# Group 96 [Raza Abbas, Alkesh Chaturvedi, Harsh Bhatia]

# Problem Statement: Predict class of Iris plant using a decision tree ## 1. Import the data from Iris Dataset (Links to an external site.) (1 point) ## 2. Consider all columns as independent variables and assign to variable X except the last column and consider the last ## column as dependent variable and assign to variable y. (1 point) ## 3. Remove columns which don't help the problem statement. (1 point) ## 4. Compute some basic statistical details like percentile, mean, standard deviation of dataset (1 point) ## 5. Encode all the categorical columns into numeric (1 point) ## 6. Do Feature Scaling on Independent variables (2 points) ## 7. Split the data into train and test dataset (1 point) ## 8. Use sklearn library to train on train dataset on decision tree and predict on test dataset (3 points) ## 9. Compute the accuracy and precision. (2 points)

# Importing the required libraries

In [1]:
```
import pandas as pd
import numpy as np
import statistics
from urllib.request import urlretrieve
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import accuracy_score, classification_report, confusion_m
atrix
from sklearn.model_selection import train_test_split
from sklearn.tree import DecisionTreeClassifier
import seaborn as sns
```

# 1. Import the data from Iris Dataset (Links to an external site.) (1 point)

import the data from iris dataset & assign url of the file

In [2]:
```
iris = "http://archive.ics.uci.edu/ml/machine-learning-databases/iris/iris.dat
a"
```

In [3]:
```
urlretrieve(iris)
```

Out[3]:
```
('C:\\Users\\ealkcha\\AppData\\Local\\Temp\\tmpwm93a7c5',
 <http.client.HTTPMessage at 0x2563c2b3310>)
```

Observation: saves the file locally

Read file into a dataframe and print its head

In [4]:
```
df=pd.read_csv(iris,sep=',',names=["sepal_length", "sepal_width", "petal_length", "petal_width", "class"])
```

In [5]:
```
df
```

Out[5]:

| | sepal_length | sepal_width | petal_length | petal_width | class |
|---|---|---|---|---|---|
| **0** | 5.1 | 3.5 | 1.4 | 0.2 | Iris-setosa |
| **1** | 4.9 | 3.0 | 1.4 | 0.2 | Iris-setosa |
| **2** | 4.7 | 3.2 | 1.3 | 0.2 | Iris-setosa |
| **3** | 4.6 | 3.1 | 1.5 | 0.2 | Iris-setosa |
| **4** | 5.0 | 3.6 | 1.4 | 0.2 | Iris-setosa |
| **...** | ... | ... | ... | ... | ... |
| **145** | 6.7 | 3.0 | 5.2 | 2.3 | Iris-virginica |
| **146** | 6.3 | 2.5 | 5.0 | 1.9 | Iris-virginica |
| **147** | 6.5 | 3.0 | 5.2 | 2.0 | Iris-virginica |
| **148** | 6.2 | 3.4 | 5.4 | 2.3 | Iris-virginica |
| **149** | 5.9 | 3.0 | 5.1 | 1.8 | Iris-virginica |

150 rows × 5 columns

Observation: file is opened as data frame, first four columns are attributes and last column is class variable

In [6]:
```
# display first 5 records with headers & shape
df.head(), df.shape
```

Out[6]:
```
(   sepal_length  sepal_width  petal_length  petal_width        class
 0           5.1          3.5           1.4          0.2  Iris-setosa
 1           4.9          3.0           1.4          0.2  Iris-setosa
 2           4.7          3.2           1.3          0.2  Iris-setosa
 3           4.6          3.1           1.5          0.2  Iris-setosa
 4           5.0          3.6           1.4          0.2  Iris-setosa,
 (150, 5))
```

Observation: Displays the first 5 rows. Data has 150 rows and 5 columns

In [7]:
```
# check the data types of each attibutes
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 150 entries, 0 to 149
Data columns (total 5 columns):
 #   Column        Non-Null Count  Dtype  
---  ------        --------------  -----  
 0   sepal_length  150 non-null    float64
 1   sepal_width   150 non-null    float64
 2   petal_length  150 non-null    float64
 3   petal_width   150 non-null    float64
 4   class         150 non-null    object 
dtypes: float64(4), object(1)
memory usage: 6.0+ KB
```

Observation: Displays the data type of each variable - attributes are float and class variable is qualitative data type; there are no null values in the data

