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 [1]:
```
#Import Pandas to your workspace
import pandas as pd
```

In [2]:
```
#Read the "features.csv" file and store it into a variable
features = pd.read_csv("data/features.csv")
```

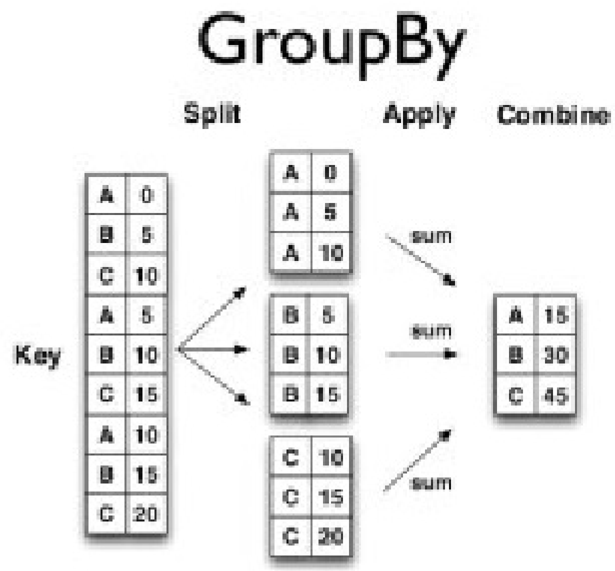
In [3]:
```
#Display the first few rows of the DataFrame
features.head()
```

Out[3]:

	Store	Date	Temp	Fuel_Price	CPI	Unemployment	IsHoliday	Year	Month
0	1	2/5/2010	42.31	2.572	211.096358	8.106	False	2010	2
1	1	2/12/2010	38.51	2.548	211.242170	8.106	True	2010	2
2	1	2/19/2010	39.93	2.514	211.289143	8.106	False	2010	2
3	1	2/26/2010	46.63	2.561	211.319643	8.106	False	2010	2
4	1	3/5/2010	46.50	2.625	211.350143	8.106	False	2010	3

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 [4]:
```
#Apply groupby to the Year and Month columns, calculating the mean of the CIP
year_CPI = features.groupby("Year")["CPI"].sum().reset_index()
year_CPI.head()
```

Out[4]:

	Year	CPI
0	2010	363099.848068
1	2011	401416.975385
2	2012	411176.892813
3	2013	135870.737569

In [5]:
```
#Groupby returns a DataFrame, so we have access to all the same methods we saw earlier
year_CPI.sort_values(by = "Year", ascending = False, inplace = True)
year_CPI.head()
```

Out[5]:

	Year	CPI
3	2013	135870.737569
2	2012	411176.892813
1	2011	401416.975385
0	2010	363099.848068

In [6]:
```
#Read the "stores.csv" file and store it into a variable called stores
stores = pd.read_csv("data/stores.csv")
```

In [7]:
```
#Display the first few rows of the stores DataFrame
stores.head()
```

Out[7]:

	Store	Type	Size
0	1	A	151315
1	2	A	202307
2	3	B	37392
3	4	A	205863
4	5	B	34875

In [8]:
```
#Redefine the Type column to lower case
stores["Type"] = stores["Type"].str.lower()
```

In [9]:
```
#Display the first few rows to verify changes
stores.head()
```

Out[9]:

	Store	Type	Size
0	1	a	151315
1	2	a	202307
2	3	b	37392
3	4	a	205863
4	5	b	34875

In [10]:
```
#Rename the Size column to 'Area'
stores.rename(columns={'Size': 'Area'}, inplace=True)
```

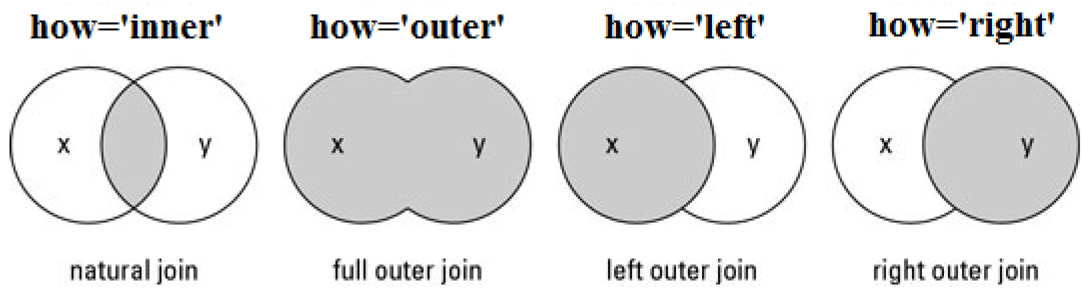
In [11]:
```
stores.head()
```

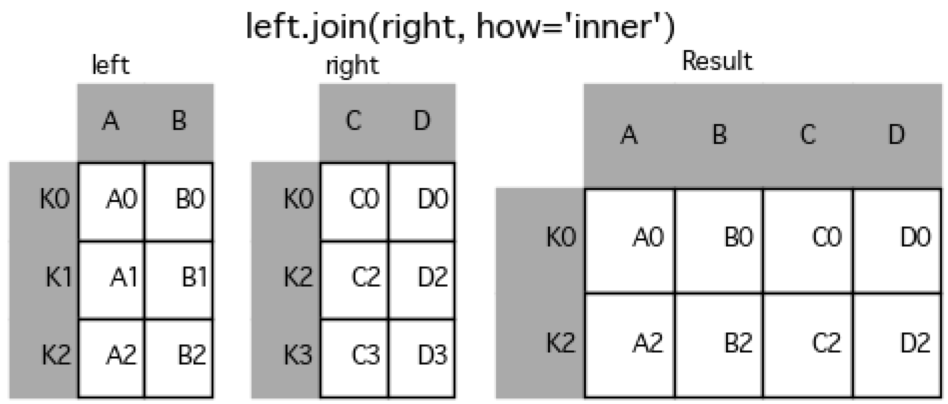
Out[11]:

	Store	Type	Area
0	1	a	151315
1	2	a	202307
2	3	b	37392
3	4	a	205863
4	5	b	34875

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





left.join(right, how='inner')

left

	A	B
K0	A0	B0
K1	A1	B1
K2	A2	B2

right

	C	D
K0	C0	D0
K2	C2	D2
K3	C3	D3

Result

	A	B	C	D
K0	A0	B0	C0	D0
K2	A2	B2	C2	D2

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

Out[12]:

	Store	Date	Temp	Fuel_Price	CPI	Unemployment	IsHoliday	Year	Month
0	1	2/5/2010	42.31	2.572	211.096358	8.106	False	2010	2
1	1	2/12/2010	38.51	2.548	211.242170	8.106	True	2010	2
2	1	2/19/2010	39.93	2.514	211.289143	8.106	False	2010	2
3	1	2/26/2010	46.63	2.561	211.319643	8.106	False	2010	2
4	1	3/5/2010	46.50	2.625	211.350143	8.106	False	2010	3

In [13]:
```
stores.head()
```

Out[13]:

	Store	Type	Area
0	1	a	151315
1	2	a	202307
2	3	b	37392
3	4	a	205863
4	5	b	34875

In [14]:
```
#Merge the stores DataFrame into the features DataFrame on the Stores column
df_merged = features.merge(stores, on = "Store")
```

In [15]:
```
#Display a few rows to verify changes
df_merged.head()
```

Out[15]:

	Store	Date	Temp	Fuel_Price	CPI	Unemployment	IsHoliday	Year	Month	Type	Area
0	1	2/5/2010	42.31	2.572	211.096358	8.106	False	2010	2	a	151315
1	1	2/12/2010	38.51	2.548	211.242170	8.106	True	2010	2	a	151315
2	1	2/19/2010	39.93	2.514	211.289143	8.106	False	2010	2	a	151315
3	1	2/26/2010	46.63	2.561	211.319643	8.106	False	2010	2	a	151315
4	1	3/5/2010	46.50	2.625	211.350143	8.106	False	2010	3	a	151315

In [16]:
```
#Export the final version of our DataFrame to a .csv file named "final_data.csv"
df_merged.to_csv('final_data.csv', index=False)
```

In [17]:
```
#Import libraries we will need

# numpy
import numpy

# scikit-learn
import sklearn

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

from sklearn import model_selection

from sklearn.tree import DecisionTreeClassifier
from sklearn.tree import plot_tree

from sklearn import datasets

from IPython.display import display

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

In [18]:
```
#2.2 Load Dataset
dataset = datasets.load_iris()
feature_names = dataset.feature_names
target_names = dataset.target_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],
```

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
```

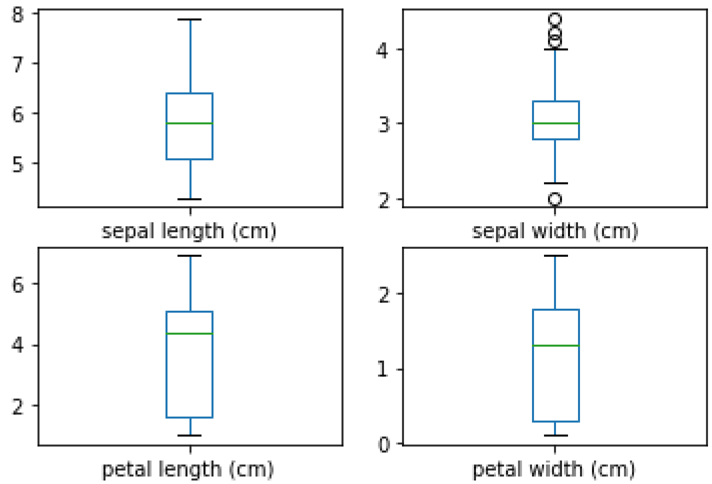
In [21]:
```
#3.3 Statistical Summary

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
```

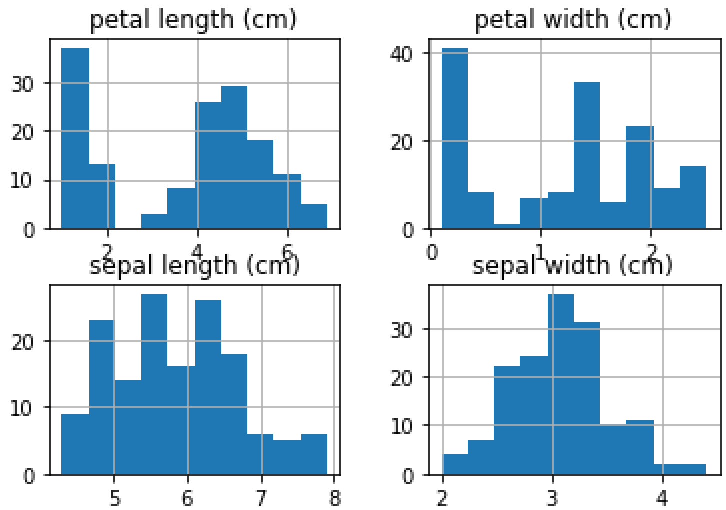
In [22]:
```
#3.4 Class Distribution
#value_counts function to see number of each class
target['class'].value_counts()
```

Out[22]:
```
2    50
1    50
0    50
Name: class, dtype: int64
```

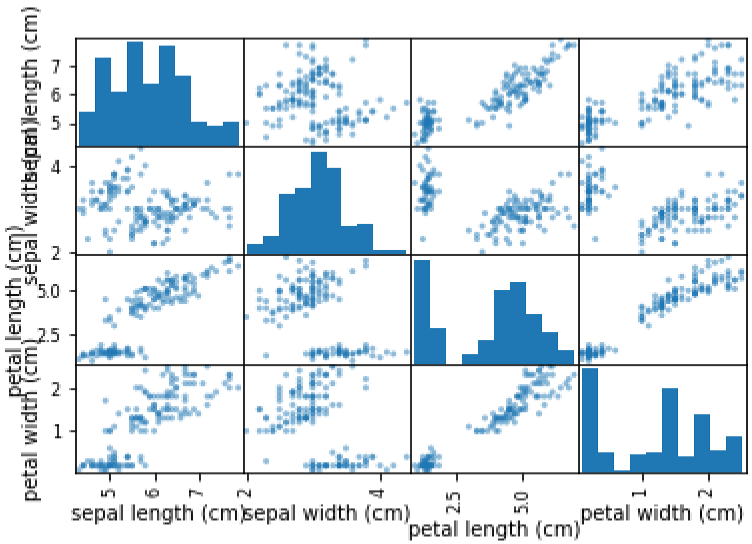
In [23]:
```
#4. Data Visualization
#Using the plot() function, we can make boxplots by simply specifying the kind of plot

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



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

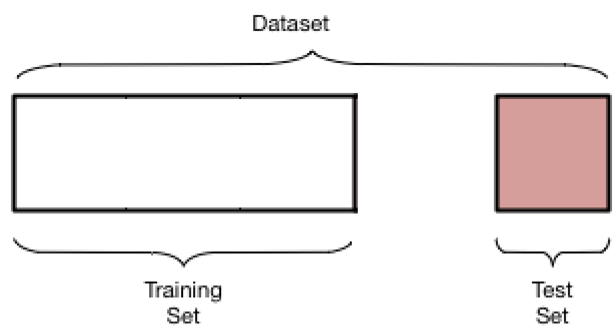


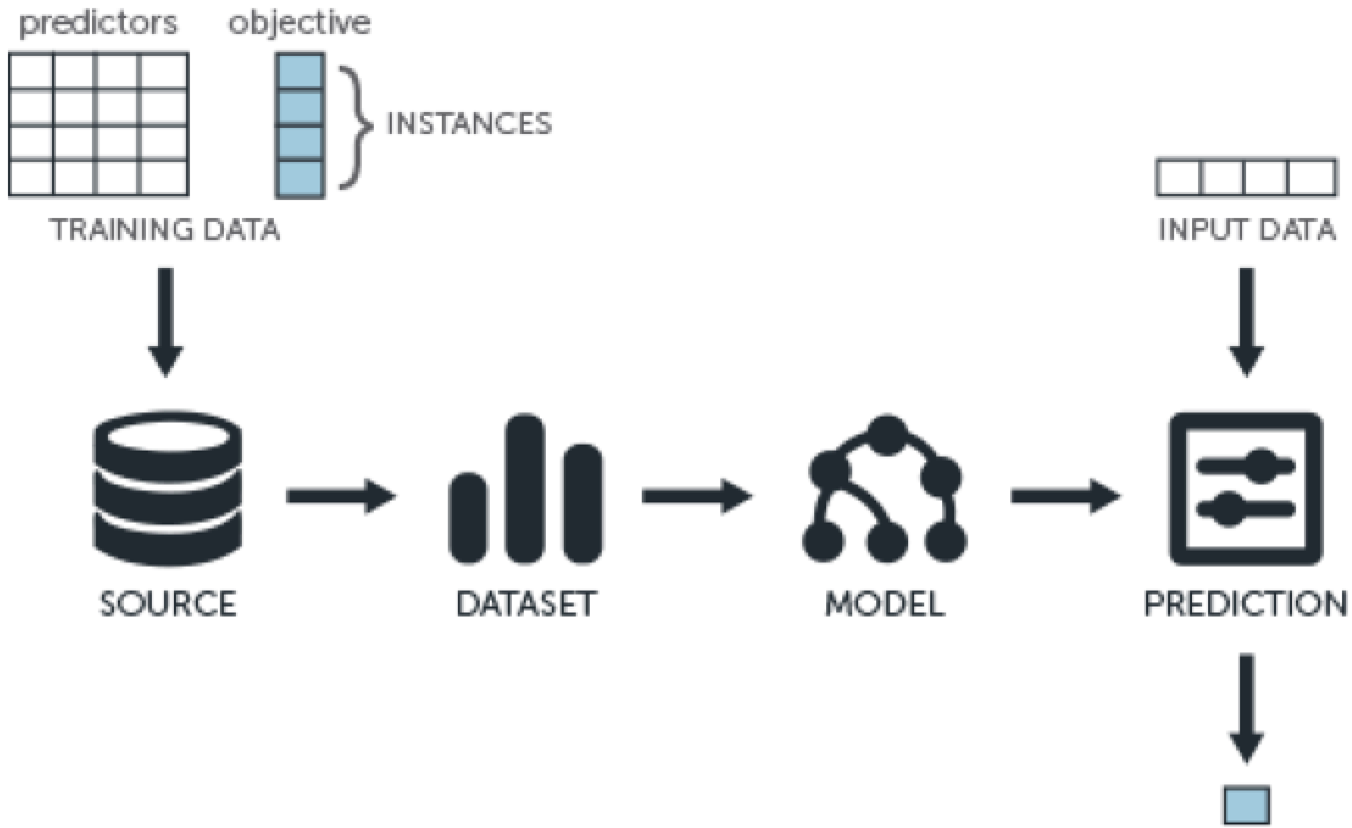
In [25]:
```
#4.2 Multivariate Plots

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



In [26]:
```
#Create the Train and Test set



#We use train_test_split to shuffle and divide our data into our train and test sets
X = iris_data[feature_names].values
Y = target.values
validation_size = 0.20
seed = 7

X_train, X_test, Y_train, Y_test = model_selection.train_test_split(X,
                                                                    Y,
                                                                    test_size=validation_size,
                                                                    random_state=seed)


#Verify our split
print(X_test.shape)
```

```
(30, 4)
```





In [27]:
```
#Create an instance of our algorithm (model)
dt = DecisionTreeClassifier(max_depth=3)
```

In [28]:
```
#Feed our training data to our model
dt.fit(X_train, Y_train)
```

Out[28]:
```
DecisionTreeClassifier(ccp_alpha=0.0, class_weight=None, criterion='gini',
                       max_depth=3, max_features=None, max_leaf_nodes=None,
                       min_impurity_decrease=0.0, min_impurity_split=None,
                       min_samples_leaf=1, min_samples_split=2,
                       min_weight_fraction_leaf=0.0, presort='deprecated',
                       random_state=None, splitter='best')
```

In [29]:
```
#Test our model on the test set
dt.score(X_test, Y_test)
```

Out[29]:
```
0.9
```

In [30]:
```
display(X_test)
display(Y_test)
```

```
array([[5.9, 3. , 5.1, 1.8],
       [5.4, 3. , 4.5, 1.5],
       [5. , 3.5, 1.3, 0.3],
       [5.6, 3. , 4.5, 1.5],
       [4.9, 2.5, 4.5, 1.7],
       [4.5, 2.3, 1.3, 0.3],
       [6.9, 3.1, 4.9, 1.5],
       [5.6, 2.7, 4.2, 1.3],
       [4.8, 3.4, 1.6, 0.2],
       [6.4, 3.2, 4.5, 1.5],
       [6.7, 3. , 5. , 1.7],
       [6. , 3.4, 4.5, 1.6],
       [5.2, 4.1, 1.5, 0.1],
       [7.2, 3.6, 6.1, 2.5],
       [5.2, 3.4, 1.4, 0.2],
       [5.9, 3.2, 4.8, 1.8],
       [6.7, 2.5, 5.8, 1.8],
       [6.4, 3.1, 5.5, 1.8],
       [5.1, 3.8, 1.6, 0.2],
       [4.9, 3.6, 1.4, 0.1],
       [5.8, 2.7, 3.9, 1.2],
       [6.9, 3.2, 5.7, 2.3],
       [6.1, 2.9, 4.7, 1.4],
       [6. , 2.2, 5. , 1.5],
       [7.2, 3. , 5.8, 1.6],
       [6. , 3. , 4.8, 1.8],
       [6.2, 2.9, 4.3, 1.3],
       [5.5, 2.4, 3.8, 1.1],
       [5.8, 2.7, 5.1, 1.9],
       [6.7, 3.1, 5.6, 2.4]])
```

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

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

In [31]:
```
#Use predict() to obtain prediction from our model on data points
dt.predict([[5.4, 3. , 4.5, 1.5]])
```

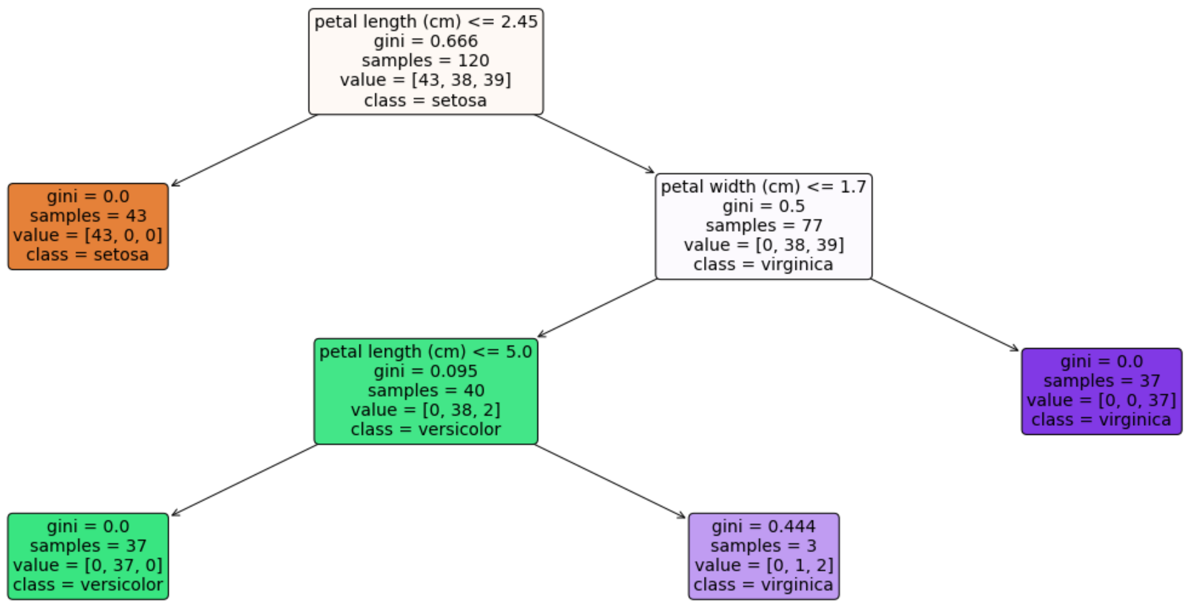
Out[31]:
```
array([1])
```

In [32]:
```
for point in X_test:

    prediction = dt.predict([point])

    print(f"Class value of {prediction}")
```

```
Class value of [2]
Class value of [1]
Class value of [0]
Class value of [1]
Class value of [2]
Class value of [0]
Class value of [1]
Class value of [1]
Class value of [0]
Class value of [1]
Class value of [2]
Class value of [1]
Class value of [0]
Class value of [2]
Class value of [0]
Class value of [2]
Class value of [2]
Class value of [2]
Class value of [0]
Class value of [0]
Class value of [1]
Class value of [2]
Class value of [1]
Class value of [1]
Class value of [2]
Class value of [2]
Class value of [1]
Class value of [1]
Class value of [2]
Class value of [2]
```

In [33]:

```
#Visualize our tree
#Value is the number of samples per split
#The left branch is True and the right branch is False
plt.figure(figsize=(25,10))
a = plot_tree(dt,
              feature_names=feature_names,
              class_names=target_names,
              filled=True,
              rounded=True,
              fontsize=14)
```



In [ ]: