```
In [1]: import pandas as pd
    import numpy as np
    import matplotlib.pyplot as plt
    import seaborn as sns
    from sklearn.linear_model import LogisticRegression
    from sklearn.model_selection import train_test_split
    from sklearn import metrics
```

```
In [2]: df = pd.read_csv('IRIS-flower.csv')
```

In [3]: df.shape

Out[3]: (150, 5)

In [4]: df.head()

#### Out[4]: sepal\_length sepal\_width petal\_length petal\_width species 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 5.0 0.2 Iris-setosa 3.6 1.4

In [5]: df.sample(10)

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	sepal_length	sepal_width	petal_length	petal_width	species
145	6.7	3.0	5.2	2.3	Iris-virginica
43	5.0	3.5	1.6	0.6	Iris-setosa
34	4.9	3.1	1.5	0.1	Iris-setosa
62	6.0	2.2	4.0	1.0	Iris-versicolor
89	5.5	2.5	4.0	1.3	Iris-versicolor
13	4.3	3.0	1.1	0.1	Iris-setosa
142	5.8	2.7	5.1	1.9	Iris-virginica
127	6.1	3.0	4.9	1.8	Iris-virginica
61	5.9	3.0	4.2	1.5	Iris-versicolor
26	5.0	3.4	1.6	0.4	Iris-setosa

```
In [6]: df.info()
        <class 'pandas.core.frame.DataFrame'>
        RangeIndex: 150 entries, 0 to 149
        Data columns (total 5 columns):
            Column
                    Non-Null Count Dtype
            sepal_length 150 non-null
        0
                                         float64
            sepal_width 150 non-null
                                        float64
         1
            petal length 150 non-null float64
         3
            petal_width 150 non-null float64
        4
            species
                          150 non-null
                                         object
        dtypes: float64(4), object(1)
        memory usage: 6.0+ KB
```

#### Reducing the size of our dataframe

```
In [7]: | df['species']=df['species'].astype('category')
In [8]: | df.info()
        <class 'pandas.core.frame.DataFrame'>
        RangeIndex: 150 entries, 0 to 149
        Data columns (total 5 columns):
                          Non-Null Count Dtype
             Column
                          _____
                                          float64
            sepal_length 150 non-null
         0
            sepal_width 150 non-null
                                         float64
         2
             petal_length 150 non-null
                                          float64
         3
             petal_width 150 non-null
                                          float64
             species
                          150 non-null
                                          category
        dtypes: category(1), float64(4)
        memory usage: 5.1 KB
```

### **Checking for null values**

```
In [9]: df.isnull().sum()

Out[9]: sepal_length  0
    sepal_width  0
    petal_length  0
    petal_width  0
    species  0
    dtype: int64
```

#### **Checking for duplicate values**

```
In [10]: df.duplicated().sum()
Out[10]: 3
```

```
In [11]: df = df.drop_duplicates()
```

### **Mathematical representation of our data**

In [12]: df.describe()

Out[12]:

	sepal_length	sepal_width	petal_length	petal_width
count	147.000000	147.000000	147.000000	147.000000
mean	5.856463	3.055782	3.780272	1.208844
std	0.829100	0.437009	1.759111	0.757874
min	4.300000	2.000000	1.000000	0.100000
25%	5.100000	2.800000	1.600000	0.300000
50%	5.800000	3.000000	4.400000	1.300000
75%	6.400000	3.300000	5.100000	1.800000
max	7.900000	4.400000	6.900000	2.500000

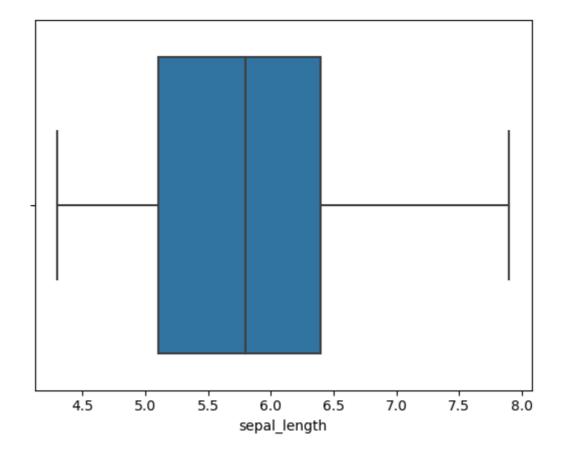
# Checking for outliers in each numerical columns

In [13]: sns.boxplot(df['sepal\_length'])

C:\Users\Hp\anaconda3\lib\site-packages\seaborn\\_decorators.py:36: FutureW arning: Pass the following variable as a keyword arg: x. From version 0.1 2, the only valid positional argument will be `data`, and passing other ar guments without an explicit keyword will result in an error or misinterpre tation.

warnings.warn(

Out[13]: <AxesSubplot:xlabel='sepal\_length'>

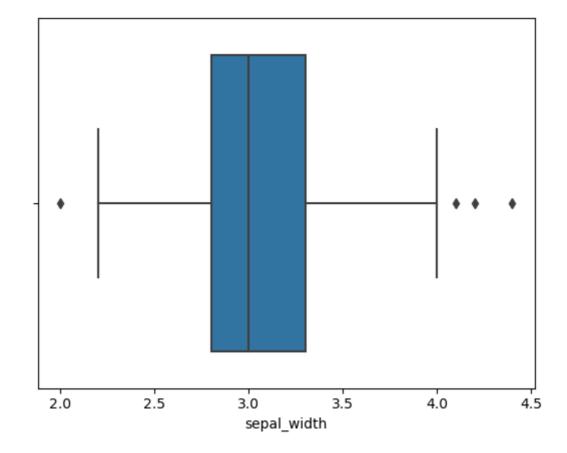


In [14]: | sns.boxplot(df['sepal\_width'])

C:\Users\Hp\anaconda3\lib\site-packages\seaborn\\_decorators.py:36: FutureW arning: Pass the following variable as a keyword arg: x. From version 0.1 2, the only valid positional argument will be `data`, and passing other ar guments without an explicit keyword will result in an error or misinterpre tation.

warnings.warn(

Out[14]: <AxesSubplot:xlabel='sepal\_width'>

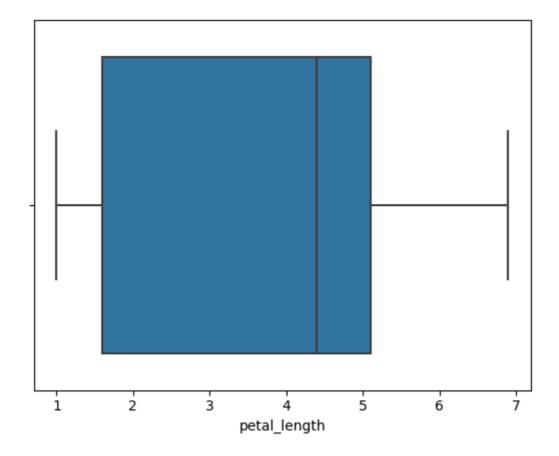


In [15]: sns.boxplot(df['petal\_length'])

C:\Users\Hp\anaconda3\lib\site-packages\seaborn\\_decorators.py:36: FutureW arning: Pass the following variable as a keyword arg: x. From version 0.1 2, the only valid positional argument will be `data`, and passing other ar guments without an explicit keyword will result in an error or misinterpre tation.

warnings.warn(

Out[15]: <AxesSubplot:xlabel='petal\_length'>

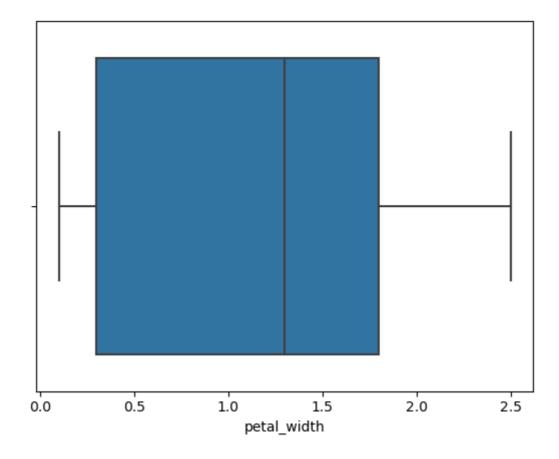


```
In [16]: sns.boxplot(df['petal_width'])
```