# 2. Consider all columns as independent variables and assign to variable X except the last column and consider the last column as dependent variable and assign to variable y. (1 point)

Print the first 5 records to check Variable X & Y

In [8]:
```
X=df.iloc[:,0:4]
X.head()
```

Out[8]:

| | sepal_length | sepal_width | petal_length | petal_width |
|---|---|---|---|---|
| **0** | 5.1 | 3.5 | 1.4 | 0.2 |
| **1** | 4.9 | 3.0 | 1.4 | 0.2 |
| **2** | 4.7 | 3.2 | 1.3 | 0.2 |
| **3** | 4.6 | 3.1 | 1.5 | 0.2 |
| **4** | 5.0 | 3.6 | 1.4 | 0.2 |

Observation: Variable X is assigned to the first four columns

In [9]:
```
Y=df.iloc[:,-1:]
Y.head()
```

Out[9]:

| | class |
|---|---|
| 0 | Iris-setosa |
| 1 | Iris-setosa |
| 2 | Iris-setosa |
| 3 | Iris-setosa |
| 4 | Iris-setosa |

Observation: Variable Y is assigned to the last columns

# 3. Remove columns which don’t help the problem statement. (1 point)

In [10]:
```
# To get a correlation we need to convert our categorical variable into numeri
cal one
df["class"] =df["class"].astype('category').cat.codes
```

In [11]:
```
df["class"].dtype
```

Out[11]: dtype('int8')

Observation: Data type of the the Dependent variable changed from categorical to numeric

In [12]:
```
# Check correlation among independent variables and also between dependent var
iable and each of the independent variables
df.corr()
```

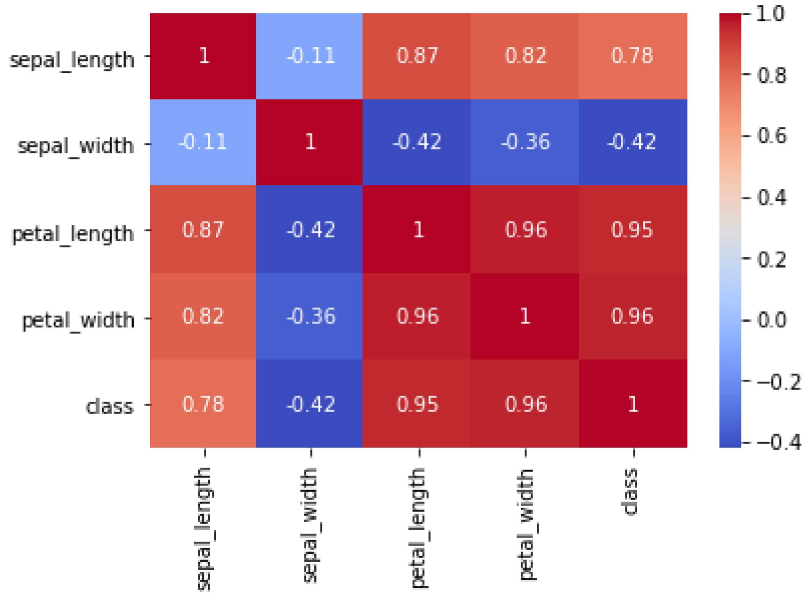
Out[12]:

| | sepal_length | sepal_width | petal_length | petal_width | class |
|---|---|---|---|---|---|
| **sepal_length** | 1.000000 | -0.109369 | 0.871754 | 0.817954 | 0.782561 |
| **sepal_width** | -0.109369 | 1.000000 | -0.420516 | -0.356544 | -0.419446 |
| **petal_length** | 0.871754 | -0.420516 | 1.000000 | 0.962757 | 0.949043 |
| **petal_width** | 0.817954 | -0.356544 | 0.962757 | 1.000000 | 0.956464 |
| **class** | 0.782561 | -0.419446 | 0.949043 | 0.956464 | 1.000000 |

Observation: Correlation table shows high correlation among sepal_length, petal_length & petal_width. These varaibles also have high correlation with dependent variable

In [13]:
```
# Plot heat map to visualize corelation among the variables
sns.heatmap(df.corr(), cmap='coolwarm', annot=True)
```

Out[13]: <matplotlib.axes._subplots.AxesSubplot at 0x2563c4270a0>




Observation: Heat map provides visual display of correclation and reconfirms - high correlation among sepal_length, petal_length & petal_width. These varaibles also have high correlation with dependent variable

# From correlation analysis, petal width has the highest correlation with the dependent variable among all highly correlated variables sepal_length, petal_length & petal_width. # we remove petal length and sepal length and keep petal width and septal width in our model.

In [14]:
```
df=df[["sepal_width","petal_width","class"]]
df.head()
```

Out[14]:

| | sepal_width | petal_width | class |
|---|---|---|---|
| **0** | 3.5 | 0.2 | 0 |
| **1** | 3.0 | 0.2 | 0 |
| **2** | 3.2 | 0.2 | 0 |
| **3** | 3.1 | 0.2 | 0 |
| **4** | 3.6 | 0.2 | 0 |

Observation: Displays data post removal of two variables - sepal_length and petal_length

# 4. Compute some basic statistical details like percentile, mean, standard deviation of dataset (1 point)

In [15]:
```
stat = df.describe()
```

In [16]:
```
stat
```

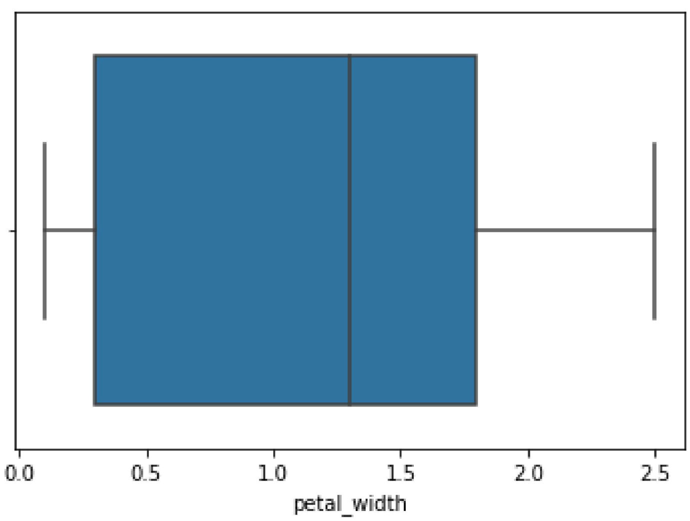
Out[16]:

| | sepal_width | petal_width | class |
|---|---|---|---|
| **count** | 150.000000 | 150.000000 | 150.000000 |
| **mean** | 3.054000 | 1.198667 | 1.000000 |
| **std** | 0.433594 | 0.763161 | 0.819232 |
| **min** | 2.000000 | 0.100000 | 0.000000 |
| **25%** | 2.800000 | 0.300000 | 0.000000 |
| **50%** | 3.000000 | 1.300000 | 1.000000 |
| **75%** | 3.300000 | 1.800000 | 2.000000 |
| **max** | 4.400000 | 2.500000 | 2.000000 |

Observation: From above statistics, we conclude the following: (1) Presence of outlier in sepal width as max entry is greater than mean+3*std (2) petal width seems to have slight skewness as seen from the mean and median values however there are no outliers

In [17]:
```
sns.boxplot(x=df['petal_width'])
```

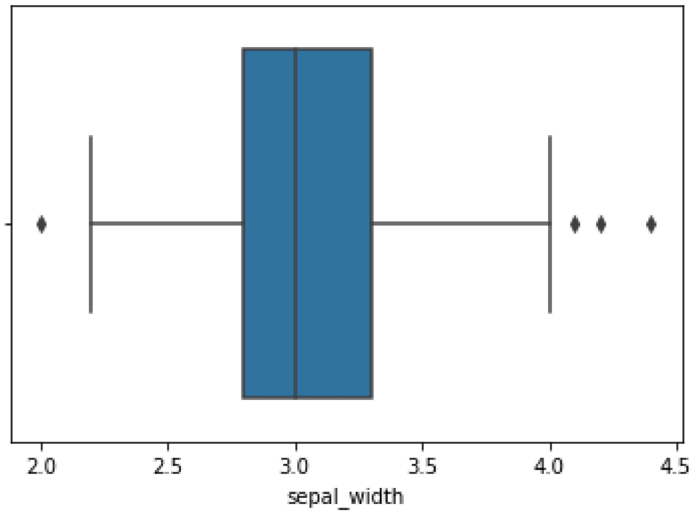
Out[17]: <matplotlib.axes._subplots.AxesSubplot at 0x2563c3bed30>




Observation: Box plot shows Petal Width data is left skewed but no outliers in the data

In [18]:
```
sns.boxplot(x=df['sepal_width'])
```

Out[18]: <matplotlib.axes._subplots.AxesSubplot at 0x2563cc92490>




Observation: Box plot indicates 4 minor outliers in sepal width data. We are not treating the outliers.

# 5. Encode all the categorical columns into numeric (1 point)

df["class"] =df["class"].astype('category').cat.codes

Above code was used earlier in the program to convert categorical variable ("class") into numeric. The variable is now numeric can be verified as below:

In [19]:
```
# df["class"] =df["class"].astype('category').cat.codes <Command used earlier
 in the program to encode categorical column into numeric
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 150 entries, 0 to 149
Data columns (total 3 columns):
 #   Column       Non-Null Count  Dtype  
---  ------       --------------  -----  
 0   sepal_width  150 non-null    float64
 1   petal_width  150 non-null    float64
 2   class        150 non-null    int8   
dtypes: float64(2), int8(1)
memory usage: 2.6 KB
```

Observation: As given above, the class variable is "int". this was categorical variable that we converted to "int" while finding the corrleation among the variables. The command used for this conversion was: df["class"] =df["class"].astype('category').cat.codes

# 6. Do Feature Scaling on Independent variables (2 points)

In [20]:
```
X=df.iloc[:,0:2]
X.head()
```

Out[20]:

| | sepal_width | petal_width |
|---|---|---|
| **0** | 3.5 | 0.2 |
| **1** | 3.0 | 0.2 |
| **2** | 3.2 | 0.2 |
| **3** | 3.1 | 0.2 |
| **4** | 3.6 | 0.2 |

Observation: Above detail shows that scales of two attributes sepal_width and petal width are significantly different

In [21]:
```
sc = StandardScaler()
X = sc.fit_transform(X)
X[:10]
```

Out[21]:
```
array([[ 1.03205722, -1.31297673],
       [-0.1249576 , -1.31297673],
       [ 0.33784833, -1.31297673],
       [ 0.10644536, -1.31297673],
       [ 1.26346019, -1.31297673],
       [ 1.95766909, -1.05003079],
       [ 0.80065426, -1.18150376],
       [ 0.80065426, -1.31297673],
       [-0.35636057, -1.31297673],
       [ 0.10644536, -1.4444497 ]])
```

Observation: Two attributes are scaled as seen above

# 7. Split the data into train and test dataset (1 point)

lets divide 80% of the data into training set to train the model and rest into testing set; 80:20 ratio

In [22]:
```
X_train, X_test, Y_train, Y_test = train_test_split(X, Y, test_size=0.20, rand
om_state=22)
```

In [23]:
```
X_train.shape
```

Out[23]:
```
(120, 2)
```

In [24]:
```
Y_train.shape
```
Out[24]:
```
(120, 1)
```

In [25]:
```
X_test.shape
```
Out[25]:
```
(30, 2)
```

In [26]:
```
Y_test.shape
```
Out[26]:
```
(30, 1)
```

Observation: 150 records are split into train and test data in the ratio of 80:20 randomly

# 8. Use sklearn library to train on train dataset on decision tree and predict on test dataset (3 points)

In [27]:
```
classifier = DecisionTreeClassifier()
```

In [28]:
```
classifier.fit(X_train, Y_train)
```
Out[28]:
```
DecisionTreeClassifier()
```

Observation: model is trained on the training data using the sklearn library

In [29]:
```
Y_pred = classifier.predict(X_test)
```

Observation: prediction is done on the test data

# 9. Compute the accuracy and precision. (2 points)

In [30]:
```
print(confusion_matrix(Y_test, Y_pred))
```
```
[[ 6  0  0]
 [ 0  8  2]
 [ 0  2 12]]
```

Observation: Confution matrix is displayed as above

In [31]:
```
accuracy_score(Y_test, Y_pred)
```
Out[31]:
```
0.8666666666666667
```

Observation: Model accuracy is 86.6%

In [32]:
```
print(classification_report(Y_test, Y_pred))
```

```
                 precision    recall  f1-score   support

    Iris-setosa       1.00      1.00      1.00         6
Iris-versicolor       0.80      0.80      0.80        10
 Iris-virginica       0.86      0.86      0.86        14

       accuracy                           0.87        30
      macro avg       0.89      0.89      0.89        30
   weighted avg       0.87      0.87      0.87        30
```

Observation: Precision, recall and f1-score are tabulated as above. All the parameters have values greater than 80% indicating reasonable performance for the model