Python 3

For this tutorial we'll be using the Iris dataset from sklearn.

In this notebook we will:

1. Import required modules and dataset
2. Define multiple Classification models
3. Fit the data to our models
4. Use our trained models to predict a class label
5. Evaluate our models and chose the best performing model

In [4]:
```
import pandas as pd
```

In [34]:
```
df = pd.read_csv("exports.csv")

print(df.head())
```

```
   year country origin country destination  export_val
0  1995        Vietnam                 BFA    67177.77
1  1995        Vietnam                 CAF   514674.15
2  1995        Vietnam                 CIV    58011.71
3  1995        Vietnam                 CMR    97669.00
4  1995        Vietnam                 COG    24018.39
```

groupby()

- groupby combines 3 steps all in one function:
  1. Split a DataFrame
  2. Apply a function
  3. Combine the results
- groupby must be given the name of the column to group by as a string
- The column to apply the function onto must also be specified, as well as the function to apply

In [36]:
```
country_dest_sum = df.groupby("country destination")\
                    ["export_val"].sum().reset_index()
country_dest_sum.head()
```

Out[36]:

	country destination	export_val
0	AFG	2971037.11
1	AGO	5580441.52
2	ALB	5569879.59
3	AND	1255339.40
4	ARE	26415443.25

In [7]:
```
country_dest_sum.sort_values(by = "export_val", ascending = False, inplace = True)
country_dest_sum.head()
```

Out[7]:

	country destination	export_val
32	CHN	1.780252e+10
83	JPN	2.546373e+09
101	MEX	1.431131e+09
24	BRA	1.331837e+09
75	IND	1.180218e+09

In [8]:
```
countries = pd.read_csv("country names - Sheet1.csv")
countries.head()
```

Out[8]:

	id	id_3char	name
0	naabw	abw	Aruba
1	asafg	afg	Afghanistan
2	afago	ago	Angola
3	naaia	aia	Anguilla
4	eualb	alb	Albania

In [9]:
```
countries["id_3char"] = countries["id_3char"].str.upper()
```

In [10]:
```
countries.head()
```

Out[10]:

	id	id_3char	name
0	naabw	ABW	Aruba
1	asafg	AFG	Afghanistan
2	afago	AGO	Angola
3	naaia	AIA	Anguilla
4	eualb	ALB	Albania

In [11]:
```
countries.columns = ["id", "code", "Name"]
```

In [12]:
```
countries.head()
```

Out[12]:

	id	code	Name
0	naabw	ABW	Aruba
1	asafg	AFG	Afghanistan
2	afago	AGO	Angola
3	naaia	AIA	Anguilla
4	eualb	ALB	Albania

merge()

- Merge two DataFrames along common columns
- Must be provided the DataFrame to merge with, as well as the names of the common columns
- Will merge and map rows where the values in both DataFrames are equal

In [13]:
```
df_merged = df.merge(countries, left_on = "country destination",
                     right_on = "code")
```

In [14]:
```
df_merged.head()
```

Out[14]:

	year	country origin	country destination	export_val	id	code	Name
0	1995	Vietnam	BFA	67177.77	afbfa	BFA	Burkina Faso
1	1996	Vietnam	BFA	141525.02	afbfa	BFA	Burkina Faso
2	1997	Vietnam	BFA	218335.84	afbfa	BFA	Burkina Faso
3	1998	Vietnam	BFA	1498090.16	afbfa	BFA	Burkina Faso
4	1999	Vietnam	BFA	384014.99	afbfa	BFA	Burkina Faso

In [15]:
```
df_merged.drop(["id", "code"], 1, inplace = True)
```

In [16]:
```
df_merged.head()
```

Out[16]:

	year	country origin	country destination	export_val	Name
0	1995	Vietnam	BFA	67177.77	Burkina Faso
1	1996	Vietnam	BFA	141525.02	Burkina Faso
2	1997	Vietnam	BFA	218335.84	Burkina Faso
3	1998	Vietnam	BFA	1498090.16	Burkina Faso
4	1999	Vietnam	BFA	384014.99	Burkina Faso

In [17]:
```
#1. Downloading, Installing and Starting Python SciPy

# Check the versions of libraries
# scipy
import scipy

# numpy
import numpy

# scikit-learn
import sklearn

#2. Load The Data

#2.1 Import  Libraries

import pandas as pd
from pandas.plotting import scatter_matrix
import matplotlib.pyplot as plt

from sklearn import model_selection

from sklearn.metrics import classification_report
from sklearn.metrics import confusion_matrix
from sklearn.metrics import accuracy_score

from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.discriminant_analysis import LinearDiscriminantAnalysis
from sklearn.naive_bayes import GaussianNB
from sklearn.svm import SVC

from sklearn import datasets

from IPython.display import display

import warnings
warnings.simplefilter(action='ignore', category=FutureWarning)
from sklearn.exceptions import DataConversionWarning
```

In [18]:
```
#2.2 Load Dataset
dataset = datasets.load_iris()
feature_names = dataset.feature_names
iris_data = pd.DataFrame(data=dataset.data, columns=feature_names)
target = pd.DataFrame(data=dataset.target, columns=['class'])

display(dataset)
```

```
{'data': 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],
```

In [19]:
```
#3. Summarize The Dataset

#3.1 Dimensions of Dataset

print(iris_data.shape)
```

```
(150, 4)
```

In [20]:
```
#3.2 Peek at the Data

print(iris_data.head(20))
```

```
    sepal length (cm)  sepal width (cm)  petal length (cm)  petal width (cm)
0                 5.1               3.5                1.4               0.2
1                 4.9               3.0                1.4               0.2
2                 4.7               3.2                1.3               0.2
3                 4.6               3.1                1.5               0.2
4                 5.0               3.6                1.4               0.2
5                 5.4               3.9                1.7               0.4
6                 4.6               3.4                1.4               0.3
7                 5.0               3.4                1.5               0.2
8                 4.4               2.9                1.4               0.2
9                 4.9               3.1                1.5               0.1
10                5.4               3.7                1.5               0.2
11                4.8               3.4                1.6               0.2
12                4.8               3.0                1.4               0.1
13                4.3               3.0                1.1               0.1
14                5.8               4.0                1.2               0.2
15                5.7               4.4                1.5               0.4
16                5.4               3.9                1.3               0.4
17                5.1               3.5                1.4               0.3
18                5.7               3.8                1.7               0.3
19                5.1               3.8                1.5               0.3
```

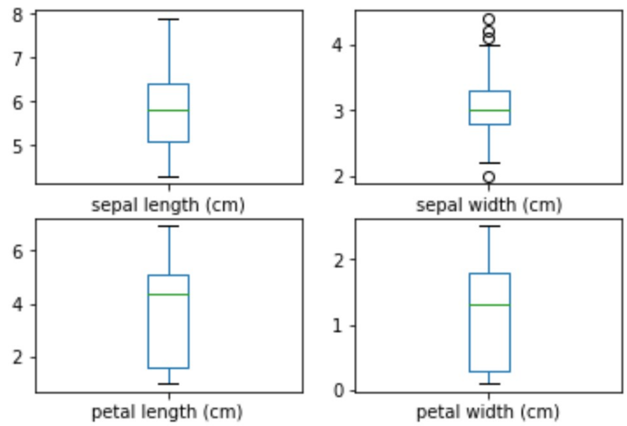
In [21]:
```
#3.3 Statistical Summary

print(iris_data.describe())
```

```
       sepal length (cm)  sepal width (cm)  petal length (cm)  \
count         150.000000        150.000000         150.000000
mean            5.843333          3.057333           3.758000
std             0.828066          0.435866           1.765298
min             4.300000          2.000000           1.000000
25%             5.100000          2.800000           1.600000
50%             5.800000          3.000000           4.350000
75%             6.400000          3.300000           5.100000
max             7.900000          4.400000           6.900000

       petal width (cm)
count        150.000000
mean           1.199333
std            0.762238
min            0.100000
25%            0.300000
50%            1.300000
75%            1.800000
max            2.500000
```

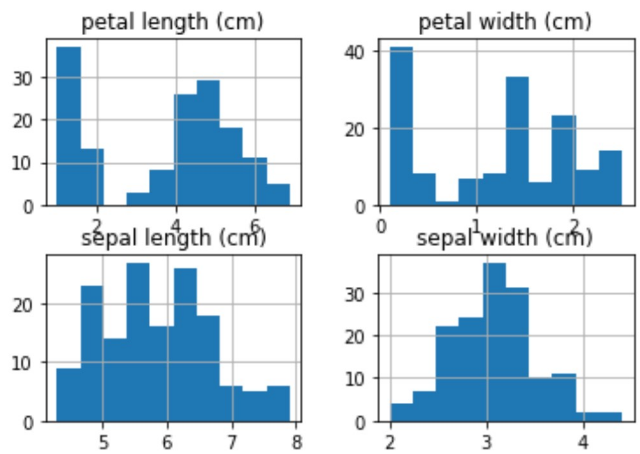
In [22]:
```
#3.4 Class Distribution

print(target.groupby('class').size())
```

```
class
0    50
1    50
2    50
dtype: int64
```

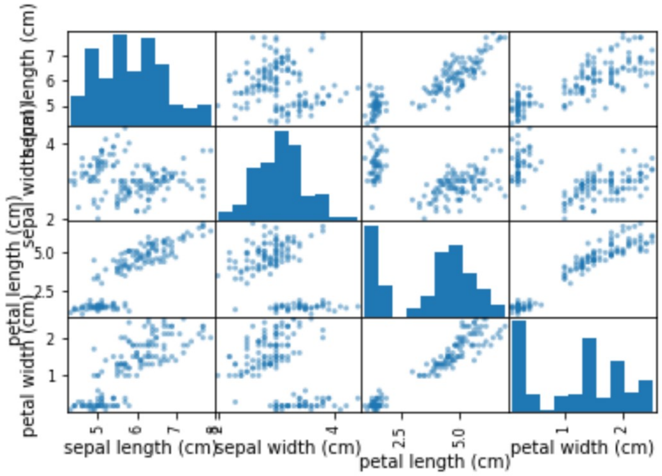
In [23]:
```
#4. Data Visualization

#4.1 Univariate Plots

# box and whisker plots
iris_data.plot(kind='box', subplots=True, layout=(2,2),
               sharex=False, sharey=False)
plt.show()
```



In [24]:
```
# histograms
iris_data.hist()
plt.show()
```



In [25]:
```
#4.2 Multivariate Plots

# scatter plot matrix
scatter_matrix(iris_data)
plt.show()
```



In [26]:
```
#5. Evaluate Some Algorithms

#5.1 Create a Validation Dataset

# Split-out validation dataset
X = iris_data[feature_names].values
Y = target.values
validation_size = 0.20
seed = 7

X_train, X_validation, Y_train, Y_validation = model_selection.train_test_split(
    X, Y, test_size=validation_size, random_state=seed)



X_validation, X_test, Y_validation, Y_test = model_selection.train_test_split(
    X_validation, Y_validation, test_size=0.5, random_state=seed)


print(X_test.shape)
```

```
(15, 4)
```

In [27]:
```
models = []
scores = []
models.append(('LR', LogisticRegression()))
models.append(('LDA', LinearDiscriminantAnalysis()))
models.append(('KNN', KNeighborsClassifier()))
models.append(('CART', DecisionTreeClassifier()))
models.append(('NB', GaussianNB()))
models.append(('SVM', SVC()))

for name, model in models:
    model.fit(X_train, Y_train)
    scores.append((name, model.score(X_validation, Y_validation)))

print(scores)
```

```
[('LR', 0.8), ('LDA', 0.9333333333333333), ('KNN', 0.8), ('CART', 0.8), ('NB', 0.6
666666666666666), ('SVM', 0.8666666666666667)]
```

In [28]:
```
LDA = LinearDiscriminantAnalysis()
LDA.fit(X_train, Y_train)
LDA.score(X_test, Y_test)
```

Out[28]:
```
1.0
```

In [29]:
```
display(X_test)
display(Y_test)
```

```
array([[5. , 3.5, 1.3, 0.3],
       [6.4, 3.1, 5.5, 1.8],
       [5.4, 3. , 4.5, 1.5],
       [6.4, 3.2, 4.5, 1.5],
       [6. , 3.4, 4.5, 1.6],
       [4.5, 2.3, 1.3, 0.3],
       [5.1, 3.8, 1.6, 0.2],
       [7.2, 3. , 5.8, 1.6],
       [5.5, 2.4, 3.8, 1.1],
       [6.7, 3.1, 5.6, 2.4],
       [5.2, 4.1, 1.5, 0.1],
       [7.2, 3.6, 6.1, 2.5],
       [6.7, 2.5, 5.8, 1.8],
       [5.9, 3. , 5.1, 1.8],
       [5.8, 2.7, 5.1, 1.9]])
```

```
array([[0],
       [2],
       [1],
       [1],
       [1],
       [0],
       [0],
       [2],
       [1],
       [2],
       [0],
       [2],
       [2],
       [2],
       [2]])
```

In [30]:
```
LDA.predict([[5.4, 3. , 4.5, 1.5]])
```

Out[30]:
```
array([1])
```

In [31]:
```
for point in X_test:
    print(LDA.predict([point]))
```

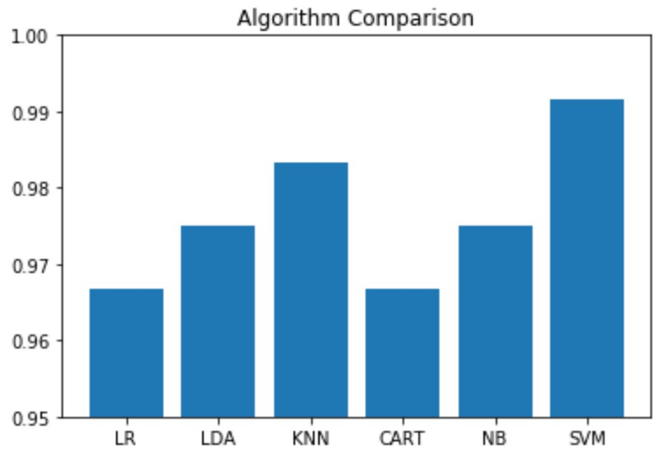
```
[0]
[2]
[1]
[1]
[1]
[0]
[0]
[2]
[1]
[2]
[0]
[2]
[2]
[2]
[2]
```

In [32]:
```
# evaluate each model in turn
results = []
results_mean = []
names = []
scoring = "accuracy"

for name, model in models:
    kfold = model_selection.KFold(n_splits=10, random_state=seed)
    cv_results = model_selection.cross_val_score(model, X_train, Y_train,
                                                 cv=kfold, scoring=scoring)
    results.append(cv_results)
    results_mean.append(cv_results.mean())
    names.append(name)
    msg = f"{name}, {cv_results.mean()}, {cv_results.std()}"
    print(msg)
```

```
LR, 0.9666666666666666, 0.04082482904638632
LDA, 0.975, 0.03818813079129868
KNN, 0.9833333333333332, 0.03333333333333335
CART, 0.9666666666666666, 0.04082482904638632
NB, 0.975, 0.053359368645273735
SVM, 0.9916666666666666, 0.025000000000000012
```

In [33]:
```
#5.4 Select Best Model

# Compare Algorithms
fig = plt.figure()
plt.title('Algorithm Comparison')
ax = fig.add_subplot(111)
plt.bar(names,results_mean)
plt.ylim([0.95,1])
ax.set_xticklabels(names)
plt.show()
```

```
C:\Users\MAIN\Anaconda3\lib\site-packages\matplotlib\figure.py:98: MatplotlibDepre
cationWarning:
Adding an axes using the same arguments as a previous axes currently reuses the ea
rlier instance.  In a future version, a new instance will always be created and re
turned.  Meanwhile, this warning can be suppressed, and the future behavior ensure
d, by passing a unique label to each axes instance.
  "Adding an axes using the same arguments as a previous axes "
```



In [ ]: