

LGM VIRTUAL INTERNSHIP PROGRAM AUGUST 2021

BEGINNER LEVEL TASK

Iris Flowers Classification ML Project

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In [1]:

```
1 # Import Libraries
2
3 import pandas as pd
4 import numpy as np
5 import matplotlib.pyplot as plt
6 import seaborn as sns
7 import scipy as sp
8 import warnings
9 import os
10 warnings.filterwarnings("ignore")
```

In [2]:

```
1 # Load Dataset
2 df = pd.read_csv("C:/Users/prate/Downloads/IRISS.csv")
```

In [3]:

```
1 #Head function
2 df.head()
```

Out[3]:

	Id	SepalLengthCm	SepalWidthCm	PetalLengthCm	PetalWidthCm	Species
0	1	5.1	3.5	1.4	0.2	Iris-setosa
1	2	4.9	3.0	1.4	0.2	Iris-setosa
2	3	4.7	3.2	1.3	0.2	Iris-setosa
3	4	4.6	3.1	1.5	0.2	Iris-setosa
4	5	5.0	3.6	1.4	0.2	Iris-setosa

In [4]:

```
1 #Tail Function
2 df.tail()
```

Out[4]:

	Id	SepalLengthCm	SepalWidthCm	PetalLengthCm	PetalWidthCm	Species
145	146	6.7	3.0	5.2	2.3	Iris-virginica
146	147	6.3	2.5	5.0	1.9	Iris-virginica
147	148	6.5	3.0	5.2	2.0	Iris-virginica
148	149	6.2	3.4	5.4	2.3	Iris-virginica
149	150	5.9	3.0	5.1	1.8	Iris-virginica

In [5]:

```
1 # Info function
2 df.info()
```

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 150 entries, 0 to 149
Data columns (total 6 columns):
Id 150 non-null int64
SepalLengthCm 150 non-null float64
SepalWidthCm 150 non-null float64
PetalLengthCm 150 non-null float64
PetalWidthCm 150 non-null float64
Species 150 non-null object
dtypes: float64(4), int64(1), object(1)
memory usage: 7.2+ KB

In [6]:

```
1 # Describe function
2 df.describe()
```

Out[6]:

	Id	SepalLengthCm	SepalWidthCm	PetalLengthCm	PetalWidthCm
count	150.000000	150.000000	150.000000	150.000000	150.000000
mean	75.500000	5.843333	3.054000	3.758667	1.198667
std	43.445368	0.828066	0.433594	1.764420	0.763161
min	1.000000	4.300000	2.000000	1.000000	0.100000
25%	38.250000	5.100000	2.800000	1.600000	0.300000
50%	75.500000	5.800000	3.000000	4.350000	1.300000
75%	112.750000	6.400000	3.300000	5.100000	1.800000
max	150.000000	7.900000	4.400000	6.900000	2.500000

In [7]:

```
1 # Shape function
2 df.shape
```

Out[7]:

(150, 6)

In [8]:

```
1 # Check missing values
2 df.isnull()
```

Out[8]:

	Id	SepalLengthCm	SepalWidthCm	PetalLengthCm	PetalWidthCm	Species
0	False	False	False	False	False	False
1	False	False	False	False	False	False
2	False	False	False	False	False	False
3	False	False	False	False	False	False
4	False	False	False	False	False	False
...
145	False	False	False	False	False	False
146	False	False	False	False	False	False
147	False	False	False	False	False	False
148	False	False	False	False	False	False
149	False	False	False	False	False	False

150 rows × 6 columns

In [9]:

```
1 # Check missing values in dataset
2 df.isnull().sum()
```

Out[9]:

```
Id                0
SepalLengthCm     0
SepalWidthCm      0
PetalLengthCm     0
PetalWidthCm      0
Species           0
dtype: int64
```

In [10]:

```
1 # Count missing values
2 df.isnull().any()
```

Out[10]:

```
Id                False
SepalLengthCm     False
SepalWidthCm      False
PetalLengthCm     False
PetalWidthCm      False
Species           False
dtype: bool
```

In [11]:

```
1 # Columns
2 df.columns
```

Out[11]:

```
Index(['Id', 'SepalLengthCm', 'SepalWidthCm', 'PetalLengthCm', 'PetalWidthCm',
      'Species'],
      dtype='object')
```

In [12]:

```
1 df.Id.unique().shape
```

Out[12]:

```
(150,)
```

In [13]:

```
1 # Dtypes attributes
2 df.dtypes
```

Out[13]:

```
Id                int64
SepalLengthCm     float64
SepalWidthCm      float64
PetalLengthCm     float64
PetalWidthCm      float64
Species           object
dtype: object
```

In [14]:

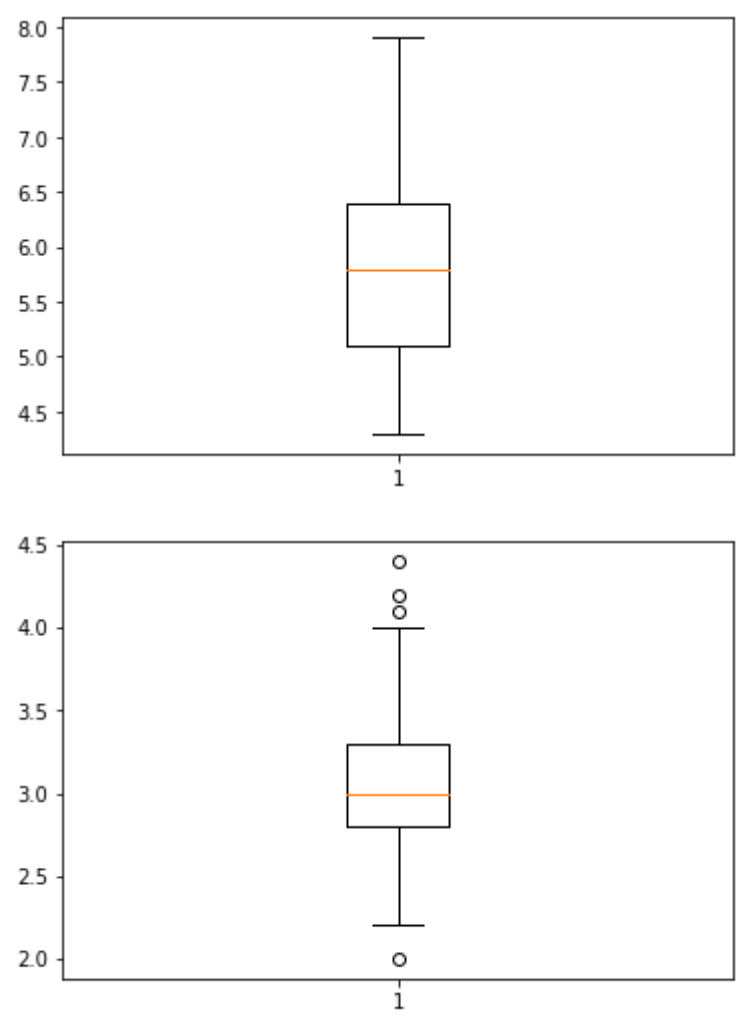
```
1 # Correlation
2 df.corr()
```

Out[14]:

	Id	SepalLengthCm	SepalWidthCm	PetalLengthCm	PetalWidthCm
Id	1.000000	0.716676	-0.397729	0.882747	0.899759
SepalLengthCm	0.716676	1.000000	-0.109369	0.871754	0.817954
SepalWidthCm	-0.397729	-0.109369	1.000000	-0.420516	-0.356544
PetalLengthCm	0.882747	0.871754	-0.420516	1.000000	0.962757
PetalWidthCm	0.899759	0.817954	-0.356544	0.962757	1.000000

In [55]:

```
1 # Boxplot figure
2 plt.figure(1)
3 plt.boxplot([df['SepalLengthCm']])
4 plt.figure(2)
5 plt.boxplot([df['SepalWidthCm']])
6 plt.show()
```

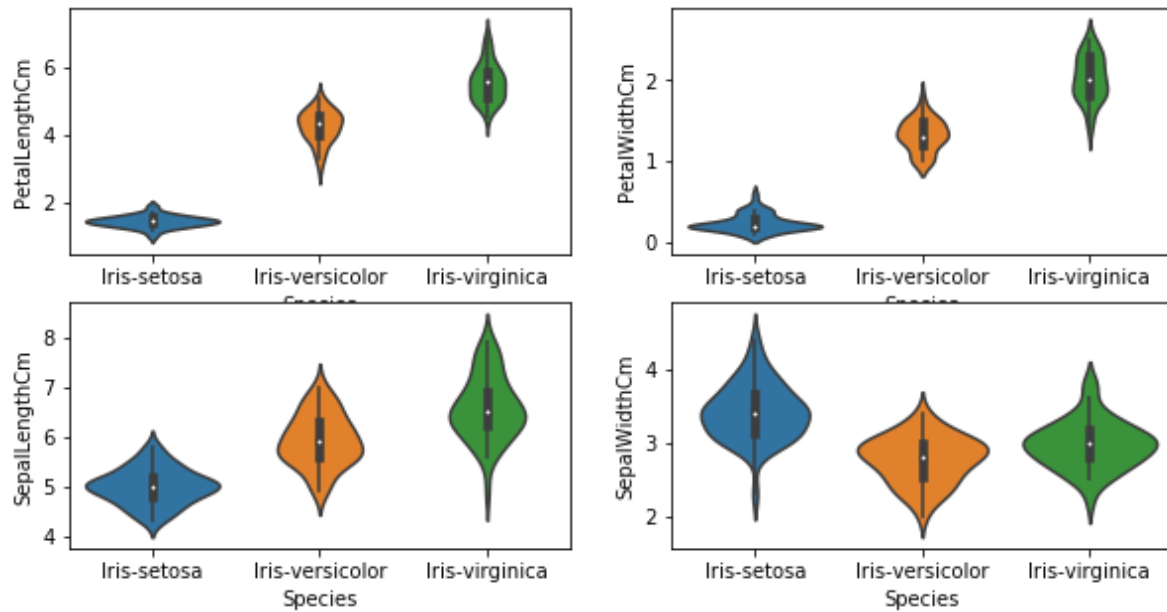


In [59]:

```
1 # Violin Plot
2 plt.figure(figsize=(10,5))
3 plt.subplot(2,2,1)
4 sns.violinplot(x='Species',y='PetalLengthCm',data=df)
5 plt.subplot(2,2,2)
6 sns.violinplot(x='Species',y='PetalWidthCm',data=df)
7 plt.subplot(2,2,3)
8 sns.violinplot(x='Species',y='SepalLengthCm',data=df)
9 plt.subplot(2,2,4)
10 sns.violinplot(x='Species',y='SepalWidthCm',data=df)
```

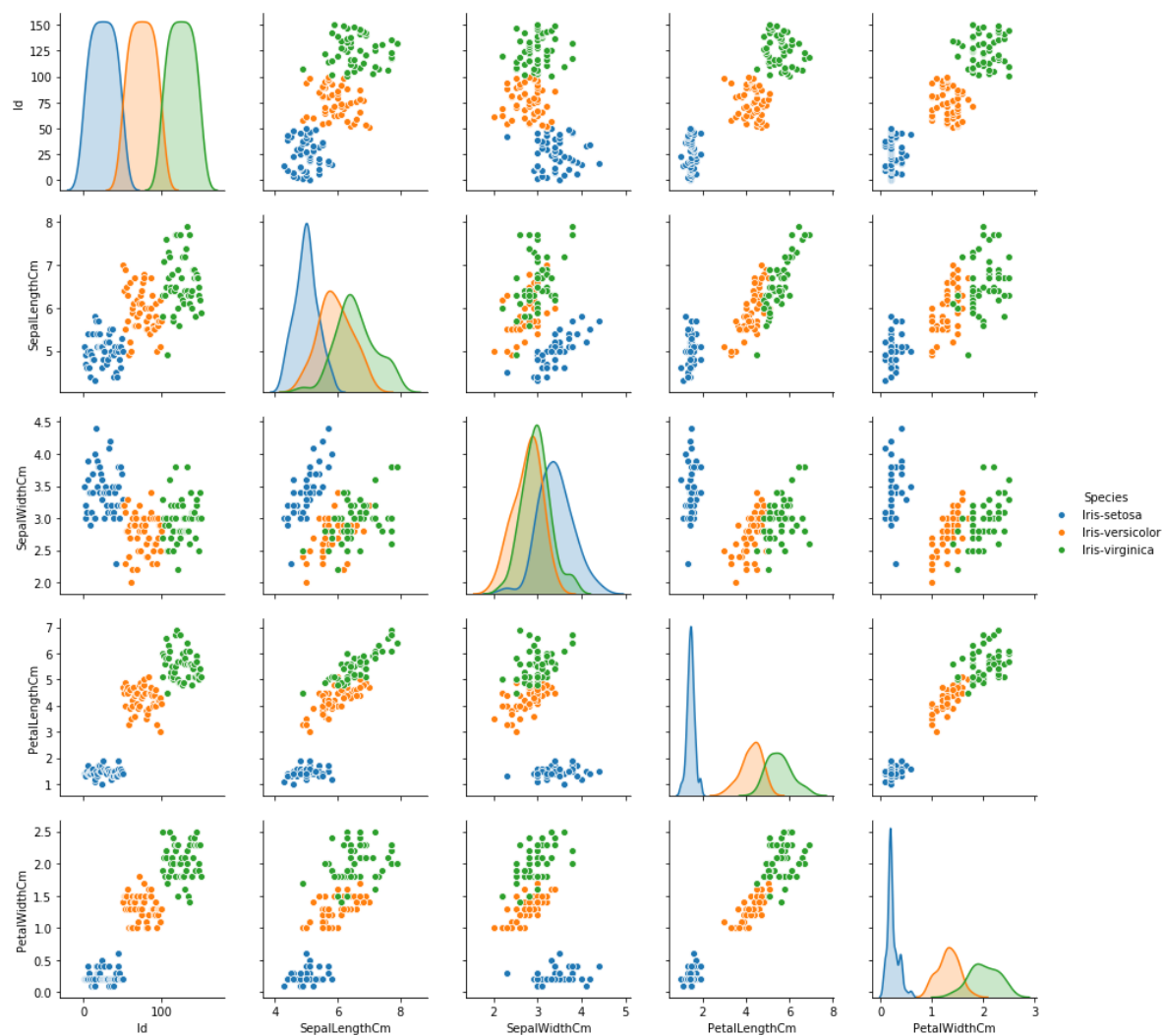
Out[59]:

<matplotlib.axes._subplots.AxesSubplot at 0x2398c49d688>



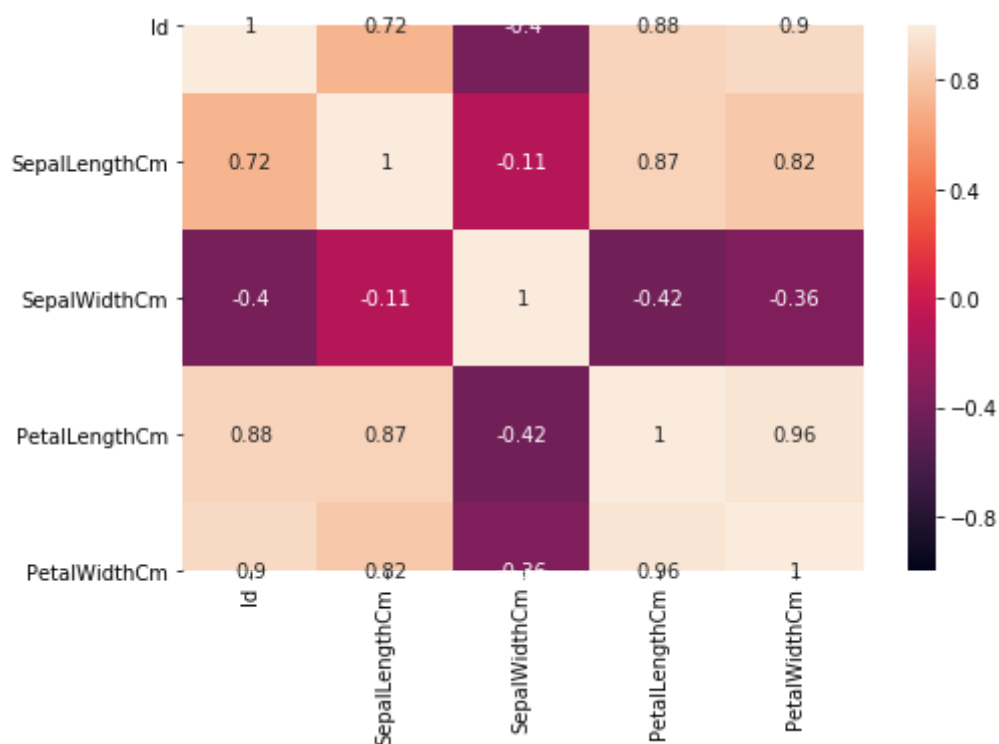
In [25]:

```
1 # Seaborn Plot
2 sns.pairplot(df, hue='Species');
```



In [75]:

```
1 #Heat Maps
2 fig=plt.gcf()
3 fig.set_size_inches(8,5)
4 fig=sns.heatmap(df.corr(),annot=True,linewidths=0,linecolor='B',square=True, vmin=-1,
```



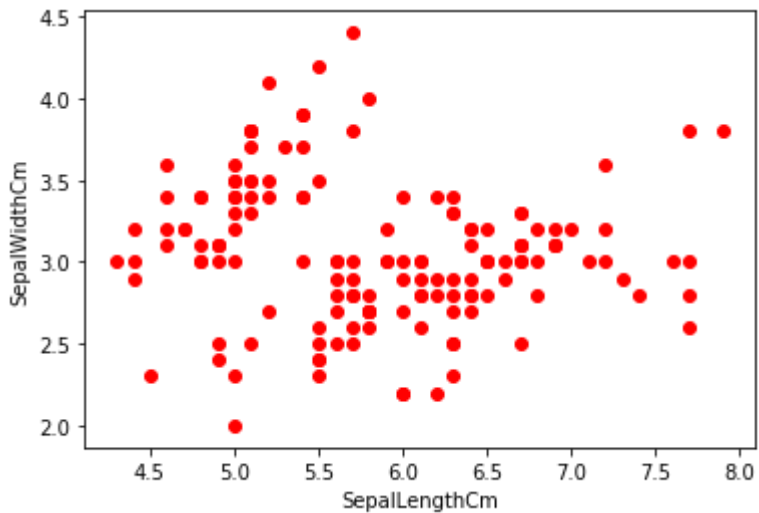
In [58]:

```
1 X = df['SepalLengthCm'].values.reshape(-1,1)
2 Y = df['SepalWidthCm'].values.reshape(-1,1)
3 print(X)
4 print(Y)
```

```
[3.2]
[2.8]
[3. ]
[2.8]
[3. ]
[2.8]
[3.8]
[2.8]
[2.8]
[2.6]
[3. ]
[3.4]
[3.1]
[3. ]
[3.1]
[3.1]
[3.1]
[3.1]
[2.7]
[3.2]
r2 21
```


In [30]:

```
1 # Scatter Plot
2 plt.xlabel("SepalLengthCm")
3 plt.ylabel("SepalWidthCm")
4 plt.scatter(X,Y,color='R')
5 plt.show()
```



In [31]:

```
1 #Correlation
2 cm = df.corr()
3 print(cm)
```

	Id	SepalLengthCm	SepalWidthCm	PetalLengthCm	\
Id	1.000000	0.716676	-0.397729	0.882747	
SepalLengthCm	0.716676	1.000000	-0.109369	0.871754	
SepalWidthCm	-0.397729	-0.109369	1.000000	-0.420516	
PetalLengthCm	0.882747	0.871754	-0.420516	1.000000	
PetalWidthCm	0.899759	0.817954	-0.356544	0.962757	

	PetalWidthCm
Id	0.899759
SepalLengthCm	0.817954
SepalWidthCm	-0.356544
PetalLengthCm	0.962757
PetalWidthCm	1.000000

Model Building

In [32]:

```
1 from sklearn.linear_model import LogisticRegression
2 from sklearn.model_selection import train_test_split
3 from sklearn.neighbors import KNeighborsClassifier
4 from sklearn import svm
5 from sklearn import metrics
6 from sklearn.tree import DecisionTreeClassifier
```

In [34]:

```
1 train, test = train_test_split(df, test_size = 0.25)
2 print(train.shape)
3 print(test.shape)
```

(112, 6)

(38, 6)

In [76]:

```
1 train_x = train[['SepalLengthCm', 'SepalWidthCm', 'PetalLengthCm', 'PetalWidthCm']]
2 train_y = train.Species
3 test_x = test[['SepalLengthCm', 'SepalWidthCm', 'PetalLengthCm', 'PetalWidthCm']]
4 test_y = test.Species
```

Logistic Regression

In [78]:

```
1 model1 = LogisticRegression()
2 model1.fit(train_x, train_y)
3 prediction = model1.predict(test_x)
4 print('Accuracy:', metrics.accuracy_score(prediction, test_y))
```

Accuracy: 0.8947368421052632

In [79]:

```
1 #Confusion matrix
2 from sklearn.metrics import confusion_matrix, classification_report
3 confusion_matrix = confusion_matrix(test_y, prediction)
4 print("Confusion matrix\n", confusion_matrix)
```

Confusion matrix

```
[[11  0  0]
 [ 0 11  3]
 [ 0  1 12]]
```

In [80]:

```
1 # Precision, recall, f1-score, accuracy
2 print(classification_report(test_y, prediction))
```

	precision	recall	f1-score	support
Iris-setosa	1.00	1.00	1.00	11
Iris-versicolor	0.92	0.79	0.85	14
Iris-virginica	0.80	0.92	0.86	13
accuracy			0.89	38
macro avg	0.91	0.90	0.90	38
weighted avg	0.90	0.89	0.89	38

KNeighborsClassifier

In [81]:

```
1 from sklearn.neighbors import KNeighborsClassifier
2 model2 = KNeighborsClassifier(n_neighbors=5)
3 model2.fit(train_x,train_y)
4 y_pred2 = model2.predict(test_x)
5 print("Accuracy:",accuracy_score(test_y,y_pred2))
```

Accuracy: 0.9473684210526315

Decision Tree

In [83]:

```
1 from sklearn.tree import DecisionTreeClassifier
2 model3 = DecisionTreeClassifier(criterion='entropy')
3 model3.fit(train_X,train_y)
4 y_pred3 = model3.predict(test_x)
5 print("Accuracy:",accuracy_score(test_y,y_pred3))
```

Accuracy: 0.8947368421052632

In []:

1
