In [9]: #for manipulation import numpy as np import pandas as pd #for data visualization import matplotlib.pyplot as plt import seaborn as sns #for implement ML from sklearn.preprocessing import LabelEncoder from sklearn.metrics import accuracy\_score #for interacitivity from ipywidgets import interact In [10]: data = pd.read\_csv('IrisDATA.csv') In [13]: print("Shape of data is: ", data.shape) Shape of data is: (150, 5) data.head() Out[14]: sepal\_length sepal\_width petal\_length petal\_width species 0 5.1 3.5 1.4 0.2 setosa 1 4.9 3.0 1.4 0.2 setosa 2 4.7 3.2 1.3 0.2 setosa 3 4.6 3.1 1.5 0.2 setosa 4 5.0 3.6 1.4 0.2 setosa In [15]: data.isnull().sum() 0 sepal\_length Out[15]: sepal\_width 0 petal\_length 0 petal\_width 0 0 species dtype: int64 In [21]: data.value\_counts() sepal\_length sepal\_width petal\_length petal\_width species Out[21]: 3.1 4.9 3 1.5 0.1 setosa 5.8 2.7 5.1 1.9 virginica 2 0.2 5.4 3.4 1.7 setosa 1 2.5 5.5 4.0 1.3 versicolor 1 2.4 3.8 1.1 versicolor 1 6.3 2.5 4.9 1.5 versicolor 1 2.3 1.3 versicolor 4.4 1 2.3 6.2 3.4 5.4 virginica 1 2.9 4.3 1.3 versicolor 1 0.1 4.3 3.0 1.1 setosa 1 Length: 147, dtype: int64 In [24]: sns.catplot(x = 'species', hue = 'species', kind = 'count', data = data) <seaborn.axisgrid.FacetGrid at 0x24d634535f8> Out[24]: 50 40 30 20 10 setosa versicolor virginica In [26]: #Paired Plot sns.set() sns.pairplot(data[['sepal\_length','sepal\_width','petal\_length','petal\_width','species']], hue = "species", diag\_kind="kde") <seaborn.axisgrid.PairGrid at 0x24d65638ba8> Out[26]: sepal\_length 4.5 4.0 sepal\_width 3.5 2.5 2.0 petal\_length 2.5 2.0 Detal\_width 0.5 0.0 sepal\_length petal\_length petal\_width In [30]: #Bar plot for Species Vs Petal Width
plt.bar(data['species'], data['petal\_width']) <BarContainer object of 150 artists> Out[30]: 2.5 2.0 1.5 1.0 0.5 0.0 versicolor virginica In [31]: **#Data Processing** data.describe() Out[31]: sepal\_length sepal\_width petal\_length petal\_width 150.000000 150.000000 count 150.000000 150.000000 5.843333 3.054000 mean 3.758667 1.198667 0.828066 0.433594 1.764420 0.763161 std 4.300000 2.000000 1.000000 0.100000 min **25**% 5.100000 2.800000 1.600000 0.300000 5.800000 3.000000 4.350000 1.300000 **50**% **75**% 6.400000 3.300000 5.100000 1.800000 7.900000 4.400000 6.900000 2.500000 max In [32]: data.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 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 In [33]: data sepal\_length sepal\_width petal\_length petal\_width species Out[33]: 1.4 0.2 setosa 4.9 3.0 1.4 1 0.2 setosa 2 4.7 3.2 1.3 0.2 setosa 1.5 4.6 3.1 0.2 setosa 4 5.0 3.6 1.4 0.2 setosa 145 3.0 5.2 2.3 virginica 146 6.3 2.5 5.0 1.9 virginica 147 2.0 virginica 148 2.3 virginica 149 1.8 virginica 150 rows × 5 columns In [41]: Label\_Encode = LabelEncoder() Y = data['species'] Y = Label\_Encode.fit\_transform(Y) In [42]: Out[42]: 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, In [44]: data['species'].nunique() Out[44]: In [45]: X = np.array(X)In [46]: X Out[46]: array([[5.1, 3.5, 1.4, 0.2], [4.9, 3. , 1.4, 0.2], [4.7, 3.2, 1.3, 0.2], [4.6, 3.1, 1.5, 0.2], [5. , 3.6, 1.4, 0.2], [5.4, 3.9, 1.7, 0.4], [4.6, 3.4, 1.4, 0.3], [5. , 3.4, 1.5, 0.2], [4.4, 2.9, 1.4, 0.2], [4.9, 3.1, 1.5, 0.1], [5.4, 3.7, 1.5, 0.2], [4.8, 3.4, 1.6, 0.2], [4.8, 3. , 1.4, 0.1], [4.3, 3., 1.1, 0.1], [5.8, 4. , 1.2, 0.2], [5.7, 4.4, 1.5, 0.4], [5.4, 3.9, 1.3, 0.4], [5.1, 3.5, 1.4, 0.3], [5.7, 3.8, 1.7, 0.3], [5.1, 3.8, 1.5, 0.3], [5.4, 3.4, 1.7, 0.2], [5.1, 3.7, 1.5, 0.4], [4.6, 3.6, 1., 0.2], [5.1, 3.3, 1.7, 0.5], [4.8, 3.4, 1.9, 0.2], [5. , 3. , 1.6, 0.2], [5. , 3.4, 1.6, 0.4], [5.2, 3.5, 1.5, 0.2], [5.2, 3.4, 1.4, 0.2], [4.7, 3.2, 1.6, 0.2], [4.8, 3.1, 1.6, 0.2], [5.4, 3.4, 1.5, 0.4], [5.2, 4.1, 1.5, 0.1], [5.5, 4.2, 1.4, 0.2], [4.9, 3.1, 1.5, 0.1], [5. , 3.2, 1.2, 0.2], [5.5, 3.5, 1.3, 0.2], [4.9, 3.1, 1.5, 0.1], [4.4, 3. , 1.3, 0.2], [5.1, 3.4, 1.5, 0.2], [5., 3.5, 1.3, 0.3], [4.5, 2.3, 1.3, 0.3], [4.4, 3.2, 1.3, 0.2], [5., 3.5, 1.6, 0.6], [5.1, 3.8, 1.9, 0.4], [4.8, 3., 1.4, 0.3], [5.1, 3.8, 1.6, 0.2], [4.6, 3.2, 1.4, 0.2], [5.3, 3.7, 1.5, 0.2], [5., 3.3, 1.4, 0.2], [7., 3.2, 4.7, 1.4],[6.4, 3.2, 4.5, 1.5], [6.9, 3.1, 4.9, 1.5], [5.5, 2.3, 4. , 1.3], [6.5, 2.8, 4.6, 1.5], [5.7, 2.8, 4.5, 1.3], [6.3, 3.3, 4.7, 1.6], [4.9, 2.4, 3.3, 1.], [6.6, 2.9, 4.6, 1.3], [5.2, 2.7, 3.9, 1.4], [5., 2., 3.5, 1.], [5.9, 3., 4.2, 1.5], [6., 2.2, 4., 1.], [6.1, 2.9, 4.7, 1.4], [5.6, 2.9, 3.6, 1.3], [6.7, 3.1, 4.4, 1.4], [5.6, 3., 4.5, 1.5], [5.8, 2.7, 4.1, 1. ], [6.2, 2.2, 4.5, 1.5], [5.6, 2.5, 3.9, 1.1], [5.9, 3.2, 4.8, 1.8], [6.1, 2.8, 4. , 1.3], [6.3, 2.5, 4.9, 1.5], [6.1, 2.8, 4.7, 1.2], [6.4, 2.9, 4.3, 1.3], [6.6, 3., 4.4, 1.4], [6.8, 2.8, 4.8, 1.4], [6.7, 3., 5., 1.7],[6., 2.9, 4.5, 1.5], [5.7, 2.6, 3.5, 1.], [5.5, 2.4, 3.8, 1.1], [5.5, 2.4, 3.7, 1.], [5.8, 2.7, 3.9, 1.2], [6., 2.7, 5.1, 1.6],[5.4, 3., 4.5, 1.5], [6. , 3.4, 4.5, 1.6], [6.7, 3.1, 4.7, 1.5], [6.3, 2.3, 4.4, 1.3], [5.6, 3. , 4.1, 1.3], [5.5, 2.5, 4. , 1.3], [5.5, 2.6, 4.4, 1.2], [6.1, 3. , 4.6, 1.4], [5.8, 2.6, 4. , 1.2], [5., 2.3, 3.3, 1.], [5.6, 2.7, 4.2, 1.3], [5.7, 3., 4.2, 1.2], [5.7, 2.9, 4.2, 1.3], [6.2, 2.9, 4.3, 1.3], [5.1, 2.5, 3. , 1.1], [5.7, 2.8, 4.1, 1.3], [6.3, 3.3, 6. , 2.5], [5.8, 2.7, 5.1, 1.9], [7.1, 3., 5.9, 2.1],[6.3, 2.9, 5.6, 1.8], [6.5, 3. , 5.8, 2.2], [7.6, 3., 6.6, 2.1], [4.9, 2.5, 4.5, 1.7], [7.3, 2.9, 6.3, 1.8], [6.7, 2.5, 5.8, 1.8], [7.2, 3.6, 6.1, 2.5], [6.5, 3.2, 5.1, 2.], [6.4, 2.7, 5.3, 1.9], [6.8, 3., 5.5, 2.1], [5.7, 2.5, 5. , 2. ], [5.8, 2.8, 5.1, 2.4], [6.4, 3.2, 5.3, 2.3],[6.5, 3., 5.5, 1.8], [7.7, 3.8, 6.7, 2.2], [7.7, 2.6, 6.9, 2.3], [6., 2.2, 5., 1.5], [6.9, 3.2, 5.7, 2.3], [5.6, 2.8, 4.9, 2.], [7.7, 2.8, 6.7, 2.], [6.3, 2.7, 4.9, 1.8], [6.7, 3.3, 5.7, 2.1], [7.2, 3.2, 6. , 1.8], [6.2, 2.8, 4.8, 1.8], [6.1, 3., 4.9, 1.8], [6.4, 2.8, 5.6, 2.1], [7.2, 3., 5.8, 1.6], [7.4, 2.8, 6.1, 1.9], [7.9, 3.8, 6.4, 2.], [6.4, 2.8, 5.6, 2.2], [6.3, 2.8, 5.1, 1.5], [6.1, 2.6, 5.6, 1.4], [7.7, 3., 6.1, 2.3],[6.3, 3.4, 5.6, 2.4], [6.4, 3.1, 5.5, 1.8], [6. , 3. , 4.8, 1.8], [6.9, 3.1, 5.4, 2.1], [6.7, 3.1, 5.6, 2.4],[6.9, 3.1, 5.1, 2.3], [5.8, 2.7, 5.1, 1.9], [6.8, 3.2, 5.9, 2.3], [6.7, 3.3, 5.7, 2.5], [6.7, 3. , 5.2, 2.3], [6.3, 2.5, 5. , 1.9], [6.5, 3., 5.2, 2.], [6.2, 3.4, 5.4, 2.3], [5.9, 3., 5.1, 1.8]]) In [49]: from sklearn.model\_selection import train\_test\_split X\_train, X\_test, Y\_train, Y\_test = train\_test\_split(X, Y, test\_size = 0.3, random\_state=0) In [50]: X\_train array([[5. , 2. , 3.5, 1. ], Out[50]: [6.5, 3., 5.5, 1.8], [6.7, 3.3, 5.7, 2.5], [6., 2.2, 5., 1.5],[6.7, 2.5, 5.8, 1.8], [5.6, 2.5, 3.9, 1.1], [7.7, 3., 6.1, 2.3],[6.3, 3.3, 4.7, 1.6], [5.5, 2.4, 3.8, 1.1], [6.3, 2.7, 4.9, 1.8], [6.3, 2.8, 5.1, 1.5], [4.9, 2.5, 4.5, 1.7], [6.3, 2.5, 5. , 1.9], [7., 3.2, 4.7, 1.4],[6.5, 3., 5.2, 2.],[6., 3.4, 4.5, 1.6], [4.8, 3.1, 1.6, 0.2], [5.8, 2.7, 5.1, 1.9], [5.6, 2.7, 4.2, 1.3], [5.6, 2.9, 3.6, 1.3], [5.5, 2.5, 4., 1.3], [6.1, 3., 4.6, 1.4],[7.2, 3.2, 6., 1.8],[5.3, 3.7, 1.5, 0.2], [4.3, 3., 1.1, 0.1], [6.4, 2.7, 5.3, 1.9], [5.7, 3., 4.2, 1.2], [5.4, 3.4, 1.7, 0.2], [5.7, 4.4, 1.5, 0.4], [6.9, 3.1, 4.9, 1.5], [4.6, 3.1, 1.5, 0.2], [5.9, 3., 5.1, 1.8], [5.1, 2.5, 3. , 1.1], [4.6, 3.4, 1.4, 0.3], [6.2, 2.2, 4.5, 1.5], [7.2, 3.6, 6.1, 2.5],[5.7, 2.9, 4.2, 1.3], [4.8, 3., 1.4, 0.1], [7.1, 3., 5.9, 2.1],[6.9, 3.2, 5.7, 2.3], [6.5, 3., 5.8, 2.2], [6.4, 2.8, 5.6, 2.1], [5.1, 3.8, 1.6, 0.2], [4.8, 3.4, 1.6, 0.2], [6.5, 3.2, 5.1, 2.],[6.7, 3.3, 5.7, 2.1], [4.5, 2.3, 1.3, 0.3], [6.2, 3.4, 5.4, 2.3], [4.9, 3., 1.4, 0.2], [5.7, 2.5, 5., 2.], [6.9, 3.1, 5.4, 2.1],[4.4, 3.2, 1.3, 0.2], [5., 3.6, 1.4, 0.2], [7.2, 3., 5.8, 1.6], [5.1, 3.5, 1.4, 0.3], [4.4, 3., 1.3, 0.2], [5.4, 3.9, 1.7, 0.4], [5.5, 2.3, 4., 1.3], [6.8, 3.2, 5.9, 2.3], [7.6, 3., 6.6, 2.1],[5.1, 3.5, 1.4, 0.2], [4.9, 3.1, 1.5, 0.1], [5.2, 3.4, 1.4, 0.2], [5.7, 2.8, 4.5, 1.3], [6.6, 3., 4.4, 1.4], [5., 3.2, 1.2, 0.2], [5.1, 3.3, 1.7, 0.5], [6.4, 2.9, 4.3, 1.3], [5.4, 3.4, 1.5, 0.4], [7.7, 2.6, 6.9, 2.3], [4.9, 2.4, 3.3, 1.], [7.9, 3.8, 6.4, 2.], [6.7, 3.1, 4.4, 1.4], [5.2, 4.1, 1.5, 0.1], [6., 3., 4.8, 1.8], [5.8, 4., 1.2, 0.2], [7.7, 2.8, 6.7, 2.], [5.1, 3.8, 1.5, 0.3], [4.7, 3.2, 1.6, 0.2], [7.4, 2.8, 6.1, 1.9], [5., 3.3, 1.4, 0.2], [6.3, 3.4, 5.6, 2.4], [5.7, 2.8, 4.1, 1.3], [5.8, 2.7, 3.9, 1.2], [5.7, 2.6, 3.5, 1.], [6.4, 3.2, 5.3, 2.3], [6.7, 3., 5.2, 2.3], [6.3, 2.5, 4.9, 1.5], [6.7, 3., 5., 1.7],[5., 3., 1.6, 0.2], [5.5, 2.4, 3.7, 1.], [6.7, 3.1, 5.6, 2.4], [5.8, 2.7, 5.1, 1.9], [5.1, 3.4, 1.5, 0.2], [6.6, 2.9, 4.6, 1.3], [5.6, 3., 4.1, 1.3], [5.9, 3.2, 4.8, 1.8], [6.3, 2.3, 4.4, 1.3], [5.5, 3.5, 1.3, 0.2], [5.1, 3.7, 1.5, 0.4], [4.9, 3.1, 1.5, 0.1], [6.3, 2.9, 5.6, 1.8], [5.8, 2.7, 4.1, 1.], [7.7, 3.8, 6.7, 2.2], [4.6, 3.2, 1.4, 0.2]]) X\_train.shape Out[51]: (105, 4) In [52]: X\_test.shape (45, 4)In [53]: Y\_test.shape Out[53]: (45,) Y\_train.shape (105,)Out[54]: In [55]: #training the model from sklearn.preprocessing import StandardScaler standard\_scaler = StandardScaler().fit(X\_train) X\_train\_std = standard\_scaler.transform(X\_train) X\_test\_std = standard\_scaler.transform(X\_test) In [56]: X\_train\_std array([[-1.02366372, -2.37846268, -0.18295039, -0.29145882], Out[56]: 0.69517462, -0.10190314, 0.93066067, 0.73721938], [ 0.92435306, 0.58106472, 1.04202177, 1.6373128 ], [0.1222285, -1.92315077, 0.6522579, 0.35146505],[0.92435306, -1.24018291, 1.09770233, 0.73721938],[-0.33612839, -1.24018291, 0.03977182, -0.16287405],[ 2.07024529, -0.10190314, 1.26474398, 1.38014325], [ 0.46599617, 0.58106472, 0.48521625, 0.48004983], [-0.45071761, -1.46783886, -0.01590873, -0.16287405],[ 0.46599617, -0.784871 , 0.59657735, 0.73721938], [ 0.46599617, -0.55721505, 0.70793846, 0.35146505], [-1.13825295, -1.24018291, 0.37385514, 0.6086346], [0.46599617, -1.24018291, 0.6522579, 0.86580415],[ 1.26812073, 0.35340877, 0.48521625, 0.22288028], [ 0.69517462, -0.10190314, 0.76361901, 0.99438893], [ 0.1222285 , 0.80872067, 0.37385514, 0.48004983], [-1.25284217, 0.12575281, -1.24088089, -1.32013702],[-0.10694994, -0.784871, 0.70793846, 0.86580415],[-0.33612839, -0.784871 , 0.20681348, 0.0942955 ], [-0.33612839, -0.32955909, -0.12726983, 0.0942955],[-0.45071761, -1.24018291, 0.09545238, 0.0942955], [0.23681773, -0.10190314, 0.42953569, 0.22288028],[ 1.49729918, 0.35340877, 1.20906343, 0.73721938], [-0.67989605, 1.49168853, -1.29656144, -1.32013702],[-1.82578828, -0.10190314, -1.51928365, -1.4487218],[ 0.5805854 , -0.784871 , 0.81929956, 0.86580415], [-0.22153916, -0.10190314, 0.20681348, -0.03428927],[-0.56530683, 0.80872067, -1.18520034, -1.32013702],[-0.22153916, 3.08528021, -1.29656144, -1.06296747], [ 1.15353151, 0.12575281, 0.59657735, 0.35146505], [-1.48202061, 0.12575281, -1.29656144, -1.32013702],[ 0.00763928, -0.10190314, 0.70793846, 0.73721938], [-0.9090745, -1.24018291, -0.46135315, -0.16287405],[-1.48202061, 0.80872067, -1.35224199, -1.19155225],[0.35140695, -1.92315077, 0.37385514, 0.35146505],[ 1.49729918, 1.26403258, 1.26474398, 1.6373128 ], [-0.22153916, -0.32955909, 0.20681348, 0.0942955],[-1.25284217, -0.10190314, -1.35224199, -1.4487218], [ 1.38270995, -0.10190314, 1.15338288, 1.1229737 ], [ 1.15353151, 0.35340877, 1.04202177, 1.38014325], [ 0.69517462, -0.10190314, 1.09770233, 1.25155848], [ 0.5805854 , -0.55721505, 0.98634122, 1.1229737 ], [-0.9090745 , 1.71934449, -1.24088089, -1.32013702] [-1.25284217, 0.80872067, -1.24088089, -1.32013702], [ 0.69517462, 0.35340877, 0.70793846, 0.99438893], [ 0.92435306, 0.58106472, 1.04202177, 1.1229737 ], [-1.59660984, -1.69549482, -1.40792255, -1.19155225], [ 0.35140695, 0.80872067, 0.87498011, 1.38014325], [-1.13825295, -0.10190314, -1.35224199, -1.32013702],[-0.22153916, -1.24018291, 0.6522579, 0.99438893], [ 1.15353151, 0.12575281, 0.87498011, 1.1229737 ], [-1.71119906, 0.35340877, -1.40792255, -1.32013702],[-1.02366372, 1.26403258, -1.35224199, -1.32013702],[ 1.49729918, -0.10190314, 1.09770233, 0.48004983], [-0.9090745 , 1.03637663, -1.35224199, -1.19155225], [-1.71119906, -0.10190314, -1.40792255, -1.32013702], [-0.56530683, 1.94700044, -1.18520034, -1.06296747], [-0.45071761, -1.69549482, 0.09545238, 0.0942955],[ 1.03894229, 0.35340877, 1.15338288, 1.38014325], [ 1.95565607, -0.10190314, 1.54314675, 1.1229737 ], [-0.9090745 , 1.03637663, -1.35224199, -1.32013702], [-1.13825295, 0.12575281, -1.29656144, -1.4487218], [-0.79448528, 0.80872067, -1.35224199, -1.32013702],[-0.22153916, -0.55721505, 0.37385514, 0.0942955], 0.80976384, -0.10190314, 0.31817459, 0.22288028], [-1.02366372, 0.35340877, -1.4636031 , -1.32013702], [-0.9090745 , 0.58106472, -1.18520034, -0.9343827 ], [ 0.5805854 , -0.32955909, 0.26249403, 0.0942955 ], [-0.56530683, 0.80872067, -1.29656144, -1.06296747], [ 2.07024529, -1.01252695, 1.71018841, 1.38014325], [-1.13825295, -1.46783886, -0.29431149, -0.29145882], [ 2.29942374, 1.71934449, 1.43178564, 0.99438893], [ 0.92435306, 0.12575281, 0.31817459, 0.22288028], [-0.79448528, 2.40231235, -1.29656144, -1.4487218], 0.1222285 , -0.10190314, 0.5408968 , 0.73721938], [-0.10694994, 2.17465639, -1.4636031 , -1.32013702], [ 2.07024529, -0.55721505, 1.5988273 , 0.99438893], [-0.9090745 , 1.71934449, -1.29656144, -1.19155225], [-1.36743139, 0.35340877, -1.24088089, -1.32013702], [ 1.72647762, -0.55721505, 1.26474398, 0.86580415], [-1.02366372, 0.58106472, -1.35224199, -1.32013702], [ 0.46599617, 0.80872067, 0.98634122, 1.50872803], [-0.22153916, -0.55721505, 0.15113293, 0.0942955], [-0.10694994, -0.784871 , 0.03977182, -0.03428927], [-0.22153916, -1.01252695, -0.18295039, -0.29145882], [ 0.5805854 , 0.35340877, 0.81929956, 1.38014325], [ 0.92435306, -0.10190314, 0.76361901, 1.38014325], [ 0.46599617, -1.24018291, 0.59657735, 0.35146505], [ 0.92435306, -0.10190314, 0.6522579 , 0.6086346 ], [-1.02366372, -0.10190314, -1.24088089, -1.32013702],[-0.45071761, -1.46783886, -0.07158928, -0.29145882],[ 0.92435306, 0.12575281, 0.98634122, 1.50872803], [-0.10694994, -0.784871 , 0.70793846, 0.86580415], [-0.9090745 , 0.80872067, -1.29656144, -1.32013702], [ 0.80976384, -0.32955909, 0.42953569, 0.0942955 ], [-0.33612839, -0.10190314, 0.15113293, 0.0942955], [ 0.00763928, 0.35340877, 0.5408968 , 0.73721938], [ 0.46599617, -1.69549482, 0.31817459, 0.0942955 ], [-0.45071761, 1.03637663, -1.40792255, -1.32013702], [-0.9090745 , 1.49168853, -1.29656144, -1.06296747], [-1.13825295, 0.12575281, -1.29656144, -1.4487218], [ 0.46599617, -0.32955909, 0.98634122, 0.73721938], [-0.10694994, -0.784871 , 0.15113293, -0.29145882], [ 2.07024529, 1.71934449, 1.5988273 , 1.25155848], [-1.48202061, 0.35340877, -1.35224199, -1.32013702]]) In [57]: array([1, 2, 2, 2, 2, 1, 2, 1, 1, 2, 2, 2, 2, 1, 2, 1, 0, 2, 1, 1, 1, 1, Out[57]: 2, 0, 0, 2, 1, 0, 0, 1, 0, 2, 1, 0, 1, 2, 1, 0, 2, 2, 2, 2, 0, 0, 2, 2, 0, 2, 0, 2, 2, 0, 0, 2, 0, 0, 0, 1, 2, 2, 0, 0, 0, 1, 1, 0, 0, 1, 0, 2, 1, 2, 1, 0, 2, 0, 2, 0, 0, 2, 0, 2, 1, 1, 1, 2, 2, 1, 1, 0, 1, 2, 2, 0, 1, 1, 1, 1, 0, 0, 0, 2, 1, 2, 0]) In [61]: #KNN Algo In [58]: from sklearn.neighbors import KNeighborsClassifier knn=KNeighborsClassifier(n\_neighbors=5) knn.fit(X\_train\_std,Y\_train) KNeighborsClassifier() Out[58] In [59]: predict\_knn=knn.predict(X\_test\_std) accuracy\_knn=accuracy\_score(Y\_test, predict\_knn)\*100 In [60]: accuracy\_knn 97.777777777777 In [62]: #K means Clustering In [65]: color\_map=np.array(['Red','green','blue']) figure=plt.scatter(data['petal\_length'], data['petal\_width'], c=color\_map[Y], s=30) 2.5 2.0 1.5 1.0 0.0 from sklearn.cluster import KMeans k\_means =KMeans(n\_clusters=3, random\_state=2, n\_jobs=4) k\_means.fit(X) c:\users\aakas\appdata\local\programs\python\python37\lib\site-packages\sklearn\cluster\\_kmeans.py:793: FutureWarning: 'n\_jobs' was deprecated in version 0.23 and will be removed i n 1.0 (renaming of 0.25). " removed in 1.0 (renaming of 0.25).", FutureWarning) KMeans(n\_clusters=3, n\_jobs=4, random\_state=2) Out[66]: In [67]:  $y_k_means = k_means.fit_predict(X)$ c:\users\aakas\appdata\local\programs\python\python37\lib\site-packages\sklearn\cluster\\_kmeans.py:793: FutureWarning: 'n\_jobs' was deprecated in version 0.23 and will be removed i n 1.0 (renaming of 0.25). " removed in 1.0 (renaming of 0.25).", FutureWarning) In [68]: centers = k\_means.cluster\_centers\_ In [69]: centers array([[5.006 , 3.418 , 1.464 , 0.244 Out[69]: [5.9016129 , 2.7483871 , 4.39354839, 1.43387097], [6.85 , 3.07368421, 5.74210526, 2.07105263]]) In [71]: color\_map=np.array(['Red','green','blue']) labels=np.array(['Iris-setosa','Iris-virginica','Iris-versicolour']) figure=plt.scatter(data['petal\_length'], data['petal\_width'], c=color\_map[k\_means.labels\_], s=20) 2.5 2.0 1.5 1.0