Discovery and Learning with Big Data/Machine Learning

Sri Charan Bodduna ¶

Machine Learning Supervised Logistic Regression

Import Libraries

In [1]:
```
# Import Python Libraries: NumPy and Pandas

import pandas as pd
import numpy as np
```

In [2]:
```
# Import Libraries & modules for data visualization

from pandas.plotting import scatter_matrix
import matplotlib.pyplot as plt
import seaborn as sns
```

In [3]:
```
# Import scikit-Learn module for the algorithm/modeL: Logistic Regression
from sklearn.linear_model import LogisticRegression
```

In [4]:
```
# Import scikit-Learn module to split the dataset into train/ test sub-data
from sklearn.model_selection import train_test_split
```

In [5]:
```
# Import scikit-Learn module for K-fold cross-validation - algorithm/modeL

from sklearn.model_selection import KFold
from sklearn.model_selection import cross_val_score
```

In [6]:
```
# Import scikit-Learn module classification report to later use for informa
#try to classify/lable each record

from sklearn.metrics import classification_report
```

Load Data

In [8]:
```
# Specify location of the dataset

filename = '/Users/sricharanbodduna/Downloads/Iris (3).csv'

# Load the data into a Pandas DataFrame

df = pd.read_csv(filename)
```

In [9]:
```
df.head()
```

Out[9]:

	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

Preprocess the Dataset

Clean the data: Find and Mark Missing Values

In [11]:
```
# mark zero values as missing or NaN

df[[ 'SepalLengthCm' , 'SepalWidthCm' , 'PetalLengthCm' ,'PetalWidthCm' ]]
= df[['SepalLengthCm' , 'SepalWidthCm' ,'PetalLengthCm' , 'PetalWidthCm' ]]

# count the number of NaN values in each column

print (df.isnull().sum())
```

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

Performing the Exploratory Data Analysis (EDA)

In [12]:
```
# get the dimensions or shape of the dataset
# i.e. number of records / rows X number of variables / columns

print("Shape of the dataset(rows, columns):",df.shape)
```

```
Shape of the dataset(rows, columns): (150, 6)
```

In [13]:
```
#get the data types of all the variables / attributes in the data set

print(df.dtypes)
```

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

In [14]:
```
#return the summary statistics of the numeric variables/attributes in the d

print(df.describe())
```

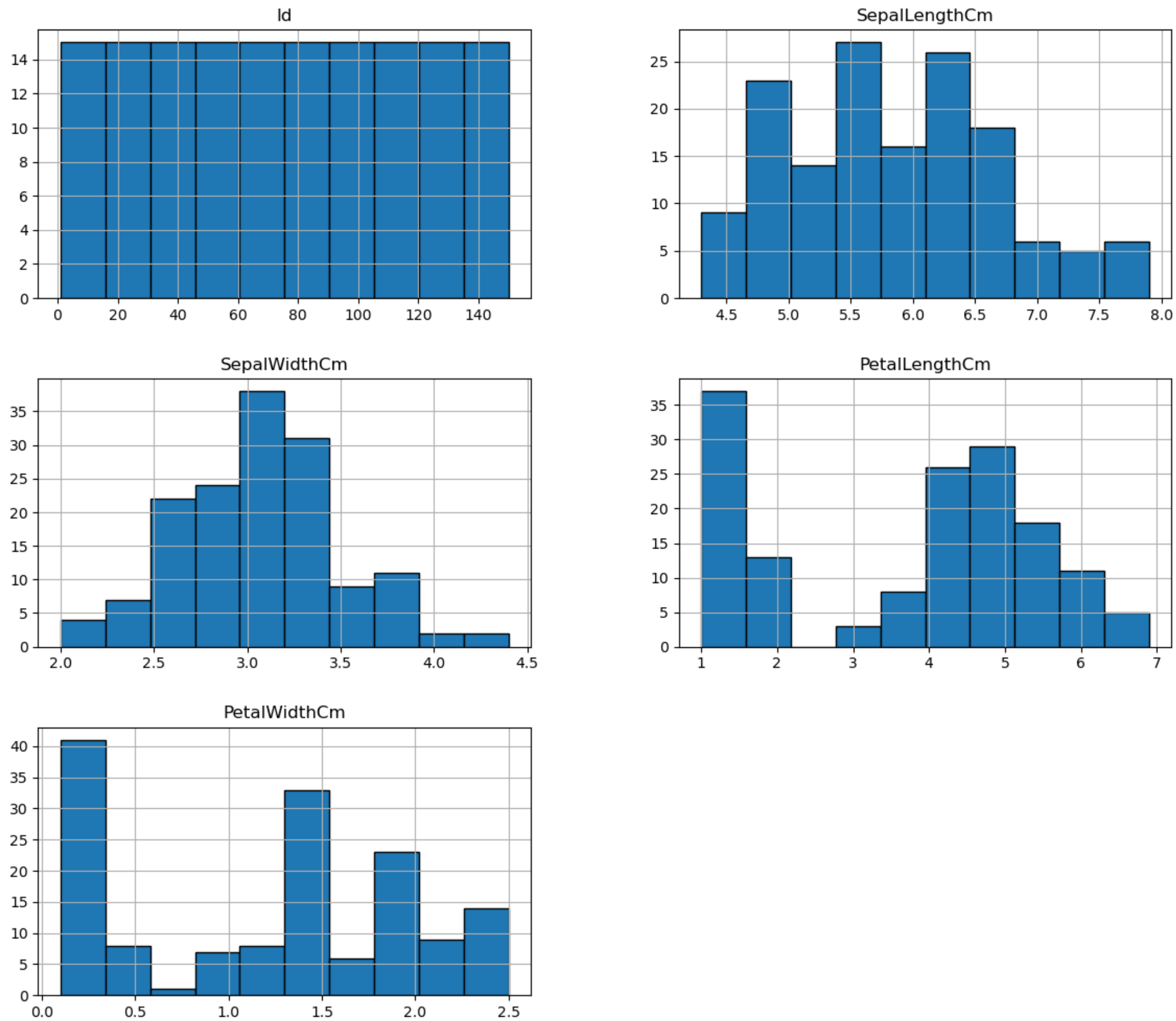
```
               Id  SepalLengthCm  SepalWidthCm  PetalLengthCm  PetalWidth
Cm
count  150.000000     150.000000    150.000000     150.000000    150.0000
00
mean    75.500000       5.843333      3.054000       3.758667      1.1986
67
std     43.445368       0.828066      0.433594       1.764420      0.7631
61
min      1.000000       4.300000      2.000000       1.000000      0.1000
00
25%     38.250000       5.100000      2.800000       1.600000      0.3000
00
50%     75.500000       5.800000      3.000000       4.350000      1.3000
00
75%    112.750000       6.400000      3.300000       5.100000      1.8000
00
max    150.000000       7.900000      4.400000       6.900000      2.5000
00
```

In [15]:
```
#class distribution i.e. how many records are in each class

print(df.groupby('Species').size())
```

```
Species
Iris-setosa        50
Iris-versicolor    50
Iris-virginica     50
dtype: int64
```

