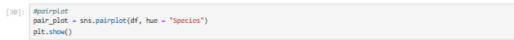
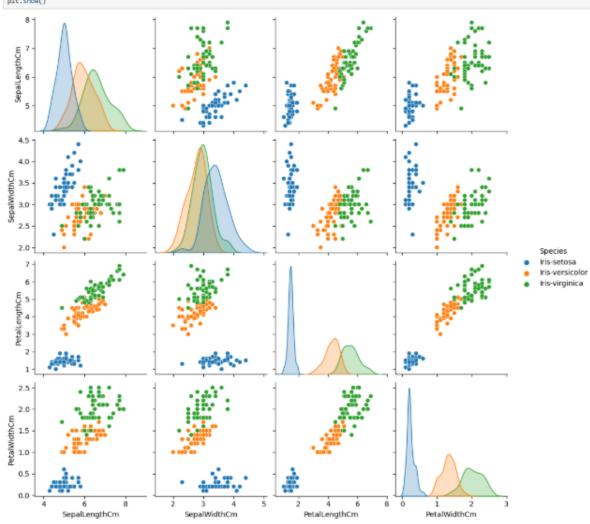


Trusted **a** + % □ □ **b** ■ C → Code JupyterLab 🖾 🐞 Python 3 (ipykernel) 🔘 [13]: # This Python 3 environment comes with many helpful analytics libraries installed # It is defined by the kaggle/python Docker image: https://github.com/kaggle/docker-python # For example, here's several helpful packages to Load import numpy as np # linear algebra
import pandas as pd # data processing, CSV file I/O (e.g. pd.read\_csv) # Input data files are available in the read-only "../input/" directory
# For example, running this (by clicking run or pressing Shift+Enter) will list all files under the input directory import os for dirname, \_, filenames in os.walk('C:\Abdullha'): for filename in filenames:# Th
 print(os.path.join(dirname, filename)) # You can write up to 2068 to the current directory (/kaggle/working/) that gets preserved as output when you create a version using "Save & Run All" # You can also write temporary files to /kaggle/temp/, but they won't be saved outside of the current session C:\Abdullha\Iris.csv la. [14]: import pandas as pd import numpy as np
import matplotlib.pyplot as plt import seaborn as sns [22]: import pandas as pd df = pd.read\_csv(r'C:\Abdullha\Iris.csv') df.head(10)

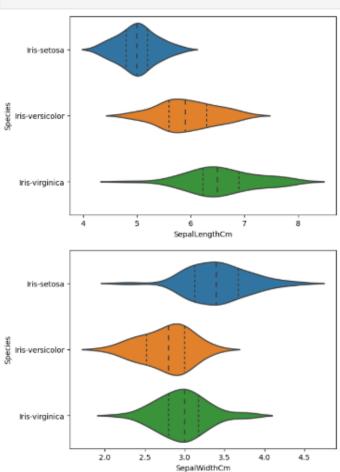
22]:		ld	SepalLengthCm	SepalWidthCm	PetalLengthCm	PetalWidthCm	Species
	0	1	5.1	3.5	1.4	0.2	Iris-setosa
	1	2	4.9	3.0	1.4	0.2	Iris-setosa
	2	3	4.7	3.2	1.3	0.2	Iris-setosa
	3	4	4.6	3.1	1.5	0.2	Iris-setosa
	4	5	5.0	3.6	1.4	0.2	Iris-setosa
	5	6	5.4	3.9	1.7	0.4	Iris-setosa
	6	7	4.6	3.4	1.4	0.3	Iris-setosa
	7	8	5.0	3.4	1.5	0.2	Iris-setosa
	8	9	4.4	2.9	1.4	0.2	Iris-setosa
	9	10	4.9	3.1	1.5	0.1	Iris-setosa

```
[23]: df.tail(10)
[23]: Id SepalLengthCm SepalWidthCm PetalLengthCm PetalWidthCm Species
      140 141
                           6.7
                                          3.1
                                                         5.6
                                                                       2.4 Iris-virginica
      141 142
                                         3.1
                                                         5.1
                           6.9
                                                                      2.3 Iris-virginica
      142 143
                           5.8
                                          2.7
                                                                       1.9 Iris-virginica
      143 144
                           6.8
                                         3.2
                                                         5.9
                                                                      2.3 Iris-virginica
      144 145
                                                         5.7
                           6.7
                                          3.3
                                                                       2.5 Iris-virginica
      145 146
                           6.7
                                          3.0
                                                         5.2
                                                                       2.3 Iris-virginica
      146 147
                           63
                                          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
                           5.9
                                                         5.1
                                                                      1.8 Iris-virginica
      149 150
                                          3.0
[24]: df.info()
       <class 'pandas.core.frame.DataFrame'>
       RangeIndex: 150 entries, 0 to 149
      Data columns (total 6 columns):
       # Column
                      Non-Null Count Dtype
                          150 non-null
       1 SepalLengthCm 150 non-null
2 SepalWidthCm 150 non-null
                                          float64
                                          float64
           PetalLengthCm 150 non-null
       4 PetalWidthCm 150 non-null
5 Species 150 non-null
                                          float64
                                          object
       dtypes: float64(4), int64(1), object(1)
       memory usage: 7.2+ KB
  [25]: df.isnull().any().values
  [25]: array([False, False, False, False, False, False])
  [26]: df.describe().T
  [26]:
                                              std min 25% 50% 75% max
                       count
                    ld 150.0 75.500000 43.445368 1.0 38.25 75.50 112.75 150.0
         SepalLengthCm 150.0 5.843333 0.828066 4.3 5.10 5.80
                                                                    6.40
                                                                            7.9
         SepalWidthCm 150.0 3.054000 0.433594 2.0 2.80 3.00
                                                                    3.30
                                                                            4.4
         PetalLengthCm 150.0 3.758667 1.764420 1.0 1.60 4.35 5.10 6.9
         PetalWidthCm 150.0 1.198667 0.763161 0.1 0.30 1.30 1.80 2.5
  [27]: df['Species'].value_counts()
  [27]: Species
         .
Iris-setosa
         Iris-versicolor
Iris-virginica
         Name: count, dtype: int64
  [28]: ## Visualization...
        import warnings
        warnings.filterwarnings('ignore')
  [29]: df = df.drop("Id", axis = 1)
        df.head()
  [29]: SepalLengthCm SepalWidthCm PetalLengthCm PetalWidthCm Species
        0
                      5.1
                                    3.5
                                                   1.4
                                                                 0.2 Iris-setosa
                      4.9
                                    3.0
                                                   1.4
        2
                      47
                                    3.2
                                                   1.3
                                                                 0.2 Iris-setosa
                                3.1
                                                            0.2 Iris-setosa
        3
                     4.6
                                                   1.5
                      5.0
                                    3.6
                                                   1.4
                                                                 0.2 Iris-setosa
```

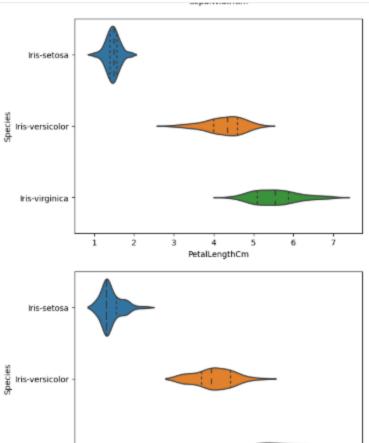




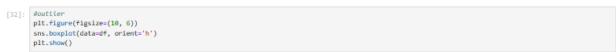
```
[31]: violin_sepal_length = sns.violinplot(y='Species', x='SepallengthCm', data=df, inner='quartile')
plt.show()
violin_sepal_width = sns.violinplot(y='Species', x='SepalMidthCm', data=df, inner='quartile')
plt.show()
violin_petal_length = sns.violinplot(y='Species', x='PetalLengthCm', data=df, inner='quartile')
plt.show()
violin_petal_width = sns.violinplot(y='Species', x='PetalMidthCm', data=df, inner='quartile')
plt.show()
```







Iris-virginica



2.0

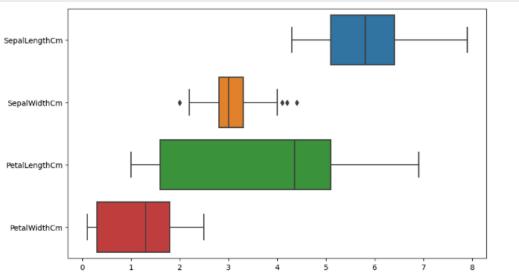
2.5

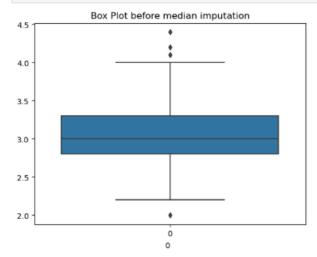
1.5 PetalWidthCm

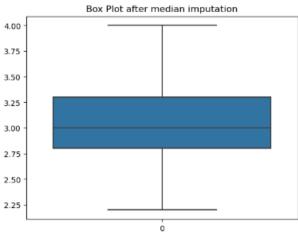
1.0

0.5

0.0





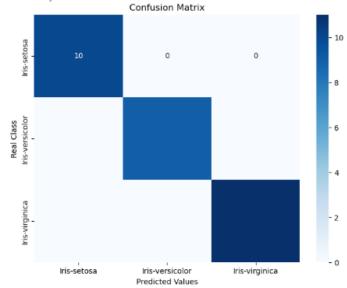


```
[35]: ##KNN
                   from sklearn import metrics
                  from sklearn.neighbors import KNeighborsClassifier
from sklearn.model_selection import train_test_split
                 from sklearn.metrics import accuracy_score
[36]: df.columns
\label{eq:continuous} \begin{tabular}{ll} \b
                                 dtype='object')
[37]: X = df[["SepalLengthCn", "SepalWidthCm", "PetalLengthCn", "PetalWidthCm"]] y = df["Species"]
[38]: from sklearn.model_selection import train_test_split
                  X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.30, random_state = 42)
[39]: knn = KNeighborsClassifier()
                   knn_model = knn.fit(X_train, y_train)
[40]: y_pred = knn_model.predict(X_test)
                 accuracy_score(y_test, y_pred)
[40]: 1.0
[41]: #modeL tuning
                   \textbf{from } \texttt{sklearn}. \texttt{model\_selection } \textbf{import } \texttt{train\_test\_split}, \texttt{GridSearchCV}, \texttt{cross\_val\_score}, \texttt{cross\_val\_predict}
                   knn_params = {"n_neighbors": np.arange(1,50)}
                   knn = KNeighborsClassifier()
                  knn_cv = GridSearchCV(knn, knn_params, cv=10)
                  knn_cv.fit(X_train, y_train)
                   print("The best score: " + str(knn_cv.best_score_))
                 print("The best parameters: " + str(knn_cv.best_params_))
                  The best score: 0.9627272727272727
                  The best parameters: {'n_neighbors': 11}
   [42]: knn = KNeighborsClassifier(11)
                     knn_tuned = knn.fit(X_train, y_train)
   [43]: knn_tuned.score(X_test, y_test)
   [43]: 1.0
    [44]: y_pred = knn_tuned.predict(X_test)
                   accuracy_score(y_test, y_pred)
```

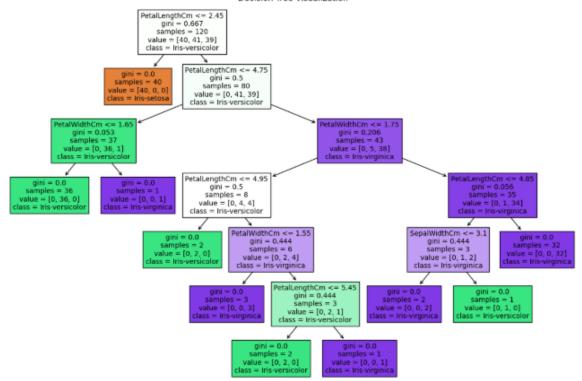
[44]: 1.0

```
[45]: ##Decision Tree
       from sklearn.model_selection import train_test_split
       from sklearn.tree import DecisionTreeClassifier, plot_tree
       from sklearn.metrics import accuracy_score, confusion_matrix
       import matplotlib.pyplot as plt
       import seaborn as sns
       import pandas as pd
       X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
       tree_clf = DecisionTreeClassifier(criterion="gini", max_depth=30, random_state=42)
       tree_clf.fit(X_train, y_train)
       y_pred = tree_clf.predict(X_test)
       accuracy = accuracy_score(y_test, y_pred)
       print(f"test accuracy: {accuracy}")
       y_pred_train = tree_clf.predict(X_train)
       accuracy_train = accuracy_score(y_train, y_pred_train)
print(f"train accuracy: {accuracy_train}")
       conf_matrix = confusion_matrix(y_test, y_pred)
       plt.figure(figsize=(8, 6))
       sns.heatmap(conf_matrix, annot=True, cmap="Blues", fmt="g",
                   xticklabels=tree_clf.classes_,
yticklabels=tree_clf.classes_)
       plt.xlabel("Predicted Values")
plt.ylabel("Real Class")
plt.title("Confusion Matrix")
       plt.show()
```

test accuracy: 1.0 train accuracy: 1.0



## Decision Tree Visualization



PetalLengthCm: 0.9861433868879218 PetalWidthCm: 0.07718647349965893 SepalWidthCm: 0.016670139612419255

SepalLengthCm: 0.0