Virtual Internship Program

Author :- Prateek Kumar Singh

Beginer Level Tasks

Task-1 Iris Flowers Classification Ml Project

This particular ML project is usually referred to as the “Hello World” of Machine Learning. The iris flowers dataset contains numeric attributes, and it is perfect for beginners to learn about supervised ML algorithms, mainly how to load and handle data. Also, since this is a small dataset, it can easily fit in memory without requiring special transformations or scaling capabilities.

Dataset link :-http://archive.ics.uci.edu/ml/datasets/Iris

1. Importing The Libraries

In [82]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score
import warnings
warnings.filterwarnings('ignore')
import os
os.environ["OMP_NUM_THREADS"] = '1'
```

2. Importing The dataset

In [30]:
```
iris = pd.read_csv('Iris.csv')
```

In [22]:
```
iris.describe()
```

Out[22]:

	sepal_length	sepal_width	petal_length	petal_width
count	150.000000	150.000000	150.000000	150.000000
mean	5.843333	3.054000	3.758667	1.198667
std	0.828066	0.433594	1.764420	0.763161
min	4.300000	2.000000	1.000000	0.100000
25%	5.100000	2.800000	1.600000	0.300000
50%	5.800000	3.000000	4.350000	1.300000
75%	6.400000	3.300000	5.100000	1.800000
max	7.900000	4.400000	6.900000	2.500000

In [23]:
```
iris.head()
```

Out[23]:

	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
4	5.0	3.6	1.4	0.2	Iris-setosa

In [24]:
```
iris.tail()
```

Out[24]:

	sepal_length	sepal_width	petal_length	petal_width	species
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

In [25]:
```
iris.shape
```

Out[25]:
```
(150, 5)
```

In [26]:
```
iris.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   species       150 non-null    object 
dtypes: float64(4), object(1)
memory usage: 6.0+ KB
```

In [35]:
```
iris['species'].value_counts()
```

Out[35]:
```
Iris-setosa        50
Iris-versicolor    50
Iris-virginica     50
Name: species, dtype: int64
```

3. Preprocesing The Dataset

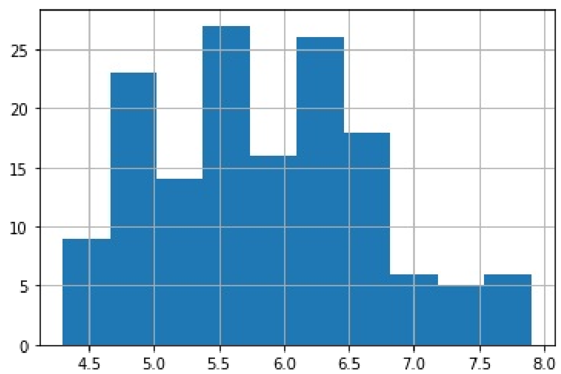
In [38]:
```
# checking for missing values
iris.isnull().sum()
```

Out[38]:
```
sepal_length    0
sepal_width     0
petal_length    0
petal_width     0
species         0
dtype: int64
```

4. Data Analysis

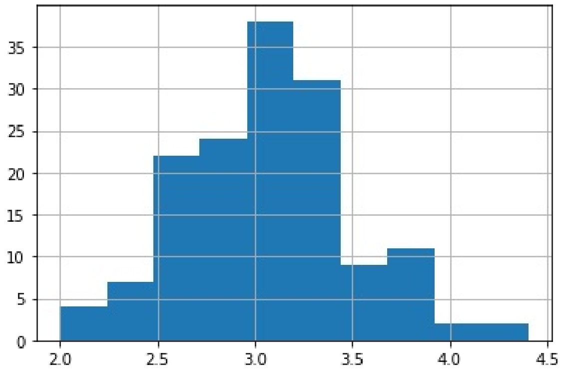
In [46]:
```
iris['sepahist()l_length'].
```

Out[46]:
```
<AxesSubplot:>
```



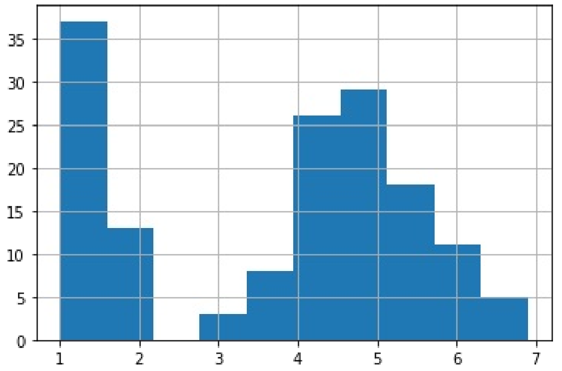
In [49]:
```
iris['sepal_width'].hist()
```

Out[49]: <AxesSubplot:>



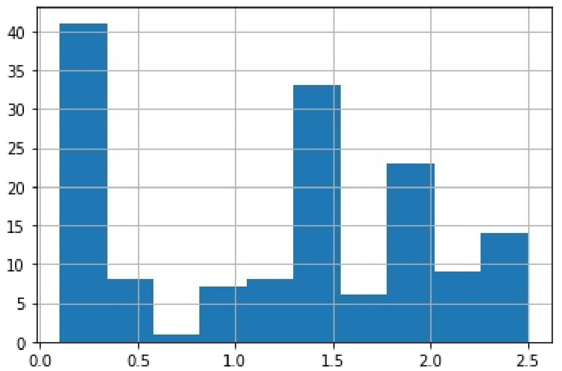
In [51]:
```
iris['petal_length'].hist()
```

Out[51]: <AxesSubplot:>



In [53]:
```
iris['petal_width'].hist()
```

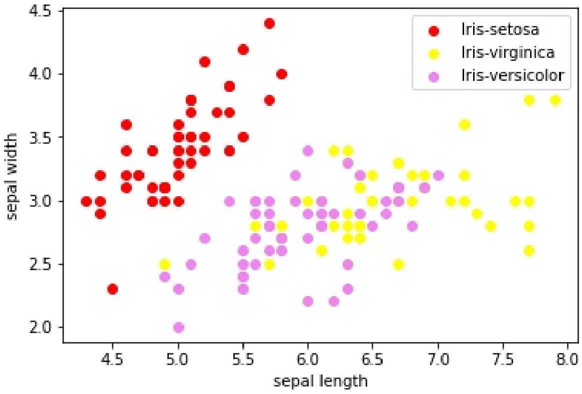
Out[53]: <AxesSubplot:>



In [59]:
```
# scatterplot
colours = ['red','yellow','violet']
species = ['Iris-setosa','Iris-virginica','Iris-versicolor']
```

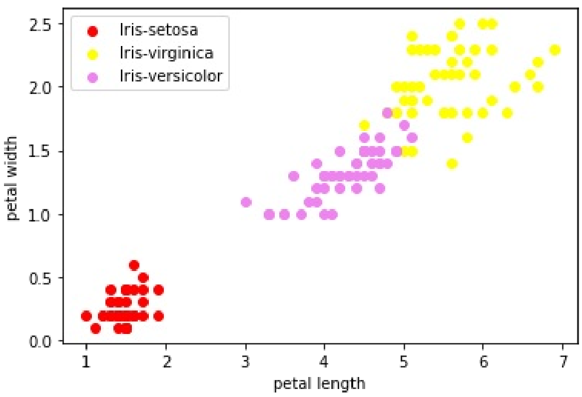
In [60]:
```
for i in range(3):
  x = iris[iris['species'] == species[i]]
  plt.scatter(x['sepal_length'],x['sepal_width'], c = colours[i], label=species[i])
plt.xlabel('sepal length')
plt.ylabel('sepal width')
plt.legend()
```

Out[60]: <matplotlib.legend.Legend at 0x214161d2bb0>



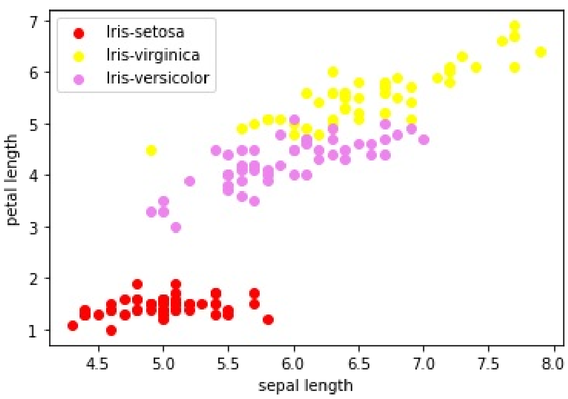
In [61]:
```
for i in range(3):
  x = iris[iris['species'] == species[i]]
  plt.scatter(x['petal_length'],x['petal_width'], c = colours[i], label=species[i])
plt.xlabel('petal length')