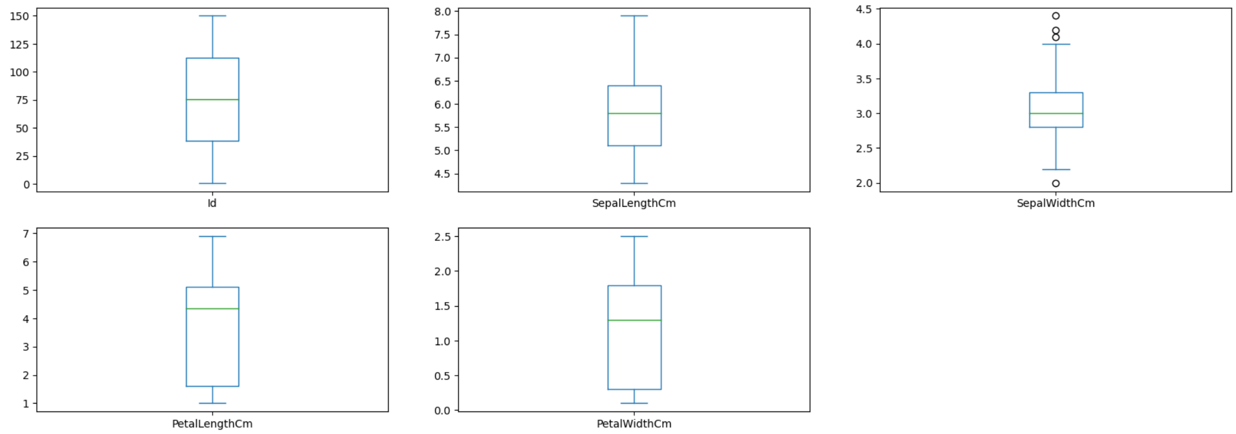
Creating a Histogram

In [16]:
```
# Plot histogram for each variable. I encourage you to work with the histog

df.hist(edgecolor= 'black',figsize=(14,12))
plt.show()
```



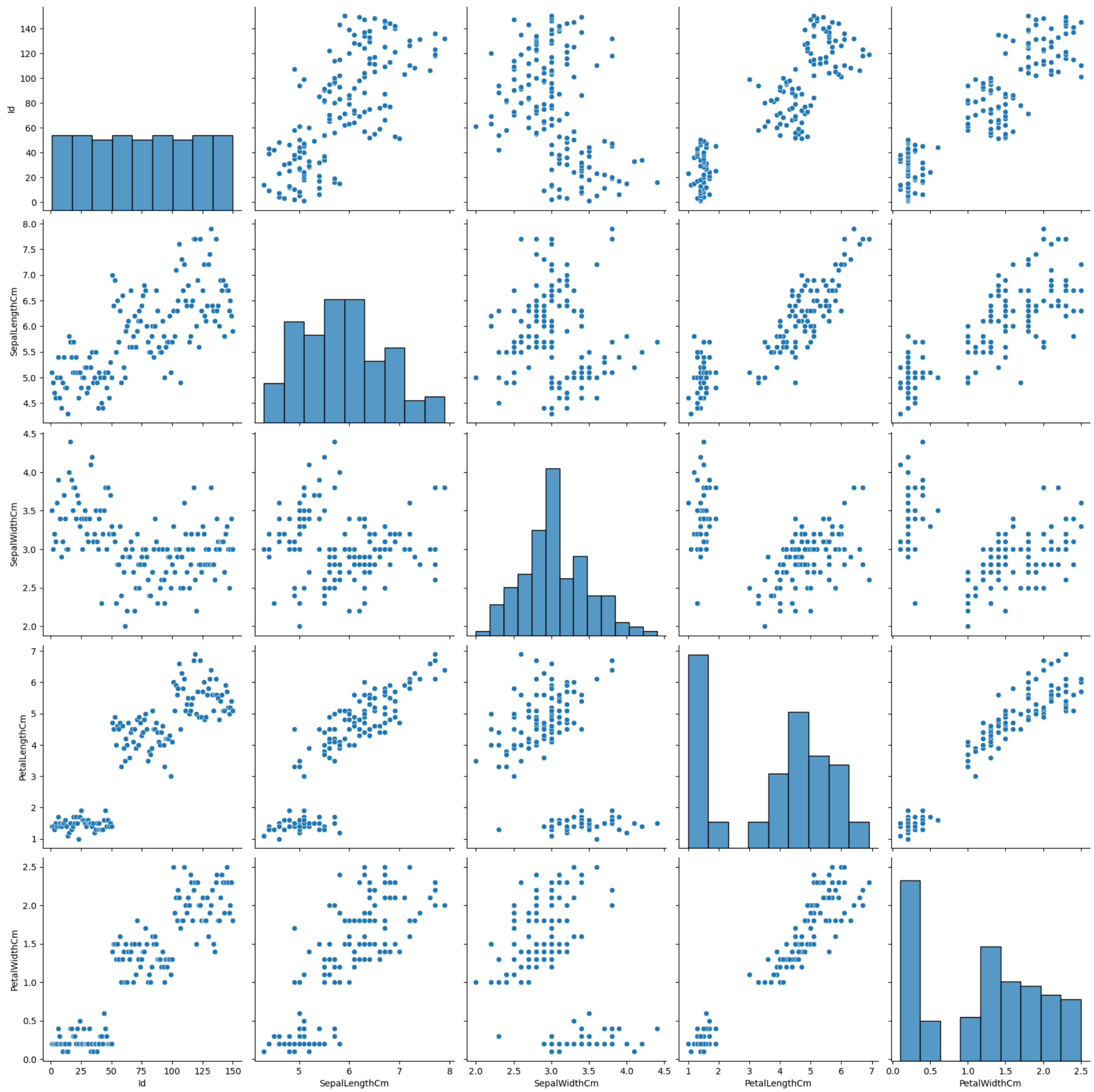
Creating a Box Plot

In [19]:
```
# Boxplots

df.plot(kind="box", subplots=True, layout=(5,3), sharex=False, figsize=(20,
plt.show()
```



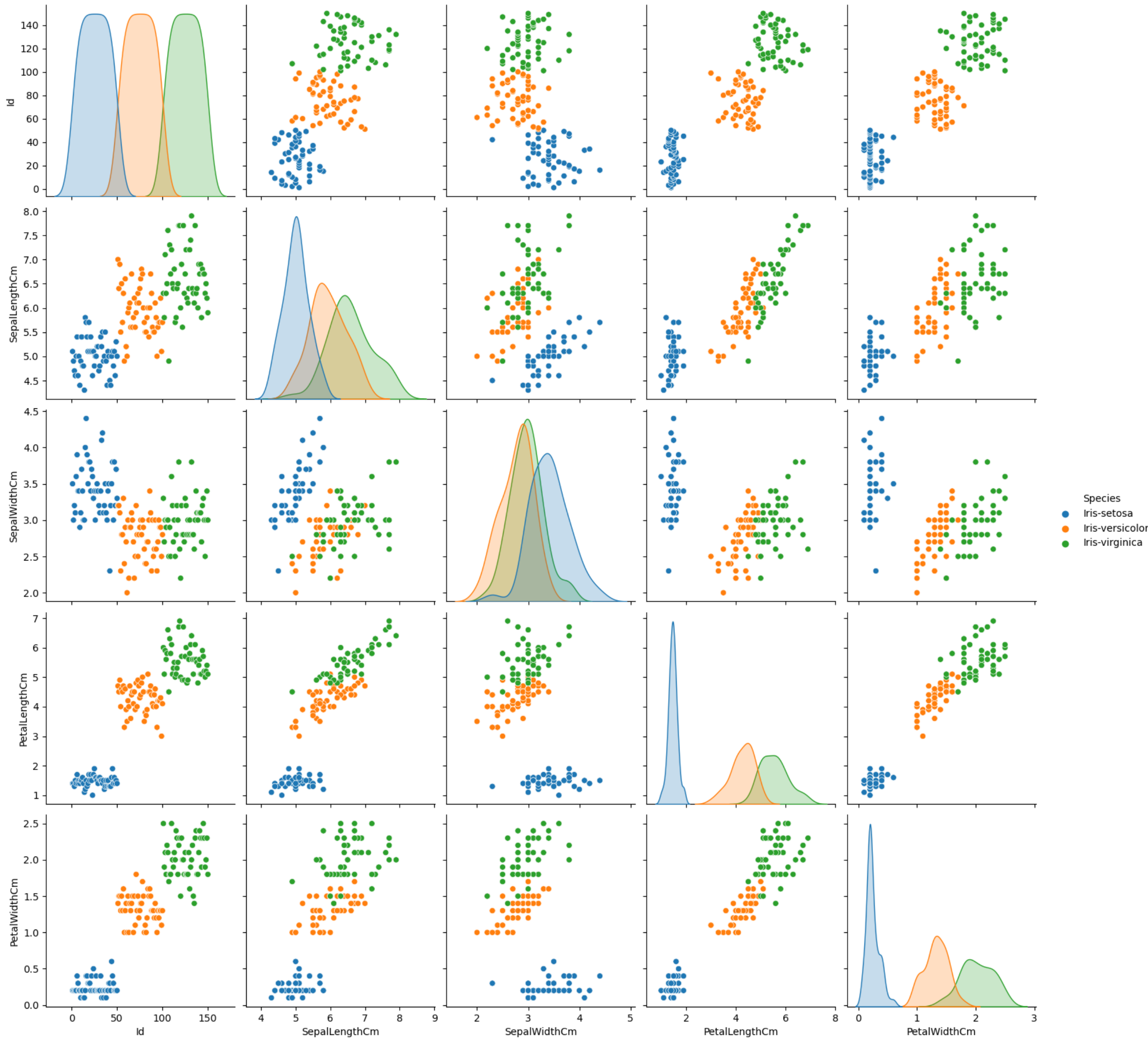
Create a Pair Plot

In [20]:
```
# Please click on the above URL to learn more about Pair Plots
# I know this is a lot of information but I wanted you to see what is possi

sns.pairplot(df, height=3.5);
plt.show()
```



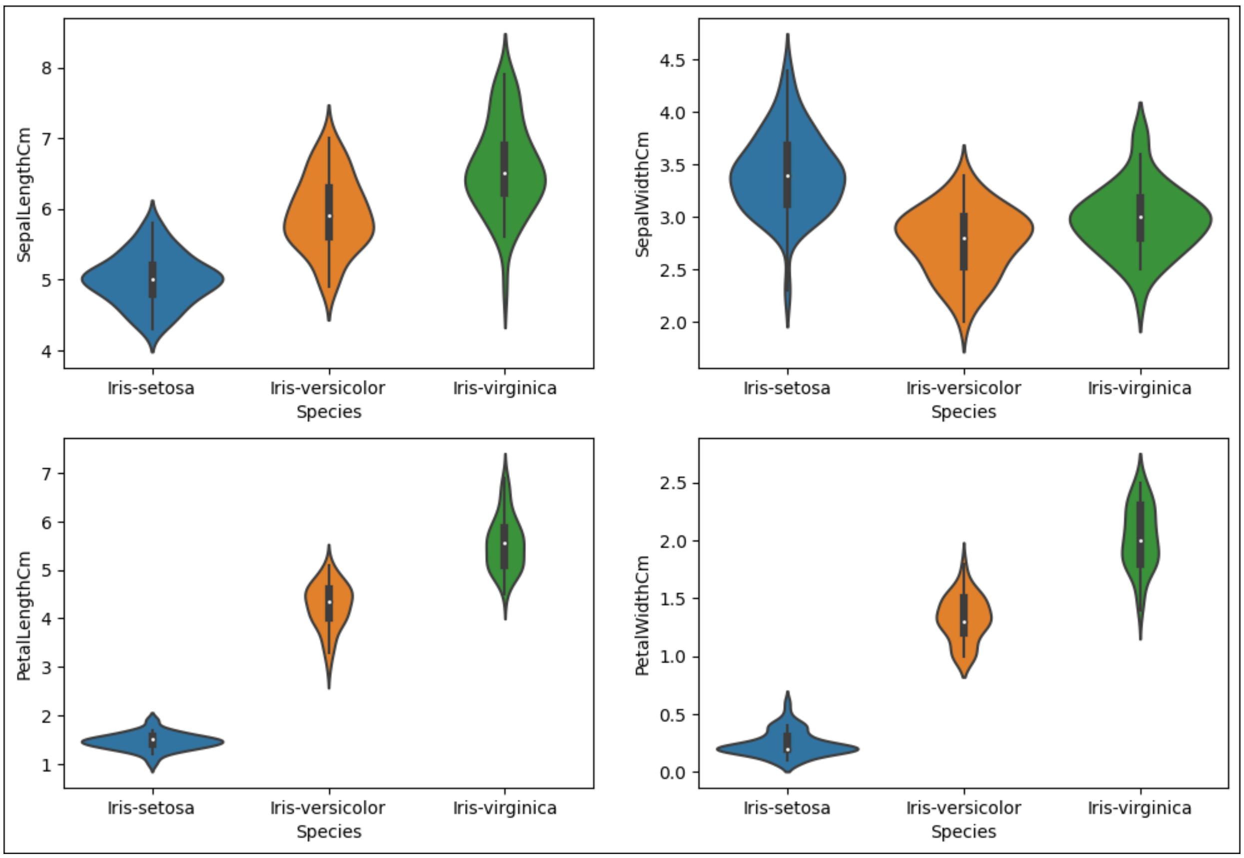
Creating a Pair Plot with Color

In [21]:
```
# Let's try that again using color.  Notice: assigning a hue variable adds

sns.pairplot(df, hue='Species', height=3, aspect= 1);
```