C:\Users\Hp\anaconda3\lib\site-packages\seaborn\\_decorators.py:36: FutureW arning: Pass the following variable as a keyword arg: x. From version 0.1 2, the only valid positional argument will be `data`, and passing other ar guments without an explicit keyword will result in an error or misinterpre tation.

warnings.warn(

Out[16]: <AxesSubplot:xlabel='petal\_width'>



# Removing outliers from sepal width column

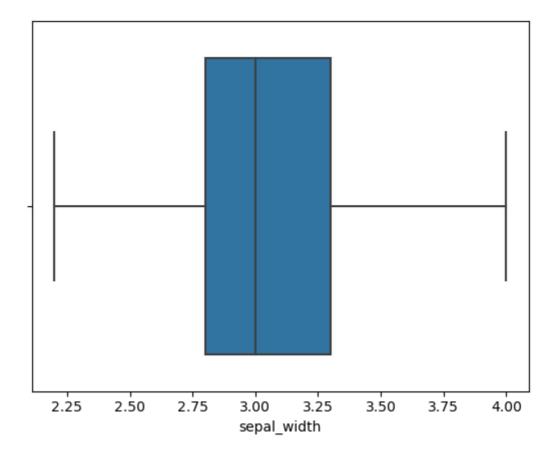
```
In [17]: data1 = df[df['sepal_width']>4.0]
In [18]: data2 = df[df['sepal_width']<2.1]
In [19]: df1 = df.drop(data1.index)
In [20]: df2 = df1.drop(data2.index)
In [21]: df2.shape
Out[21]: (143, 5)</pre>
```

In [22]: sns.boxplot(df2['sepal\_width'])

C:\Users\Hp\anaconda3\lib\site-packages\seaborn\\_decorators.py:36: FutureW arning: Pass the following variable as a keyword arg: x. From version 0.1 2, the only valid positional argument will be `data`, and passing other ar guments without an explicit keyword will result in an error or misinterpre tation.

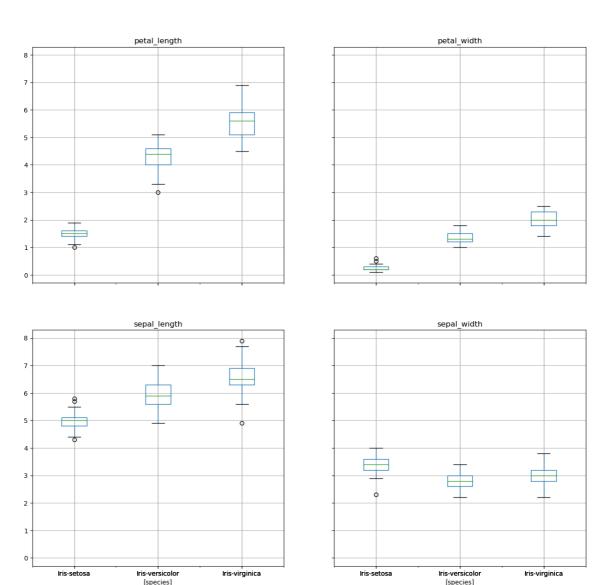
warnings.warn(

Out[22]: <AxesSubplot:xlabel='sepal\_width'>



# Checking for outliers in each column of particular species

Boxplot grouped by species



# Removing outliers in each column of particular species

```
data5=df2[df2['species']=='Iris-setosa']
In [25]:
          data6=data5[data5['sepal_length']>5.6]
          df2 = df2.drop(data6.index)
In [26]: data7=df2[df2['species']=='Iris-setosa']
          data8=data7[data7['sepal_width']<2.50]</pre>
         df2 = df2.drop(data8.index)
In [27]: | data9=df2[df2['species']=='Iris-setosa']
         data10=data9[data9['petal_length']<1.2]</pre>
          df2 = df2.drop(data10.index)
          data11=df2[df2['species']=='Iris-versicolor']
          data12=data11[data11['petal_length']<=3]</pre>
          df2 = df2.drop(data12.index)
In [28]: | data13=df2[df2['species']=='Iris-setosa']
         data14=data13[data13['petal_width']>=0.5]
          df2 = df2.drop(data14.index)
```

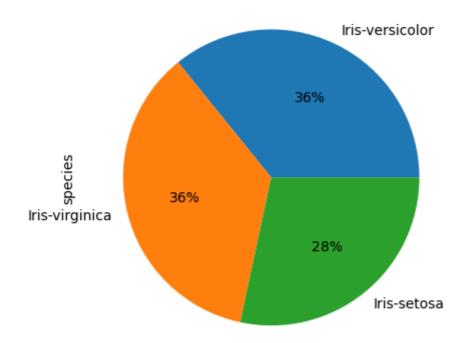
#### skewness

#### **Exploratory Data Analysis**

#### **Piechart**

```
In [30]: df2['species'].value_counts().plot(kind='pie',autopct='%.0f%%')
```

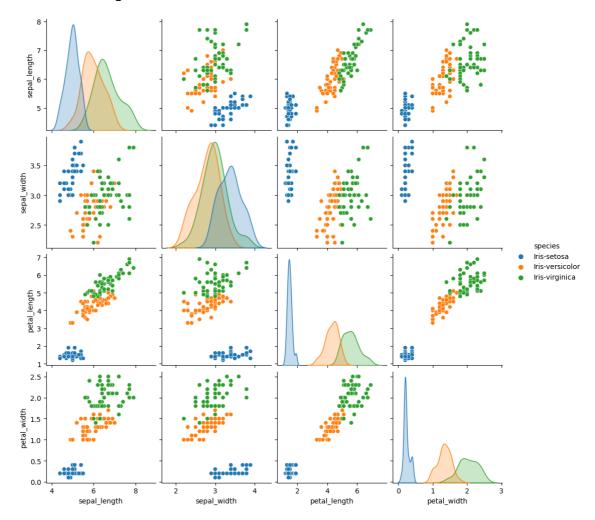
Out[30]: <AxesSubplot:ylabel='species'>



### **Pairplot**

In [31]: sns.pairplot(df2,hue='species')

Out[31]: <seaborn.axisgrid.PairGrid at 0x249d7552f70>



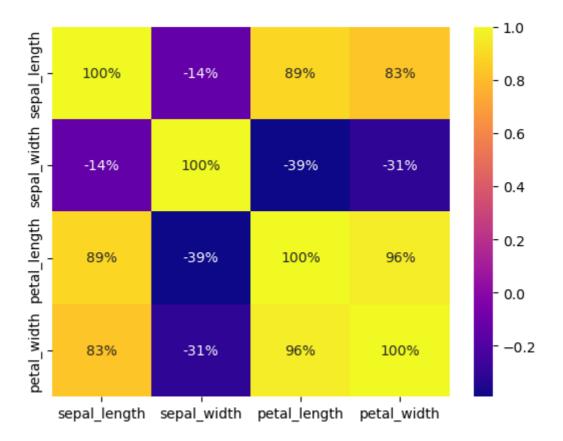
### Histogram

```
df2.hist(edgecolor='black')
In [32]:
Out[32]: array([[<AxesSubplot:title={'center':'sepal_length'}>,
                  <AxesSubplot:title={'center':'sepal_width'}>],
                 [<AxesSubplot:title={'center':'petal_length'}>,
                  <AxesSubplot:title={'center':'petal_width'}>]], dtype=object)
                                                            sepal width
                      sepal length
           20
                                                 30
           15
                                                 20
           10
                                                 10
            5
            0
                                                  0
                    5
                           6
                                   7
                                                         2.5
                                                                 3.0
                                                                        3.5
                                          8
                                                            petal width
                      petal length
                                                 30
           30
                                                 20
           20
                                                 10
           10
                   2
                            4
                                      6
                                                    0
                                                               1
                                                                          2
```