plt.ylabel('petal width')
plt.legend()
```

Out[61]:
```
<matplotlib.legend.Legend at 0x214159e8250>
```



In [62]:
```
for i in range(3):
  x = iris[iris['species'] == species[i]]
  plt.scatter(x['sepal_length'],x['petal_length'], c = colours[i], label=species[i])
plt.xlabel('sepal length')
plt.ylabel('petal length')
plt.legend()
```

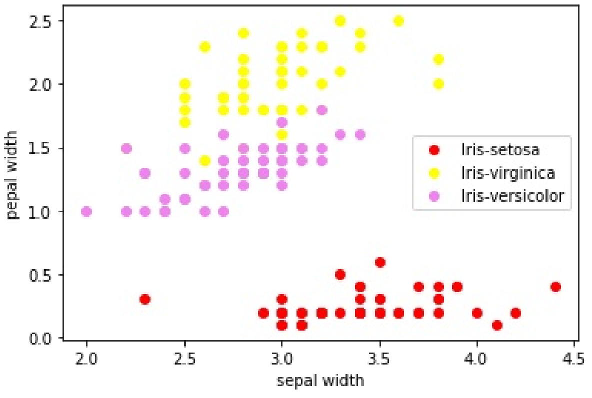
Out[62]:
```
<matplotlib.legend.Legend at 0x214160bf970>
```



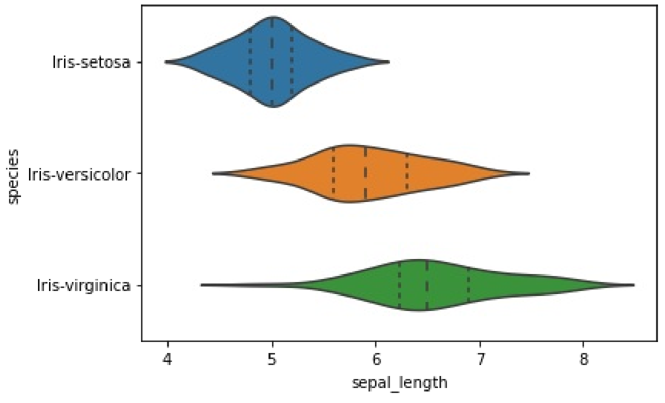
In [63]:
```
for i in range(3):
  x = iris[iris['species'] == species[i]]
```

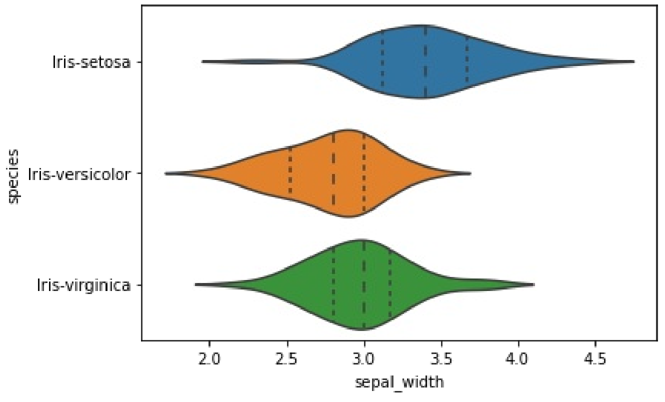
```
  plt.scatter(x['sepal_width'],x['petal_width'], c = colours[i], label=species[i])
plt.xlabel('sepal width')
plt.ylabel('pepal width')
plt.legend()
```

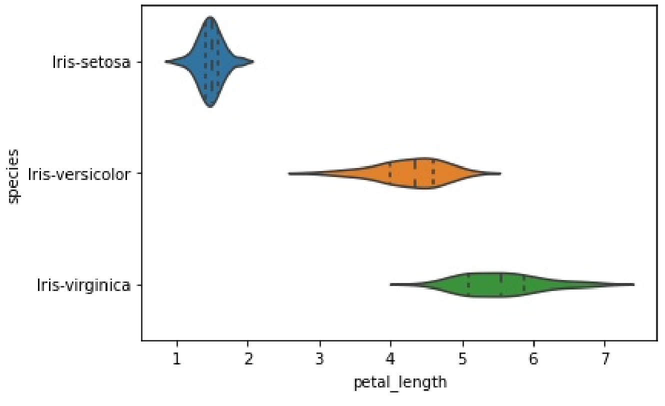
Out[63]: <matplotlib.legend.Legend at 0x21415fe0700>

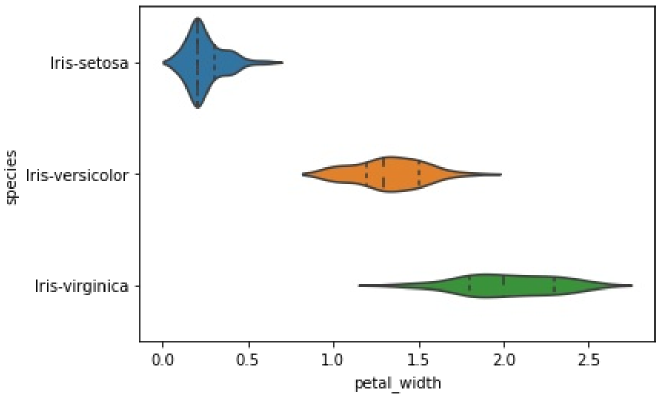


In [64]:
```
sns.violinplot(y='species', x='sepal_length', data=iris, inner='quartile')
plt.show()
sns.violinplot(y='species', x='sepal_width', data=iris, inner='quartile')
plt.show()
sns.violinplot(y='species', x='petal_length', data=iris, inner='quartile')
plt.show()
sns.violinplot(y='species', x='petal_width', data=iris, inner='quartile')
plt.show()
```









5. Level Encoding

Label Encoding is a popular encoding technique for handling categorical variables. In this technique, each label is assigned a unique integer based on alphabetical ordering. Let's see how to implement label encoding in Python using the scikit-learn library and also understand the challenges with label encoding

In [65]:
```
from sklearn.preprocessing import LabelEncoder
le = LabelEncoder()
```

In [67]:
```
iris['species'] = le.fit_transform(iris['species'])
iris.head()
```

Out[67]:

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

In [68]:
```
iris.tail()
```

Out[68]:

	sepal_length	sepal_width	petal_length	petal_width	species
145	6.7	3.0	5.2	2.3	2
146	6.3	2.5	5.0	1.9	2
147	6.5	3.0	5.2	2.0	2
148	6.2	3.4	5.4	2.3	2
149	5.9	3.0	5.1	1.8	2

In [70]:
```
iris.species
```

Out[70]:
```
0      0
1      0
2      0
3      0
4      0
      ..
