.4 3.9 1.7 0.4 Iris-setosa
```

```
names(df)<-c('sepal.len','sepal.wd','petal.len',
                        'petal.wd','class')#setting the names of the columns
dim(df)#the dimensions of the dataset
```

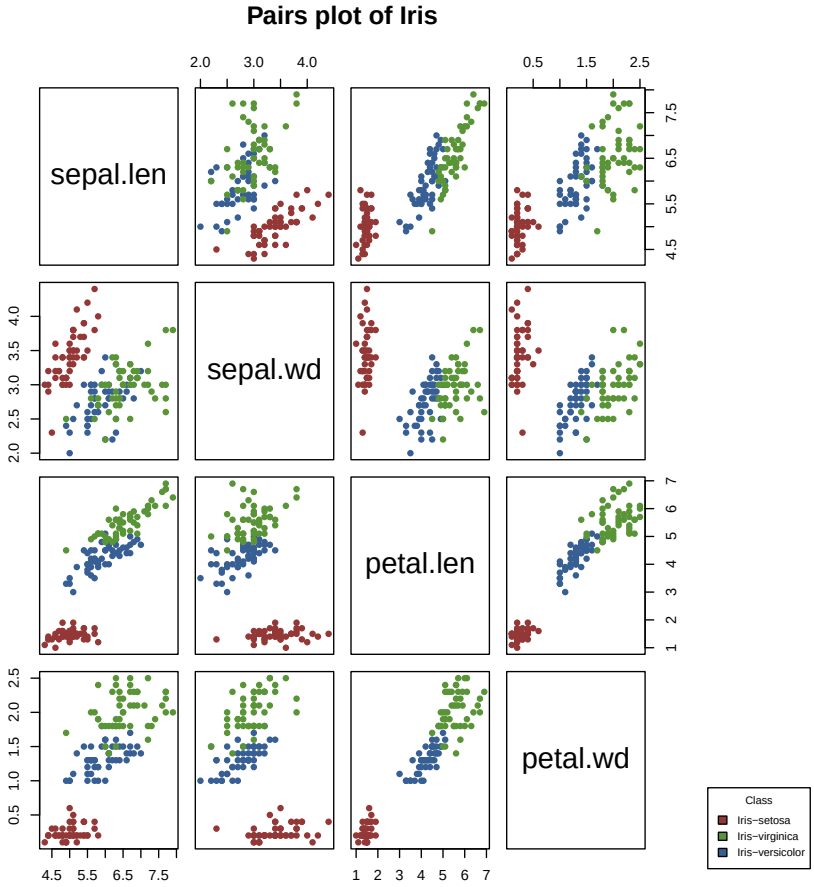
```
## [1] 150   5
```

```
summary(df)#a brief summary of the dataset
```

```
##    sepal.len        sepal.wd       petal.len        petal.wd
##  Min.   :4.300   Min.   :2.000   Min.   :1.000   Min.   :0.100
##  1st Qu.:5.100   1st Qu.:2.800   1st Qu.:1.600   1st Qu.:0.300
##  Median :5.800   Median :3.000   Median :4.350   Median :1.300
##  Mean   :5.843   Mean   :3.054   Mean   :3.759   Mean   :1.199
##  3rd Qu.:6.400   3rd Qu.:3.300   3rd Qu.:5.100   3rd Qu.:1.800
##  Max.   :7.900   Max.   :4.400   Max.   :6.900   Max.   :2.500
##     class
##  Length:150
##  Class :character
##  Mode  :character
##
##
##
```

```
classno<-ifelse(df$class=='Iris-setosa',1,
                                ifelse(df$class=='Iris-virginica',2,3))#factoring on the bas

pairs(df[,-5],col=c('#943737','#599437','#375f94')[classno],
                main='Pairs plot of Iris',pch=16,oma=c(3,5,5,12))#plots of the data by varia
par(xpd=T)
legend("bottomright",fill=c('#943737','#599437','#375f94'),
                legend=c('Iris-setosa','Iris-virginica','Iris-versicolor'),
                cex=0.5,title='Class')
```



Splitting the dataset into training and test set

We next split our dataset into training and testing sets.

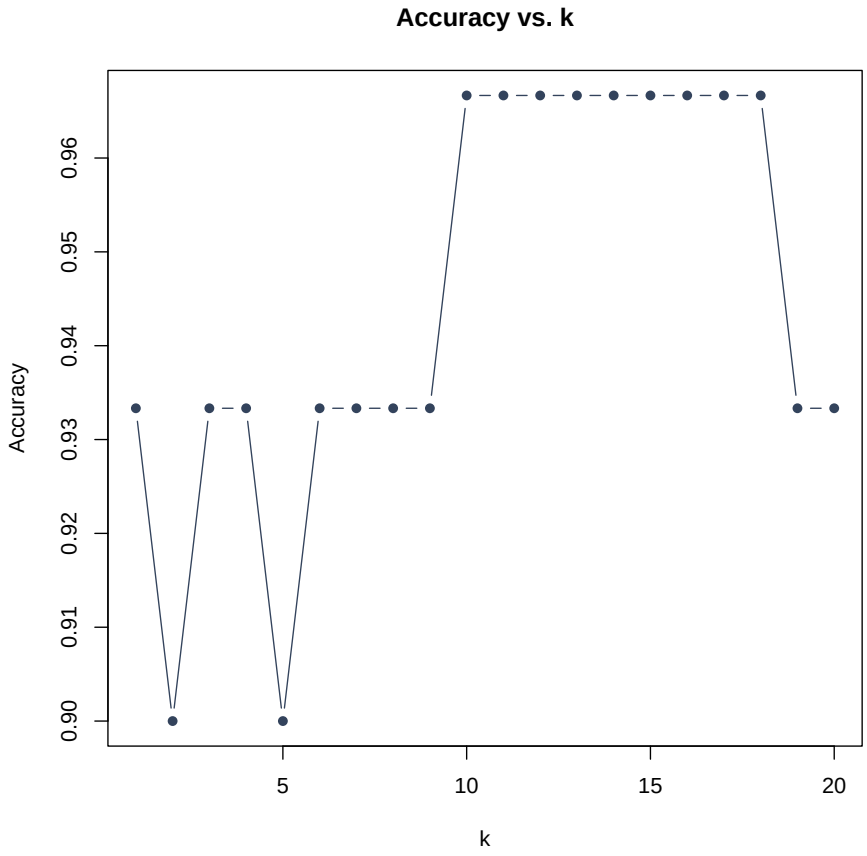
```
t_sample<-sample(nrow(df),0.8*nrow(df)) #contains the row numbers of the training set
train<-df[t_sample,];test<-df[-t_sample,]
```

We will use the K nearest neighbours to classify the dataset.

Value of k

First, we obtain the the number of neighbours that are to be considered. We'll choose the `k` which has the max accuracy. We start by taking `k` as 1 and then simulate the accuracy incrementing `k` in each step.

```
model_knn<-list();accuracy_knn<-numeric()
for(i in 1:20)
{
        model_knn[[i]]<-knn(train[,-5],test[,-5],train$class,k=i,prob=T)
        accuracy_knn[i]<-sum(model_knn[[i]]==test$class)/length(test$class)
}
plot(1:20,accuracy_knn,type='b',main='Accuracy vs. k',ylab='Accuracy',xlab='k',col='#33435c'
```



From the plot, we find that there are many values of `k` which have maximum accuracy among all the values of `k`.

We proceed to find the maximum accuracy.

```
max(accuracy_knn)

## [1] 0.9666667
```

Thus, we find that the max accuracy that was obtained by this method is 96.67%.

Further, we find the least vaue of `k` with maximum accuracy. This is due to the fact that a greater value of `k` may lead to overfitting of the data.

```
k<-min(which(accuracy_knn==max(accuracy_knn)))#min value of k which has the max accuracy
k

## [1] 10
```

Thus, we find the value of `k` as 10 with an accuracy level of 96.67%.

Predictions

We finally classify the iris dataset into the respective classes.

```
final_model <- knn(train[,-5], test[,-5], train$class, k, prob=TRUE)
model_tab <- table(test$class, final_model)
model_tab

##                 final_model
##                  Iris-setosa Iris-versicolor Iris-virginica
##   Iris-setosa              8               0              0
##   Iris-versicolor          0               8              1
##   Iris-virginica           0               1             12
```

We find that, while `Iris-setosa` was correctly classified, `Iris-versicolor` and `Iris-virginica` were not classified perfectly, as one of them was interchanged.

The below dataframe gives the details of the test set along with the original and predicted classes:

```
cbind(test,final_model)

##     sepal.len sepal.wd petal.len petal.wd           class     final_model
## 12        4.8      3.4       1.6      0.2     Iris-setosa     Iris-setosa
## 14        4.3      3.0       1.1      0.1     Iris-setosa     Iris-setosa
## 21        5.4      3.4       1.7      0.2     Iris-setosa     Iris-setosa
## 28        5.2      3.5       1.5      0.2     Iris-setosa     Iris-setosa
## 32        5.4      3.4       1.5      0.4     Iris-setosa     Iris-setosa
## 33        5.2      4.1       1.5      0.1     Iris-setosa     Iris-setosa
## 43        4.4      3.2       1.3      0.2     Iris-setosa     Iris-setosa
## 47        5.1      3.8       1.6      0.2     Iris-setosa     Iris-setosa
## 60        5.2      2.7       3.9      1.4 Iris-versicolor Iris-versicolor
## 65        5.6      2.9       3.6      1.3 Iris-versicolor Iris-versicolor
## 68        5.8      2.7       4.1      1.0 Iris-versicolor Iris-versicolor
```

```
## 69        6.2       2.2        4.5       1.5 Iris-versicolor Iris-versicolor
## 73        6.3       2.5        4.9       1.5 Iris-versicolor  Iris-virginica
## 75        6.4       2.9        4.3       1.3 Iris-versicolor Iris-versicolor
## 80        5.7       2.6        3.5       1.0 Iris-versicolor Iris-versicolor
## 81        5.5       2.4        3.8       1.1 Iris-versicolor Iris-versicolor
## 92        6.1       3.0        4.6       1.4 Iris-versicolor Iris-versicolor
## 107       4.9       2.5        4.5       1.7  Iris-virginica Iris-versicolor
## 110       7.2       3.6        6.1       2.5  Iris-virginica  Iris-virginica
## 112       6.4       2.7        5.3       1.9  Iris-virginica  Iris-virginica
## 117       6.5       3.0        5.5       1.8  Iris-virginica  Iris-virginica
## 125       6.7       3.3        5.7       2.1  Iris-virginica  Iris-virginica
## 126       7.2       3.2        6.0       1.8  Iris-virginica  Iris-virginica
## 130       7.2       3.0        5.8       1.6  Iris-virginica  Iris-virginica
## 132       7.9       3.8        6.4       2.0  Iris-virginica  Iris-virginica
## 133       6.4       2.8        5.6       2.2  Iris-virginica  Iris-virginica
## 138       6.4       3.1        5.5       1.8  Iris-virginica  Iris-virginica
## 142       6.9       3.1        5.1       2.3  Iris-virginica  Iris-virginica
## 144       6.8       3.2        5.9       2.3  Iris-virginica  Iris-virginica
## 149       6.2       3.4        5.4       2.3  Iris-virginica  Iris-virginica
```