# Checking the correlation between the columns

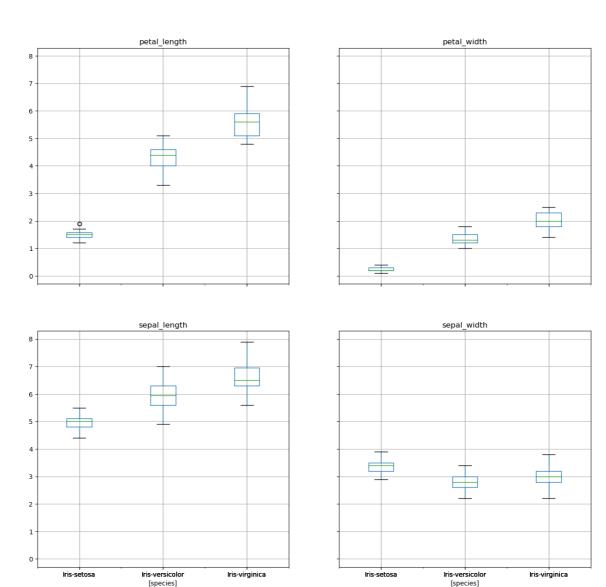
```
In [33]: sns.heatmap(df2.corr(),annot=True,fmt=".0%",cmap='plasma')
```

Out[33]: <AxesSubplot:>



### **Boxplot**

Boxplot grouped by species



## Splitting our data into training and testing dataset

```
In [35]: X = df2.iloc[:,:-1] # Input columns
Y = df2['species'] # output column
```

```
In [36]:
          X.sample(10)
Out[36]:
                sepal_length sepal_width petal_length petal_width
            42
                        4.4
                                   3.2
                                                1.3
                                                           0.2
           146
                        6.3
                                   2.5
                                                5.0
                                                           1.9
           139
                        6.9
                                   3.1
                                                5.4
                                                           2.1
            70
                        5.9
                                   3.2
                                               4.8
                                                           1.8
           124
                        6.7
                                   3.3
                                                5.7
                                                           2.1
                        5.1
                                                           0.2
            46
                                   3.8
                                                1.6
           125
                        7.2
                                   3.2
                                               6.0
                                                           1.8
            39
                        5.1
                                   3.4
                                                1.5
                                                           0.2
             3
                        4.6
                                   3.1
                                                1.5
                                                           0.2
            74
                                               4.3
                        6.4
                                   2.9
                                                           1.3
In [37]: X_train, X_test, Y_train, Y_test=train_test_split(X, Y, test_size=0.1)
In [38]: X_test.shape
Out[38]: (14, 4)
In [39]: X_train.shape
Out[39]: (120, 4)
In [40]: Y_test.shape
Out[40]: (14,)
In [41]: Y_train.shape
Out[41]: (120,)
          Scaling
In [42]: | from sklearn.preprocessing import StandardScaler
In [44]: scaler = StandardScaler() # object of class StandardScaler
In [49]: | X_train = scaler.fit_transform(X_train)
```

### **Model Training**

In [50]: X\_test = scaler.transform(X\_test)

```
In [ ]: clf = LogisticRegression()
In [52]: clf.fit(X_train,Y_train)
Out[52]: LogisticRegression()
```

#### **Model Evaluation**

```
In [58]: Y_pred = clf.predict(X_test)
In [59]:
         Y_test
Out[59]: 80
                 Iris-versicolor
                 Iris-versicolor
         50
         29
                     Iris-setosa
         101
                  Iris-virginica
         90
                 Iris-versicolor
         49
                     Iris-setosa
         117
                  Iris-virginica
                 Iris-versicolor
         65
         134
                  Iris-virginica
         5
                     Iris-setosa
         124
                  Iris-virginica
         75
                 Iris-versicolor
         144
                  Iris-virginica
         36
                     Iris-setosa
         Name: species, dtype: category
         Categories (3, object): ['Iris-setosa', 'Iris-versicolor', 'Iris-virginic
         a']
         from sklearn.metrics import accuracy_score,classification_report,confusion_
In [65]:
In [67]: Accuracy = accuracy_score(Y_test,Y_pred)
         class report = classification report(Y test,Y pred)
In [69]: print("Accuracy =",Accuracy)
         Accuracy = 0.9285714285714286
In [70]:
         print("classification report")
         print(class_report)
         classification report
                           precision
                                        recall f1-score
                                                            support
                                                                  4
              Iris-setosa
                                1.00
                                           1.00
                                                     1.00
         Iris-versicolor
                                0.83
                                           1.00
                                                     0.91
                                                                  5
                                                                  5
                                          0.80
                                                     0.89
           Iris-virginica
                                1.00
                                                     0.93
                 accuracy
                                                                 14
                                0.94
                                          0.93
                                                     0.93
                                                                 14
                macro avg
             weighted avg
                                0.94
                                          0.93
                                                     0.93
                                                                 14
```