145    2
146    2
147    2
148    2
149    2
Name: species, Length: 150, dtype: int32
```

6. Model Training

Model training is the phase in the data science development lifecycle where practitioners try to fit the best combination of weights and bias to a machine learning algorithm to minimize a loss function over the prediction range

In [71]:
```
X = iris.drop(columns='species', axis=1)
Y = iris['species']
```

In [72]:
```python
X_train, X_test, Y_train, Y_test = train_test_split(X, Y, test_size=0.20, stratify=Y, random_state=2)
```

In [73]:
```python
model = LogisticRegression()
```

In [83]:
```python
model.fit(X_train, Y_train)
```

Out[83]:
```
LogisticRegression()
```

In [75]:
```python
# accuracy on training data
X_train_prediction = model.predict(X_train)
training_data_accuracy = accuracy_score(X_train_prediction, Y_train)
```

In [76]:
```python
print('Accuracy on Training data : ', training_data_accuracy*100)
```

```
Accuracy on Training data :  96.66666666666667
```

In [77]:
```python
# accuracy on test data
X_test_prediction = model.predict(X_test)
test_data_accuracy = accuracy_score(X_test_prediction, Y_test)
```

In [78]:
```python
print('Accuracy on Test data : ', test_data_accuracy*100)
```

```
Accuracy on Test data :  100.0
```

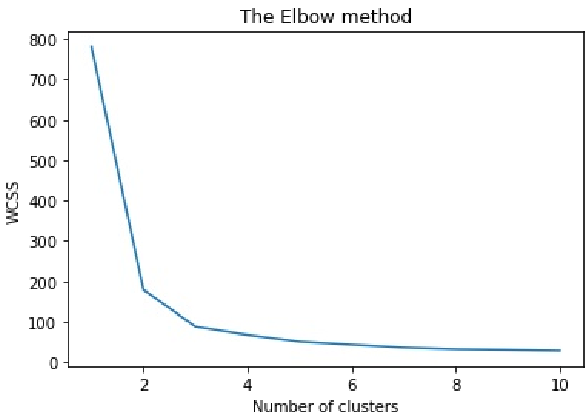
7. Optimal Number Of Clustring For K-Means Classification Algoritham

In [81]:
```python
# Finding the optimal number of clusters for k-means classification Algoritham

x = iris.iloc[:, [0, 1, 2, 3, 4]].values
# we import KMeans algorithm using sklearn library
from sklearn.cluster import KMeans
# we use the very first method is Elbow Method
wcss = []
# WCSS means Within Cluster Sum of Squares

for i in range(1, 11):
    kmeans = KMeans(n_clusters = i, init = 'k-means++',
                    max_iter = 300, n_init = 10, random_state = 0)
    kmeans.fit(x)
    wcss.append(kmeans.inertia_)

# plotting above result in line graph format
plt.plot(range(1, 11), wcss)
plt.title('The Elbow method')
plt.xlabel('Number of clusters')
plt.ylabel('WCSS')
plt.show()
```



In cluster analysis, the elbow method is a heuristic used in determining the number of clusters in a data set. The method consists of plotting the explained variation as a function of the number of clusters and picking the elbow of the curve as the number of clusters to use.

8. Applying K-MEANS Method On Given Dataset

In [85]:
```python
kmeans = KMeans(n_clusters=4,init='k-means++',max_iter=300,
               n_init=10,random_state=5)
y_kmeans = kmeans.fit_predict(x)
print(y_kmeans)
```

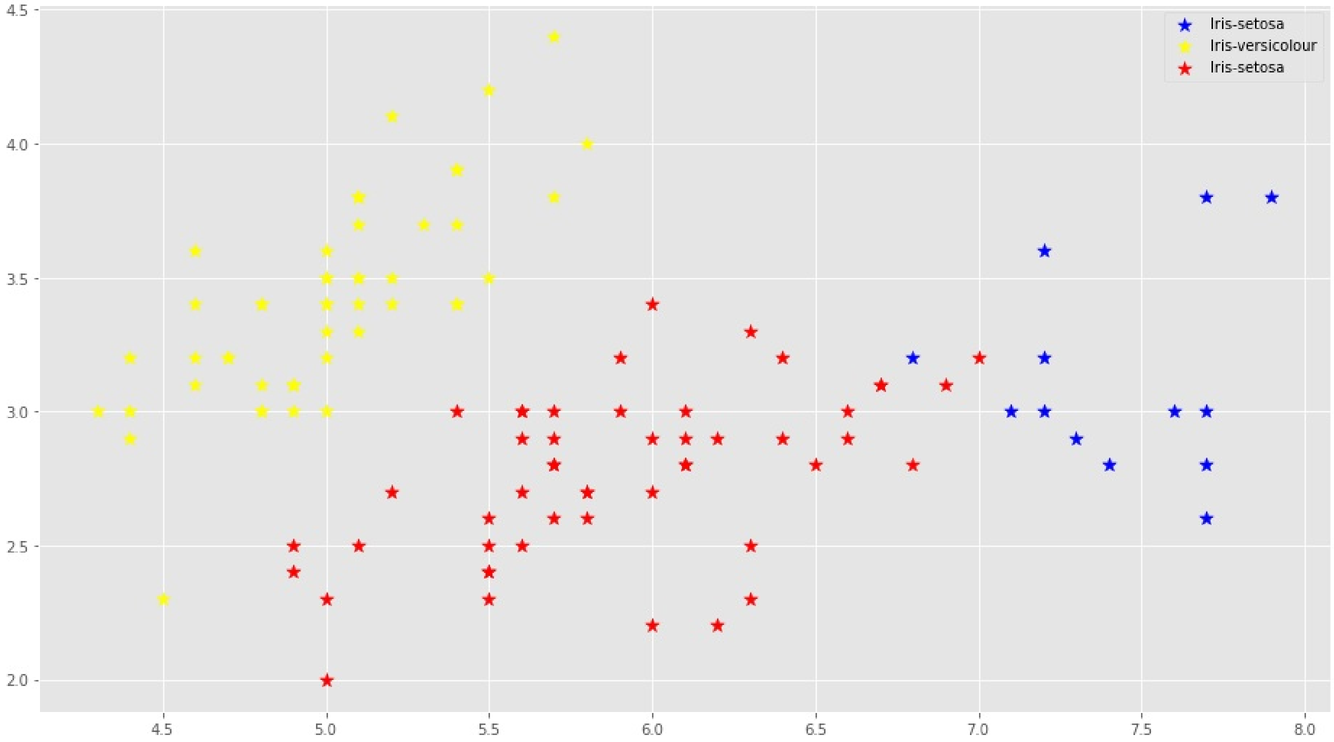
```
[1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
 1 1 1 1 1 1 1 1 1 1 1 1 1 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2
 2 2 2 3 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 3 3 0 3 3 0 2 0 3 0 3
 3 3 3 3 3 0 0 3 3 3 0 3 3 0 3 3 3 0 0 0 3 3 3 0 3 3 3 3 3 3 3 0 3 3 3 3
 3 3]
```

In [86]:
```
kmeans.cluster_centers_
```

Out[86]:
```
array([[7.42307692, 3.13076923, 6.26923077, 2.06923077, 2.        ],
       [5.006     , 3.418     , 1.464     , 0.244     , 0.        ],
       [5.9       , 2.76      , 4.25      , 1.326     , 1.02      ],
       [6.34324324, 2.93243243, 5.31351351, 2.01081081, 1.97297297]])
```

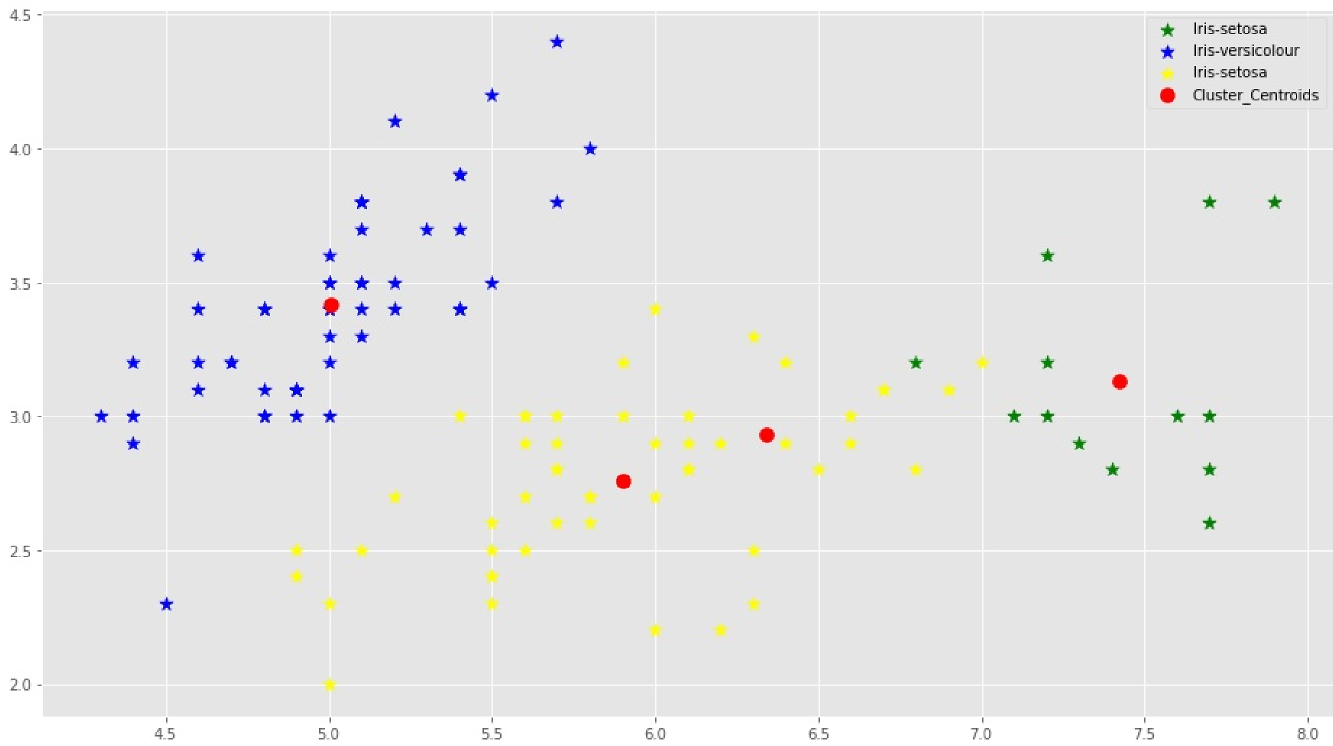
In [89]:
```
# Visualizing the clusters
plt.figure(figsize = (16,9))
from matplotlib import style
style.use('ggplot')
plt.scatter(x[y_kmeans == 0,0],x[y_kmeans == 0,1],s = 100,
           c = 'blue',label = 'Iris-setosa',marker='*')
plt.scatter(x[y_kmeans == 1,0],x[y_kmeans == 1,1],s = 100,
           c = 'yellow',label = 'Iris-versicolour',marker='*')
plt.scatter(x[y_kmeans == 2,0],x[y_kmeans == 2,1],s = 100,
           c = 'red',label = 'Iris-setosa',marker='*')
plt.legend()
```

Out[89]:
```
<matplotlib.legend.Legend at 0x21417fdfdc0>
```



In [90]:
```
# plotting Centroids of the clusters in above graph
plt.figure(figsize = (16,9))
style.use('ggplot')
plt.scatter(x[y_kmeans == 0,0],x[y_kmeans == 0,1],s = 100,
           c = 'green',label = 'Iris-setosa',marker='*')
plt.scatter(x[y_kmeans == 1,0],x[y_kmeans == 1,1],s = 100,
           c = 'blue',label = 'Iris-versicolour',marker='*')
plt.scatter(x[y_kmeans == 2,0],x[y_kmeans == 2,1],s = 100,
           c = 'yellow',label = 'Iris-setosa',marker='*')
#add centers
plt.scatter(kmeans.cluster_centers_[:,0],kmeans.cluster_centers_[:,1],
           s=100,c='red',label='Cluster_Centroids')
plt.legend()
```

Out[90]:
```
<matplotlib.legend.Legend at 0x21417fcba30>
```



Thank You

Loading [MathJax]/jax/output/CommonHTML/fonts/TeX/fontdata.js