1. Install and set up Python and essential libraries like NumPy and pandas.

Installing Python:

1. **Download Python**: Go to the official Python website download the latest version suitable for your operating system (Windows, macOS, or Linux).
2. **Install Python**:
   - For Windows: Run the downloaded installer and make sure to check the box that says "Add Python x.x to PATH" during installation.
   - For Linux: Python might already be installed. If not, use your package manager to install it (e.g., **sudo apt-get install python3** for Ubuntu).
3. **Verify Installation**:
   - Open a command prompt (Windows) or terminal (macOS/Linux).
   - Type **python --version** or **python3 --version** and press Enter. You should see the installed Python version.

Installing NumPy and pandas:

1. **Using pip**:
   - Pip is Python's package manager. It usually comes installed with Python. Open a terminal/command prompt.
2. **Install NumPy**:
   - Type **pip install numpy** and press Enter. This command will download and install NumPy.
3. **Install pandas**:
   - Type **pip install pandas** and press Enter. This will download and install pandas.
4. **Verify installations**:
   - Open a Python interpreter by typing **python** or **python3** in the terminal.
   - Inside the interpreter, import NumPy and pandas:

```
import numpy
import pandas
```

If no errors occur, both libraries are installed correctly.

2. Introduce scikit-learn as a machine learning library.

Scikit-learn is a widely-used Python library that provides a comprehensive suite of tools and functionalities for machine learning tasks.

1. **Versatility**: Scikit-learn offers a wide range of tools and functionalities for various machine learning tasks, including but not limited to:
   - **Supervised Learning**: Classification, Regression
   - **Unsupervised Learning**: Clustering, Dimensionality Reduction
   - **Model Selection and Evaluation**: Cross-validation, Hyperparameter Tuning
   - **Preprocessing**: Data cleaning, Feature Engineering
2. **Consistent Interface**: It provides a consistent and user-friendly API, making it easy to experiment with different algorithms and techniques without needing to learn new syntax for each.
3. **Integration with Other Libraries**: Scikit-learn seamlessly integrates with other Python libraries like NumPy, pandas, and Matplotlib, allowing smooth data manipulation, preprocessing, and visualization.
4. **Ease of Learning**: Its well-documented and straightforward interface makes it suitable for both beginners and experienced machine learning practitioners. It's often recommended for educational purposes due to its simplicity.
5. **Performance and Scalability**: While focusing on simplicity, scikit-learn also emphasizes performance. It's optimized for efficiency and scalability, making it suitable for handling large datasets and complex models.
6. **Community and Development**: As an open-source project, scikit-learn benefits from a vibrant community of developers and contributors. Regular updates, bug fixes, and enhancements ensure it stays relevant and up-to-date with the latest advancements in machine learning.
7. **Application in Industry and Academia**: Scikit-learn's robustness and ease of use have made it a go-to choose in various domains, including finance, healthcare, natural language processing, and more. It's widely used in research and production environments.

Example:

```
from sklearn.datasets import load_iris
from sklearn.model_selection import train_test_split
from sklearn.neighbors import KNeighborsClassifier
from sklearn import metrics
# Load Iris dataset (a popular example dataset in machine learning)
iris = load_iris()
X = iris.data  # Features
y = iris.target  # Target variable
# Split the dataset into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3)
# Initialize the model (K-Nearest Neighbors Classifier in this case)
model = KNeighborsClassifier(n_neighbors=3)
# Train the model
model.fit(X_train, y_train)
# Make predictions
predictions = model.predict(X_test)
# Evaluate model accuracy
accuracy = metrics.accuracy_score(y_test, predictions)
print(f"Accuracy: {accuracy}")
```

OUTPUT:

Accuracy: 0.9333333333333333

3. Install and set up scikit-learn and other necessary tools. Procedure

Install scikit-learn and other libraries:

1. **Install NumPy and pandas** (if not installed):
   - Open a terminal/command prompt.
   - Type **pip install numpy pandas** and press Enter. This will install NumPy and pandas, essential libraries for data manipulation and computation.
2. **Install scikit-learn**:
   - In the same terminal/command prompt, type **pip install scikit-learn** and press Enter. This will install scikit-learn, the machine learning library.

Test the installations:

- Open a Python interpreter by typing **python** or **python3** in the terminal.
- Import scikit-learn: **import sklearn**
- If there are no errors, scikit-learn is successfully installed and ready for use.

Simple Example

```
from sklearn import datasets
from sklearn.model_selection import train_test_split
from sklearn.neighbors import KNeighborsClassifier
# Load an example dataset (iris dataset)
iris = datasets.load_iris()
X_train, X_test, y_train, y_test = train_test_split(iris.data, iris.target,
test_size=0.3)
# Initialize and train a classifier (K-Nearest Neighbors)
clf = KNeighborsClassifier(n_neighbors=3)
clf.fit(X_train, y_train)
# Evaluate the classifier
accuracy = clf.score(X_test, y_test)
print(f"Accuracy: {accuracy}")
```

OUTPUT:
Accuracy: 0.9777777777777777

4. Write a program to Load and explore the dataset of .CVS and excel files using pandas.

Load and Explore CSV File:

```
import pandas as pd
# Load CSV file
csv_data = pd.read_csv('train.csv')
# Display the first few rows of the CSV file
print("First few rows of CSV file:")
print(csv_data.head())
# Summary statistics
print("\nSummary statistics of CSV file:")
print(csv_data.describe())
# Information about columns
print("\nInformation about columns in CSV file:")
print(csv_data.info())
```

Output:

```
First few rows of CSV file:
   PassengerId  Survived  Pclass  \
0            1         0       3
1            2         1       1
2            3         1       3
3            4         1       1
4            5         0       3

                                                Name     Sex   Age  SibSp  \
0                            Braund, Mr. Owen Harris    male  22.0      1
1  Cumings, Mrs. John Bradley (Florence Briggs Th...  female  38.0      1
2                             Heikkinen, Miss. Laina  female  26.0      0
3       Futrelle, Mrs. Jacques Heath (Lily May Peel)  female  35.0      1
4                           Allen, Mr. William Henry    male  35.0      0

   Parch            Ticket     Fare Cabin Embarked
0      0         A/5 21171   7.2500   NaN        S
1      0          PC 17599  71.2833   C85        C
2      0  STON/O2. 3101282   7.9250   NaN        S
3      0            113803  53.1000  C123        S
4      0            373450   8.0500   NaN        S
```

Summary statistics of CSV file:

```
       PassengerId    Survived      Pclass         Age       SibSp  \
count   891.000000  891.000000  891.000000  714.000000  891.000000
mean    446.000000    0.383838    2.308642   29.699118    0.523008
std     257.353842    0.486592    0.836071   14.526497    1.102743
min       1.000000    0.000000    1.000000    0.420000    0.000000
25%     223.500000    0.000000    2.000000   20.125000    0.000000
50%     446.000000    0.000000    3.000000   28.000000    0.000000
75%     668.500000    1.000000    3.000000   38.000000    1.000000
max     891.000000    1.000000    3.000000   80.000000    8.000000

            Parch        Fare
count  891.000000  891.000000
mean     0.381594   32.204208
std      0.806057   49.693429
min      0.000000    0.000000
25%      0.000000    7.910400
50%      0.000000   14.454200
75%      0.000000   31.000000
max      6.000000  512.329200
```

Information about columns in CSV file:

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 891 entries, 0 to 890
Data columns (total 12 columns):
 #   Column       Non-Null Count  Dtype
---  ------       --------------  -----
 0   PassengerId  891 non-null    int64
 1   Survived     891 non-null    int64
 2   Pclass       891 non-null    int64
 3   Name         891 non-null    object
 4   Sex          891 non-null    object
 5   Age          714 non-null    float64
 6   SibSp        891 non-null    int64
 7   Parch        891 non-null    int64
 8   Ticket       891 non-null    object
 9   Fare         891 non-null    float64
```

```
 10  Cabin        204 non-null    object
 11  Embarked     889 non-null    object
dtypes: float64(2), int64(5), object(5)
memory usage: 83.7+ KB
None
```

Load and Explore Excel File:

```
import pandas as pd

# Load Excel file

excel_data = pd.read_excel('Sample - Superstore.xlsx', sheet_name='Orders')

# Display the first few rows of the Excel file

print("First few rows of Excel file:")

print(excel_data.head())

# Summary statistics

print("\nSummary statistics of Excel file:")

print(excel_data.describe())

# Information about columns

print("\nInformation about columns in Excel file:")

print(excel_data.info())
```

Output:

```
First few rows of Excel file:
   Row ID        Order ID Order Date  Ship Date       Ship Mode Customer ID  \
0       1  CA-2016-152156 2016-11-08 2016-11-11    Second Class    CG-
12520
1       2  CA-2016-152156 2016-11-08 2016-11-11    Second Class    CG-
12520
2       3  CA-2016-138688 2016-06-12 2016-06-16    Second Class    DV-
13045
```

```
3       4  US-2015-108966 2015-10-11 2015-10-18  Standard Class    SO-
20335
4       5  US-2015-108966 2015-10-11 2015-10-18  Standard Class    SO-
20335

     Customer Name     Segment        Country           City  ...  \
0      Claire Gute    Consumer  United States       Henderson  ...
1      Claire Gute    Consumer  United States       Henderson  ...
2  Darrin Van Huff   Corporate  United States     Los Angeles  ...
3   Sean O'Donnell    Consumer  United States  Fort Lauderdale  ...
4   Sean O'Donnell    Consumer  United States  Fort Lauderdale  ...

  Postal Code  Region       Product ID         Category Sub-Category  \
0       42420   South  FUR-BO-10001798        Furniture    Bookcases
1       42420   South  FUR-CH-10000454        Furniture       Chairs
2       90036    West  OFF-LA-10000240  Office Supplies       Labels
3       33311   South  FUR-TA-10000577        Furniture       Tables
4       33311   South  OFF-ST-10000760  Office Supplies      Storage

                                          Product Name     Sales  Quantity  \
0                Bush Somerset Collection Bookcase  261.9600         2
1  Hon Deluxe Fabric Upholstered Stacking Chairs,...  731.9400         3
2  Self-Adhesive Address Labels for Typewriters b...   14.6200         2
3      Bretford CR4500 Series Slim Rectangular Table  957.5775         5
4                   Eldon Fold 'N Roll Cart System   22.3680         2

   Discount    Profit
0      0.00   41.9136
1      0.00  219.5820
2      0.00    6.8714
3      0.45 -383.0310
4      0.20    2.5164

[5 rows x 21 columns]
```

Summary statistics of Excel file:

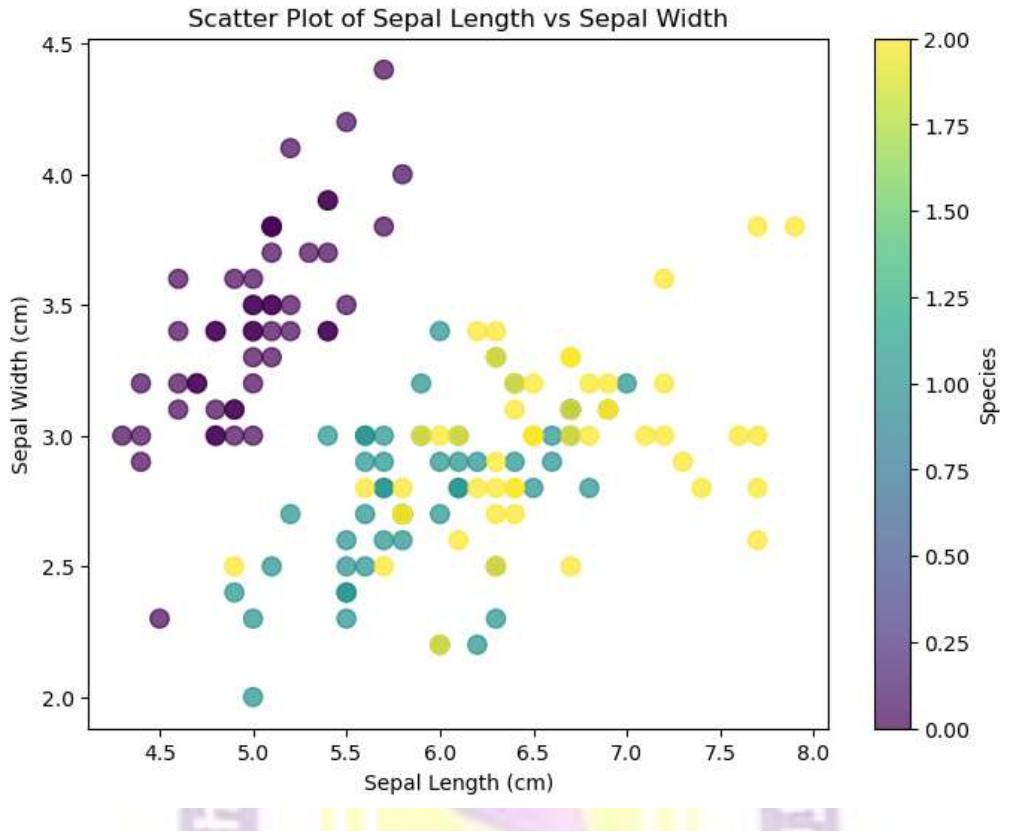
```
          Row ID                Order Date  \
count  9994.000000                    9994
mean   4997.500000  2016-04-30 00:07:12.259355648
min       1.000000         2014-01-03 00:00:00
25%    2499.250000         2015-05-23 00:00:00
50%    4997.500000         2016-06-26 00:00:00
75%    7495.750000         2017-05-14 00:00:00
max    9994.000000         2017-12-30 00:00:00
std    2885.163629                  NaN

                      Ship Date   Postal Code       Sales     Quantity  \
count                      9994   9994.000000   9994.000000  9994.000000
mean   2016-05-03 23:06:58.571142912  55190.379428    229.858001
3.789574
min            2014-01-07 00:00:00   1040.000000     0.444000     1.000000
25%            2015-05-27 00:00:00  23223.000000    17.280000     2.000000
50%            2016-06-29 00:00:00  56430.500000    54.490000     3.000000
75%            2017-05-18 00:00:00  90008.000000   209.940000     5.000000
max            2018-01-05 00:00:00  99301.000000  22638.480000
14.000000
std                    NaN  32063.693350   623.245101     2.225110

         Discount       Profit
count  9994.000000  9994.000000
mean      0.156203    28.656896
min       0.000000 -6599.978000
25%       0.000000     1.728750
50%       0.200000     8.666500
75%       0.200000    29.364000
max       0.800000  8399.976000
std       0.206452   234.260108

Information about columns in Excel file:
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 9994 entries, 0 to 9993
Data columns (total 21 columns):
```

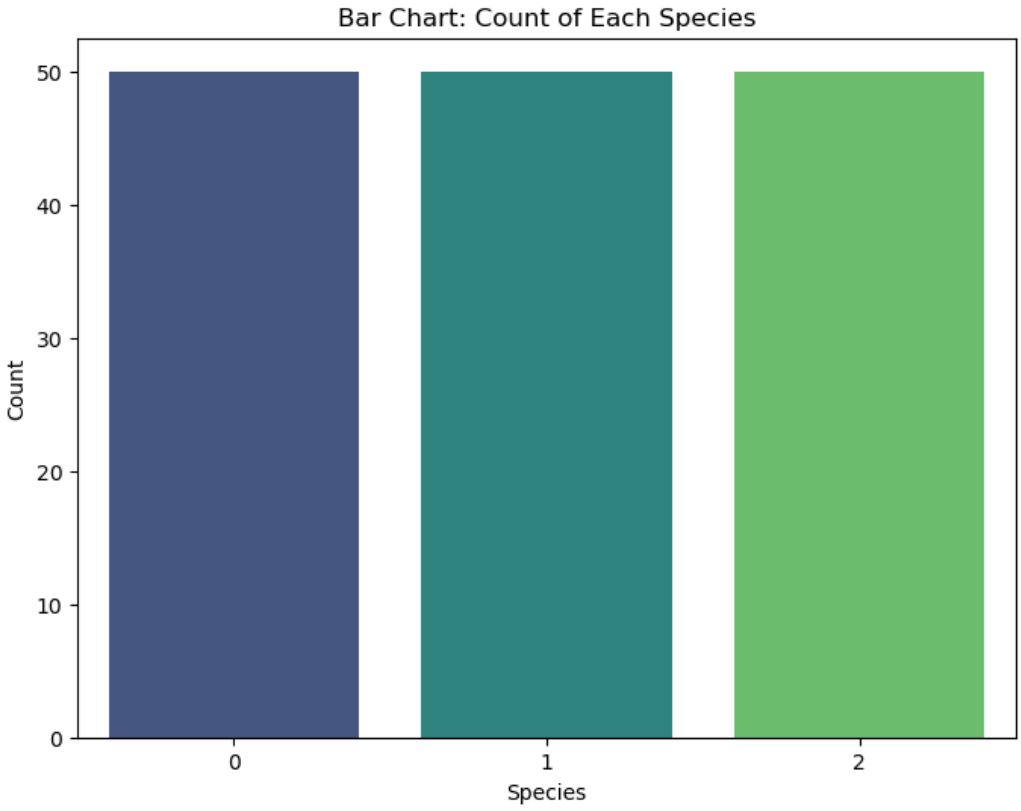
```
 #   Column        Non-Null Count  Dtype
---  ------        --------------  -----
 0   Row ID        9994 non-null   int64
 1   Order ID      9994 non-null   object
 2   Order Date    9994 non-null   datetime64[ns]
 3   Ship Date     9994 non-null   datetime64[ns]
 4   Ship Mode     9994 non-null   object
 5   Customer ID   9994 non-null   object
 6   Customer Name 9994 non-null   object
 7   Segment       9994 non-null   object
 8   Country       9994 non-null   object
 9   City          9994 non-null   object
 10  State         9994 non-null   object
 11  Postal Code   9994 non-null   int64
 12  Region        9994 non-null   object
 13  Product ID    9994 non-null   object
 14  Category      9994 non-null   object
 15  Sub-Category  9994 non-null   object
 16  Product Name  9994 non-null   object
 17  Sales         9994 non-null   float64
 18  Quantity      9994 non-null   int64
 19  Discount      9994 non-null   float64
 20  Profit        9994 non-null   float64
dtypes: datetime64[ns](2), float64(3), int64(3), object(13)
memory usage: 1.6+ MB
None
```

5. Write a program to Visualize the dataset to gain insights using Matplotlib or Seaborn by plotting scatter plots, bar charts.

```
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.datasets import load_iris
import pandas as pd
# Load the Iris dataset
iris = load_iris()
# Convert the dataset to a pandas DataFrame
iris_df = pd.DataFrame(data=iris.data, columns=iris.feature_names)
iris_df['target'] = iris.target
# Scatter plot using Matplotlib
plt.figure(figsize=(8, 6))
plt.scatter(iris_df['sepal length (cm)'], iris_df['sepal width (cm)'],
c=iris_df['target'], cmap='viridis', s=80, alpha=0.7)
plt.xlabel('Sepal Length (cm)')
plt.ylabel('Sepal Width (cm)')
plt.title('Scatter Plot of Sepal Length vs Sepal Width')
plt.colorbar(label='Species')
plt.show()
# Bar chart using Seaborn
plt.figure(figsize=(8, 6))
sns.countplot(x='target', data=iris_df, palette='viridis')
plt.xlabel('Species')
plt.ylabel('Count')
plt.title('Bar Chart: Count of Each Species')
plt.show()
```

Output:


Scatter Plot of Sepal Length vs Sepal Width
Sepal Width (cm)
Sepal Length (cm)
Species
4.5
4.0
3.5
3.0
2.5
2.0
4.5
5.0
5.5
6.0
6.5
7.0
7.5
8.0
2.00
1.75
1.50
1.25
1.00
0.75
0.50
0.25
0.00


Bar Chart: Count of Each Species
Count
Species
50
40
30
20
10
0
0
1
2

6. Write a program to Handle missing data, encode categorical variables, and perform feature scaling.

```
import pandas as pd
from sklearn.impute import SimpleImputer
from sklearn.preprocessing import LabelEncoder, OneHotEncoder,
StandardScaler

# Sample DataFrame with missing values and categorical variables
data = {
   'A': [1, 2, None, 4, 5],
   'B': ['X', None, 'Y', 'Z', 'X'],
   'C': [7, 8, 9, None, 11]
}
df = pd.DataFrame(data)
print("DataSet:\n",df)

# Handling missing values using SimpleImputer from scikit-learn
print("\nHandling missing Values\n")
print(".....\n")
imputer = SimpleImputer(strategy='mean')  # Other strategies: median,
most_frequent, constant
df[['A', 'C']] = imputer.fit_transform(df[['A', 'C']])
print("DataSet after handling Missing Values of A and C Columns:\n",df[['A',
'C']])

# Encoding categorical variables using LabelEncoder and OneHotEncoder
print("\nEncoding\n")
print(".....\n")
label_encoder = LabelEncoder()
df['B'] = df['B'].fillna('Unknown')  # Handle NaNs before label encoding
print("\nDataSet after handling Missing Values of B Before Label
encoding:\n", df['B'])

df['B_encoded'] = label_encoder.fit_transform(df['B'])
print("\nDataSet after handling Missing Values of B After Label
encoding:\n", df['B_encoded'])
```

```
one_hot_encoder = OneHotEncoder()
encoded_data = one_hot_encoder.fit_transform(df[['B_encoded']]).toarray()
encoded_df = pd.DataFrame(encoded_data, columns=[f'B_{i}' for i in
range(encoded_data.shape[1])])
df1 = pd.concat([df, encoded_df], axis=1)
print("DataSet after handling Missing Values of B After
one_hot_encoder:\n",df1)

# Feature scaling using StandardScaler from scikit-learn
print("\nFeature scaling\n")
print("....................................................................\n")
scaler = StandardScaler()
scaled_data = scaler.fit_transform(df[['A', 'C']])
scaled_df = pd.DataFrame(scaled_data, columns=['A_scaled', 'C_scaled'])
df2 = pd.concat([df, scaled_df], axis=1)
print("Feature Scaling using Standard scaler\n", df2)
```

Output:

DataSet:

	A	B	C
0	1.0	X	7.0
1	2.0	None	8.0
2	NaN	Y	9.0
3	4.0	Z	NaN
4	5.0	X	11.0

Handling missing Values

.....

DataSet after handling Missing Values of A and C Columns:

	A	C
0	1.0	7.00
1	2.0	8.00
2	3.0	9.00
3	4.0	8.75
4	5.0	11.00

Encoding

.....

DataSet after handling Missing Values of B Before Label encoding:

```
 0         X
1    Unknown
2         Y
3         Z
4         X
Name: B, dtype: object
```

DataSet after handling Missing Values of B After Label encoding:

```
 0    1
1    0
2    2
3    3
4    1
Name: B_encoded, dtype: int32
```

DataSet after handling Missing Values of B After one_hot_encoder:

```
     A        B      C  B_encoded  B_0  B_1  B_2  B_3
0  1.0        X   7.00          1  0.0  1.0  0.0  0.0
1  2.0  Unknown   8.00          0  1.0  0.0  0.0  0.0
2  3.0        Y   9.00          2  0.0  0.0  1.0  0.0
3  4.0        Z   8.75          3  0.0  0.0  0.0  1.0
4  5.0        X  11.00          1  0.0  1.0  0.0  0.0
```

Feature scaling

.....

Feature Scaling using Standard scaler

```
     A        B      C  B_encoded  A_scaled  C_scaled
0  1.0        X   7.00          1 -1.414214 -1.322876
1  2.0  Unknown   8.00          0 -0.707107 -0.566947
2  3.0        Y   9.00          2  0.000000  0.188982
3  4.0        Z   8.75          3  0.707107  0.000000
4  5.0        X  11.00          1  1.414214  1.700840
```

7. Write a program to implement a k-Nearest Neighbours (k-NN) classifier using scikitlearn and Train the classifier on the dataset and evaluate its performance.

```
from sklearn.datasets import load_iris
from sklearn.model_selection import train_test_split
from sklearn.neighbors import KNeighborsClassifier
from sklearn import metrics

# Load the Iris dataset (or any other dataset you want to use)
iris = load_iris()
X = iris.data
y = iris.target

# Split the dataset into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=42)

# Initialize the k-NN classifier
k = 3  # Set the number of neighbors
knn_classifier = KNeighborsClassifier(n_neighbors=k)

# Train the classifier on the training data
knn_classifier.fit(X_train, y_train)

# Make predictions on the testing data
predictions = knn_classifier.predict(X_test)

# Evaluate the performance of the classifier
accuracy = metrics.accuracy_score(y_test, predictions)
print(f"Accuracy: {accuracy}")

# You can also print other evaluation metrics if needed
# For example, classification report and confusion matrix
print("Classification Report:")
print(metrics.classification_report(y_test, predictions))
print("Confusion Matrix:")
print(metrics.confusion_matrix(y_test, predictions))
```

Output:
Accuracy: 1.0
Classification Report:

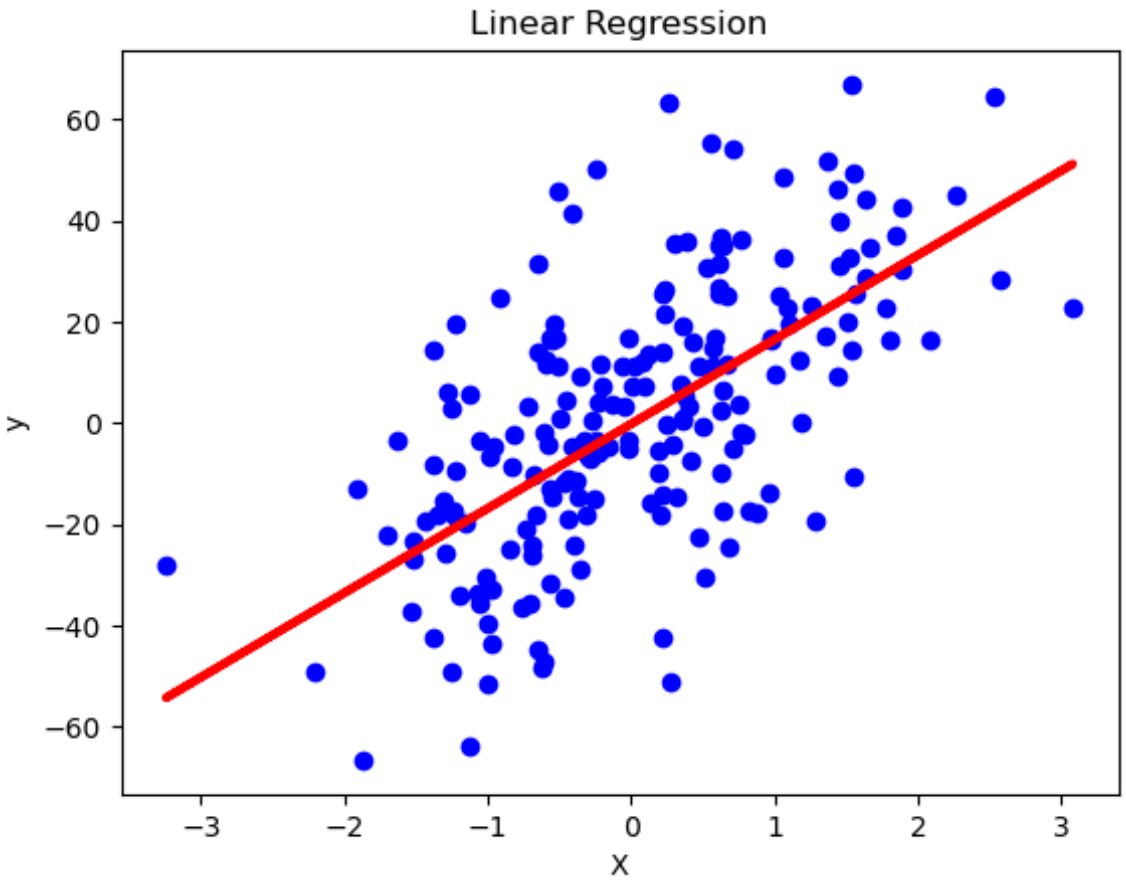
	precision	recall	f1-score	support
0	1.00	1.00	1.00	19
1	1.00	1.00	1.00	13
2	1.00	1.00	1.00	13
accuracy			1.00	45
macro avg	1.00	1.00	1.00	45
weighted avg	1.00	1.00	1.00	45

Confusion Matrix:
[[19 0 0]
[0 13 0]
[0 0 13]]

8. Write a program to implement a linear regression model for regression tasks and Train the model on a dataset with continuous target variables.

```
import numpy as np
from sklearn.linear_model import LinearRegression
from sklearn.datasets import make_regression
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_squared_error, r2_score
import matplotlib.pyplot as plt

# Generate a synthetic dataset
X,y = make_regression(n_samples=1000, n_features=1, noise=20,
random_state=42)

# Split the dataset into training and testing sets
X_train,X_test,y_train,y_test=train_test_split(X,y,test_size=0.2,
random_state=42)

# Initialize the Linear Regression model
linear_reg = LinearRegression()

# Train the model on the training data
linear_reg.fit(X_train, y_train)

# Make predictions on the testing data
predictions = linear_reg.predict(X_test)

# Evaluate the model's performance
mse = mean_squared_error(y_test, predictions)
r2 = r2_score(y_test, predictions)
print("Mean Squared Error (MSE):\n",mse)
print("R-squared:\n",r2)
# Plotting the regression line (optional)
plt.scatter(X_test, y_test, color='blue')
plt.plot(X_test, predictions, color='red', linewidth=3)
plt.xlabel('X')
plt.ylabel('y')
plt.title('Linear Regression')
plt.show()
```

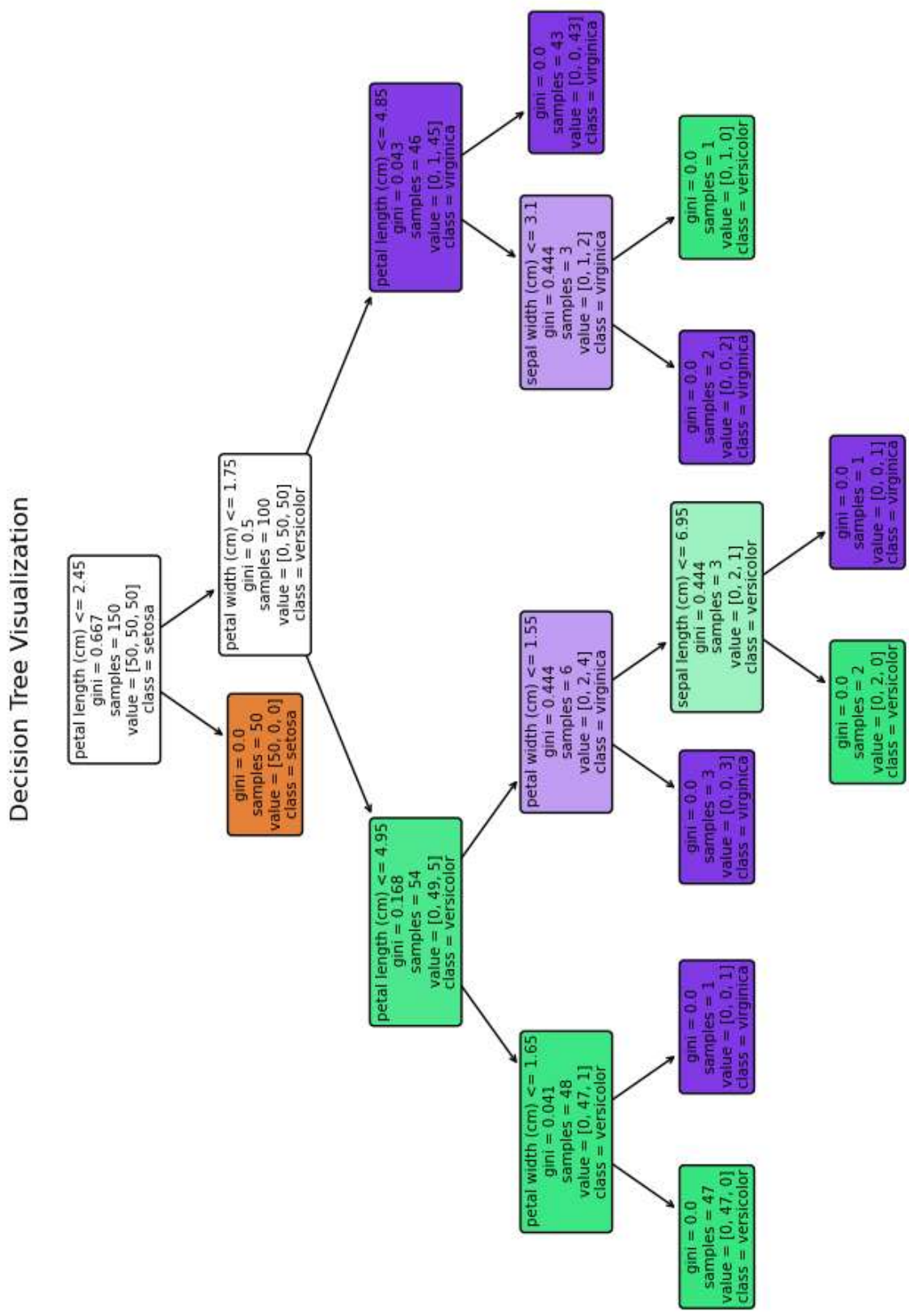
Output:
Mean Squared Error (MSE):
431.59967479663896
R-squared:
0.375734632146025



e

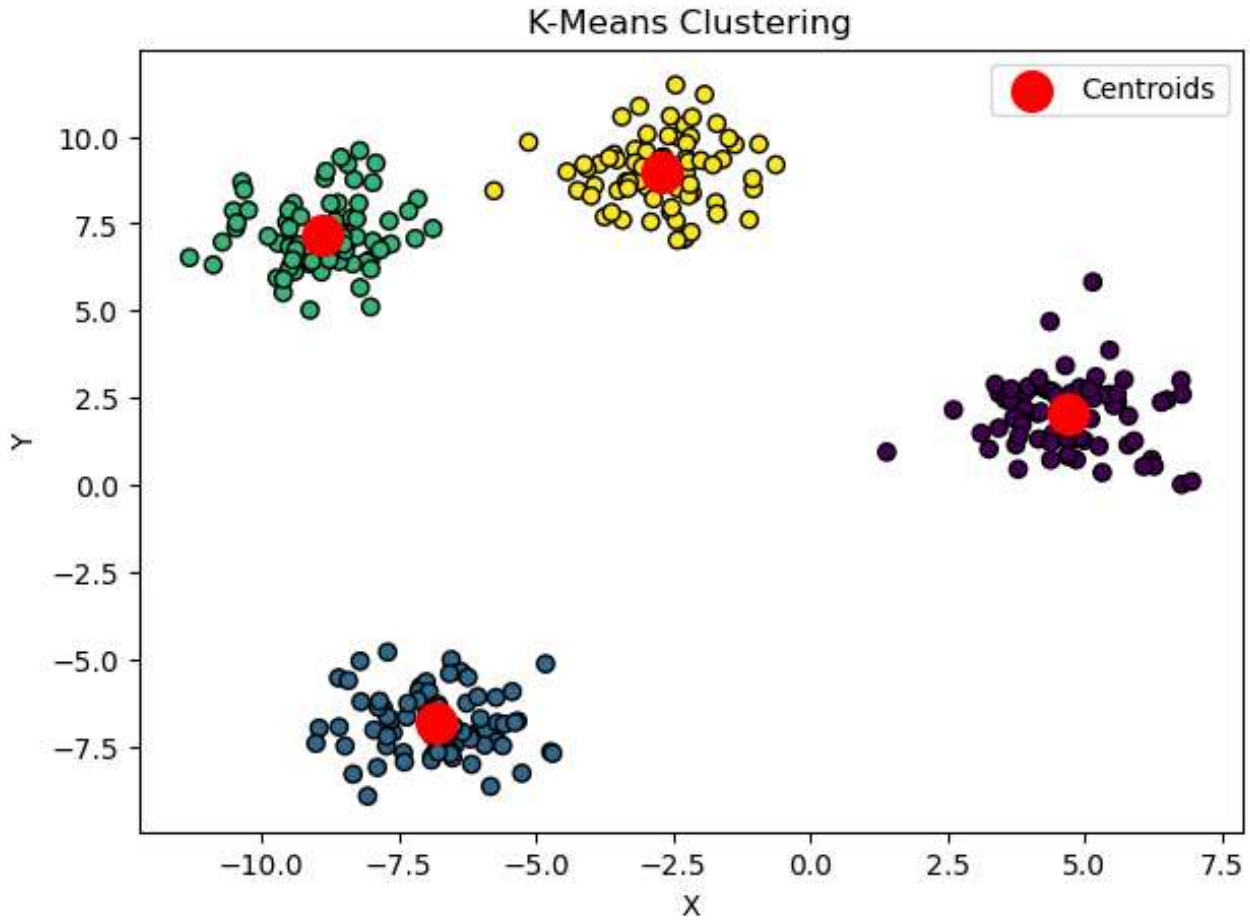
9. Write a program to implement a decision tree classifier using scikit-learn and visualize the decision tree and understand its splits.

```
from sklearn.datasets import load_iris
from sklearn.tree import DecisionTreeClassifier, plot_tree
import matplotlib.pyplot as plt

# Load the Iris dataset
iris = load_iris()
X = iris.data
y = iris.target
class_names = [str(name) for name in iris.target_names]

# Initialize the Decision Tree Classifier
decision_tree = DecisionTreeClassifier()

# Train the classifier on the entire dataset
decision_tree.fit(X, y)

# Visualize the Decision Tree
plt.figure(figsize=(12, 8))
plot_tree(decision_tree, feature_names=iris.feature_names,
class_names=class_names, filled=True, rounded=True)
plt.title("Decision Tree Visualization")
plt.show()
```


Decision Tree Visualization
petal length (cm) <= 2.45
gini = 0.667
samples = 150
value = [50, 50, 50]
class = setosa
gini = 0.0
samples = 50
value = [50, 0, 0]
class = setosa
petal width (cm) <= 1.75
gini = 0.5
samples = 100
value = [0, 50, 50]
class = versicolor
petal length (cm) <= 4.85
gini = 0.043
samples = 46
value = [0, 1, 45]
class = virginica
gini = 0.0
samples = 43
value = [0, 0, 43]
class = virginica
sepal width (cm) <= 3.1
gini = 0.444
samples = 3
value = [0, 1, 2]
class = virginica
gini = 0.0
samples = 1
value = [0, 1, 0]
class = versicolor
gini = 0.0
samples = 2
value = [0, 0, 2]
class = virginica
petal length (cm) <= 4.95
gini = 0.168
samples = 54
value = [0, 49, 5]
class = versicolor
petal width (cm) <= 1.55
gini = 0.444
samples = 6
value = [0, 2, 4]
class = virginica
sepal length (cm) <= 6.95
gini = 0.444
samples = 3
value = [0, 2, 1]
class = versicolor
gini = 0.0
samples = 1
value = [0, 0, 1]
class = virginica
gini = 0.0
samples = 2
value = [0, 2, 0]
class = versicolor
gini = 0.0
samples = 3
value = [0, 0, 3]
class = virginica
petal width (cm) <= 1.65
gini = 0.041
samples = 48
value = [0, 47, 1]
class = versicolor
gini = 0.0
samples = 1
value = [0, 0, 1]
class = virginica
gini = 0.0
samples = 47
value = [0, 47, 0]
class = versicolor

10. Write a program to Implement K-Means clustering and Visualize clusters.

```
import matplotlib.pyplot as plt
from sklearn.datasets import make_blobs
from sklearn.cluster import KMeans
# Generating synthetic data
X, _ = make_blobs(n_samples=300, centers=4, cluster_std=1.0, random_state=42)
# Initialize K-Means with the number of clusters
kmeans = KMeans(n_clusters=4)
# Fit the K-Means model to the data
kmeans.fit(X)
# Predict cluster labels
cluster_labels = kmeans.predict(X)
# Visualize the clusters
plt.figure(figsize=(7,5))
plt.scatter(X[:, 0], X[:, 1], c=cluster_labels, cmap='viridis', edgecolors='k')
plt.scatter(kmeans.cluster_centers_[:, 0], kmeans.cluster_centers_[:, 1], marker='o', s=200, color='red', label='Centroids')
plt.title('K-Means Clustering')
plt.xlabel('X')
plt.ylabel('Y')
plt.legend()
plt.show()
```


K-Means Clustering
Centroids
10.0
7.5
5.0
2.5
0.0
−2.5
−5.0
−7.5
Y
−10.0
−7.5
−5.0
−2.5
0.0
2.5
5.0
7.5
X