4 5.0 3.6 1.4 0.2 Iris-setosa #Step4: Let's understand what are the datatypes irisDataset.info() <class 'pandas.core.frame.DataFrame'> RangeIndex: 150 entries, 0 to 149 Data columns (total 5 columns): Non-Null Count Dtype # Column sepal_length 150 non-null float64 sepal width 150 non-null float64 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 #Step5: Let's find out if there are any missing values irisDataset.isnull().sum() Out[50]: sepal_length sepal_width 0 petal_length 0 petal width species 0 dtype: int64 #Step6: Use shape attribute to know the dimensions (rows, columns) print(irisDataset.shape) (150, 5)In [40]: #Step7 : Find out what columns/features are present in the dataset and also plot them print(irisDataset.columns) sns.countplot(x='species',data=irisDataset) Index(['sepal length', 'sepal width', 'petal length', 'petal width', 'species'], dtype='object') <AxesSubplot:xlabel='species', ylabel='count'> 50 40 30 20 10 0 Iris-setosa Iris-versicolor Iris-virginica species In [41]: #Step8: Use describe to find out the summary statistics of the data print(irisDataset.describe()) sepal length sepal width petal length petal width 150.000000 150.000000 150.000000 count 150.000000 3.054000 5.843333 3.758667 1.198667 mean 0.433594 1.764420 0.763161 std 0.828066 min 4.300000 2.000000 1.000000 0.100000 25% 0.300000 5.100000 2.800000 1.600000 50% 1.300000 5.800000 3.000000 4.350000 75% 6.400000 5.100000 1.800000 3.300000 7.900000 4.400000 6.900000 2.500000 In [42]: #Step9: Let's try to understand what are the different class labels that are present in rhe dataset. print(irisDataset["species"].value_counts()) 50 Iris-virginica Iris-setosa Iris-versicolor 50 Name: species, dtype: int64 In [43]: #Step10: Visulaizing this dataset with the help of a scatter plot by taking'sepal_length' as x-axis and 'sepal

irisDataset = pd.read_csv(r"C:\Users\ayesh\OneDrive\Desktop\BI Program\1 SEM\CST2101-Business Intelligence Prog

#Step1: Import all the important Libraries

sepal_length sepal_width petal_length petal_width

#Step2: Load the CSV file in the irisDataset dataframe

#Step3: Let's get a quick idea about what the data looks like

1.4

1.4

1.3

1.5

0.2 Iris-setosa

0.2 Iris-setosa

0.2 Iris-setosa

0.2 Iris-setosa

import pandas as pd
import numpy as np
import seaborn as sns

irisDataset.head()

5.1

4.9

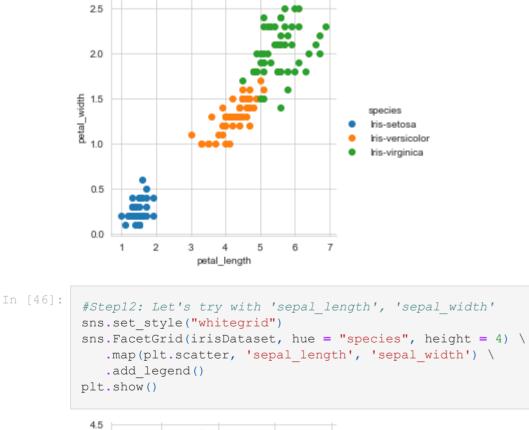
4.7

0

2

3

import matplotlib.pyplot as plt



irisDataset.plot(kind = "scatter", x = "sepal_length", y = "sepal_width")

8.0

#Step11:Since the previous plot was not very helpful ,Lets visulaize the dataset with the help of seaborn libra

plt.show()

4.5

4.0

3.5

3.0

2.5

2.0

In [47]:

4.5

5.0

sns.set_style("whitegrid")

.add legend()

plt.show()

4.0

3.5

5.5

6.0

sepal_length

6.5

sns.FacetGrid(irisDataset, hue = "species", height = 4) \
.map(plt.scatter, "petal_length", "petal_width") \

7.0

7.5

species
his-setosa
his-versicolor
his-virginica

In [49]:

#Step13: Let's try to visulaize the different combinations between the remaining features by using pain

#Step13: Let's try to visulaize the different combinations between the remaining features by using pairplots sns.pairplot(irisDataset, hue='species') Out[49]: <seaborn.axisgrid.PairGrid at 0x1c5db4cadf0> 7.5 7.0 6.5 6.0 5.5 5.0 4.5 4.5 4.0 3.5 sepal width 3.0 2.5 2.0 species lris-setosa Iris-versicolor Iris-virginica peta 2.5 2.0 petal_width 0.5 0.0 2 8 0 Conclusion:

The seaborn library helps us visualize the data points in a more appealing manner comapred to a scatter plot.

- By visulaizing a 2D plot between Sepal length Vs Sepal Width and Petal Length Vs Petal Width we see that the datapoints separated well when we consider the Petal Length Vs Petal Width
- When we try to extend our analysis using pair plots which is used to gain insights into the relationships between the four features, it becomes evident that Petal Length and Petal Width continue to stand out as superior features for classifying the data.