Creating a Violin Plot

In [22]:
```
#  Please click on the URL above to learn more about Violin Plots

plt.figure(edgecolor="black", linewidth= 1.2,figsize=(12,8));
plt.subplot(2,2,1)
sns.violinplot(x='Species', y = 'SepalLengthCm', data=df)
plt.subplot(2,2,2)
sns.violinplot(x='Species', y = 'SepalWidthCm', data=df)
plt.subplot(2,2,3)
sns.violinplot(x='Species', y = 'PetalLengthCm', data=df)
plt.subplot(2,2,4)
sns.violinplot(x='Species', y = 'PetalWidthCm', data=df);
```



Separate the Dataset into Input & Output NumPy Arrays

In [23]:
```
# store dataframe values into a numpy array

array = df.values

# separate array into input and output by slicing
# for X(input) [:, 1:5] --> all the rows, columns from 1 - 5
# these are the independent variables or predictors

X = array[:,1:5]

# for Y(input) [:, 5] --> all the rows, column 5
# this is the value we are trying to predict

Y = array[:,5]
```

Spilt into Input/Output Array into Training/Testing Datasets

In [24]:
```
# split the dataset --> training sub-dataset: 67%; test sub-dataset: 33%

test_size = 0.33

#selection of records to include in each data sub-dataset must be done rand

seed = 7

#split the dataset (input and output) into training / test datasets

X_train, X_test, Y_train, Y_test = train_test_split(X, Y, test_size=test_si
random_state=seed)
```

Build and Train the Model

In [25]:
```
#build the model

model = LogisticRegression(random_state=seed, max_iter=1000)

# train the model using the training sub-dataset

model.fit(X_train, Y_train)

#print the classification report

predicted = model.predict(X_test)
report = classification_report(Y_test, predicted)
print("Classification Report: ", "\n", "\n",report)
```

```
Classification Report: 

                  precision    recall  f1-score   support

    Iris-setosa       1.00      1.00      1.00        14
Iris-versicolor       0.89      0.89      0.89        18
 Iris-virginica       0.89      0.89      0.89        18

       accuracy                           0.92        50
      macro avg       0.93      0.93      0.93        50
   weighted avg       0.92      0.92      0.92        50
```

Score the Accuracy of the Model

In [26]:
```
#score the accuracy level

result = model.score(X_test, Y_test)

#print out the results

print(("Accuracy: %.3f%%") % (result*100.0))
```

```
Accuracy: 92.000%
```

Classify/Prediction

In [27]:
```
model.predict([[5.3, 3.0, 4.5, 1.5]])
```

Out[27]:
```
array(['Iris-versicolor'], dtype=object)
```

In [28]:
```
model.predict([[5, 3.6, 1.4, 1.5]])
```

Out[28]:
```
array(['Iris-setosa'], dtype=object)
```

Evaluate the Model using the 10-fold Cross-Validation Technique.

In [29]:
```
Evaluate the algorithm and specify the number of times of repeated splitting
splits=10
ix the random seed.  You must use the same seed value so that the same subse
ed=7
old=KFold(n_splits, random_state=seed, shuffle=True)
for logistic regression, we can use the accuracy level to evaluate the model
oring="accuracy"
rain the model and run K-fold cross validation to validate / evaluate the mo
sults=cross_val_score (model, X, Y, cv=kfold, scoring=scoring)
print the evaluation results.  The result is the average of all the results
int("Accuracy: %.3f (%.3f)"% (results.mean(), results.std()))
```

```
Accuracy: 0.967 (0.054)
```

In [ ]: