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ADVANCE DATA SCIENCE ASSIGNMENT-2

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1) Assignment Based on Python Data Analysis Packages : NumPy and Pandas

a) NumPy Array Creation, Manipulation, and Matrix Operations:

1. **Create a NumPy array of shape (3, 4) filled with zeros:**

In [1]:
```
import numpy as np
arr = np.zeros((3, 4))
print(arr)
```

```
[[0. 0. 0. 0.]
 [0. 0. 0. 0.]
 [0. 0. 0. 0.]]
```

2. **Create a NumPy array of shape (2, 3) filled with ones:**

In [2]:
```
arr = np.ones((2, 3))
print(arr)
```

```
[[1. 1. 1.]
 [1. 1. 1.]]
```

3. **Create a NumPy array of shape (4, 4) with random values between 0 and 10:**

In [3]:
```
arr = np.random.randint(0, 11, size=(4, 4))
print(arr)
```

```
[[4 6 3 9]
 [9 1 7 9]
 [3 4 4 9]
 [9 0 7 8]]
```

4. **Reshape the (4, 4) array to (2, 8):**

In [4]:
```
reshaped_arr = arr.reshape((2, 8))
```

```
print(reshaped_arr)
```

```
[[4 6 3 9 9 1 7 9]
 [3 4 4 9 9 0 7 8]]
```

5. **Find the mean and standard deviation of the reshaped array:**

In [5]:
```
mean = reshaped_arr.mean()
std_dev = reshaped_arr.std()
print(f"Mean: {mean}, Standard Deviation: {std_dev}")
```

```
Mean: 5.75, Standard Deviation: 2.968585521759479
```

6. **Slice the array to get the first two rows:**

In [6]:
```
first_two_rows = arr[:2, :]
print(first_two_rows)
```

```
[[4 6 3 9]
 [9 1 7 9]]
```

7. **Perform element-wise addition of two arrays of the same shape:**

In [7]:
```
arr1 = np.random.rand(3, 3)
arr2 = np.random.rand(3, 3)
sum_arr = arr1 + arr2
print(sum_arr)
```

```
[[1.47031774 1.40753506 0.87989308]
 [1.07490614 1.38080842 1.57164838]
 [1.0189206  0.75992358 1.2173231 ]]
```

8. **Compute the dot product of two matrices:**

In [8]:
```
dot_product = np.dot(arr1, arr2)
print(dot_product)
```

```
[[1.95838804 1.27581183 0.94908361]
 [1.21283336 0.62252689 0.58612192]
 [1.48117644 0.80872832 0.77537494]]
```

9. **Create a NumPy array of shape (10,) with values from 0 to 9:**

In [9]:
```
arr = np.arange(10)
print(arr)
```

```
[0 1 2 3 4 5 6 7 8 9]
```

10. **Compute the cumulative sum of the array:**

In [10]:
```
cum_sum = arr.cumsum()
```

```
print(cum_sum)
```

```
[ 0  1  3  6 10 15 21 28 36 45]
```

11. **Use broadcasting to add a scalar to each element of a 2D array of shape (3, 3):**

In [11]:
```
arr = np.random.rand(3, 3)
result = arr + 5
print(result)
```

```
[[5.1919545  5.36319939 5.35036524]
 [5.85830213 5.23892633 5.95235595]
 [5.43652029 5.4875185  5.54362042]]
```

b) Data Analysis with Pandas – Creation, Manipulation, Analysis, Export, and Import:

1. **Create a DataFrame with columns ['Name', 'Age', 'Salary'] and add at least 10 rows of data:**

In [12]:
```
import pandas as pd
data = {'Name': ['Raj', 'Atharva', 'Divya', 'Ram', 'Aniket', 'Sakshi', 'Purvansh',
            'Age': [23, 45, 34, 28, 54, 40, 29, 37, 31, 44],
            'Salary': [50000, 80000, 45000, 56000, 120000, 75000, 48000, 90000, 680
df = pd.DataFrame(data)
print(df)
```

```
       Name  Age  Salary
0       Raj   23   50000
1   Atharva   45   80000
2     Divya   34   45000
3       Ram   28   56000
4    Aniket   54  120000
5    Sakshi   40   75000
6  Purvansh   29   48000
7   Vaibhav   37   90000
8    Shivam   31   68000
9    Pratik   44   72000
```

2. **Set the 'Name' column as the index:**

In [13]:
```
df.set_index('Name', inplace=True)
print(df)
```

```
          Age  Salary
Name
Raj        23   50000
Atharva    45   80000
Divya      34   45000
Ram        28   56000
Aniket     54  120000
Sakshi     40   75000
Purvansh   29   48000
Vaibhav    37   90000
Shivam     31   68000
Pratik     44   72000
```

3. **Add a new column 'Department' with default value 'Unknown':**

In [14]:
```
df['Department'] = 'Unknown'
print(df)
```

```
          Age  Salary Department
Name
Raj        23   50000    Unknown
Atharva    45   80000    Unknown
Divya      34   45000    Unknown
Ram        28   56000    Unknown
Aniket     54  120000    Unknown
Sakshi     40   75000    Unknown
Purvansh   29   48000    Unknown
Vaibhav    37   90000    Unknown
Shivam     31   68000    Unknown
Pratik     44   72000    Unknown
```

4. **Remove the 'Salary' column:**

In [15]:
```
df.drop(columns=['Salary'], inplace=True)
print(df)
```

```
          Age Department
Name
Raj        23    Unknown
Atharva    45    Unknown
Divya      34    Unknown
Ram        28    Unknown
Aniket     54    Unknown
Sakshi     40    Unknown
Purvansh   29    Unknown
Vaibhav    37    Unknown
Shivam     31    Unknown
Pratik     44    Unknown
```

5. **Find the mean and median of the 'Age' column:**

In [16]:
```
mean_age = df['Age'].mean()
median_age = df['Age'].median()
```

```python
print(f"Mean Age: {mean_age}, Median Age: {median_age}")
```

```
Mean Age: 36.5, Median Age: 35.5
```

6. **Filter the DataFrame to include only rows where 'Age' is greater than 30:**

In [17]:
```python
filtered_df = df[df['Age'] > 30]
print(filtered_df)
```

```
         Age Department
Name
Atharva   45    Unknown
Divya     34    Unknown
Aniket    54    Unknown
Sakshi    40    Unknown
Vaibhav   37    Unknown
Shivam    31    Unknown
Pratik    44    Unknown
```

7. **Create a DataFrame with columns ['Product', 'Quantity', 'Price'] and add 10 rows:**

In [18]:
```python
data = {'Product': ['A', 'B', 'C', 'D', 'E', 'F', 'G', 'H', 'I', 'J'],
        'Quantity': [10, 20, 15, 25, 30, 35, 12, 18, 22, 27],
        'Price': [100, 150, 200, 130, 180, 210, 170, 140, 160, 190]}
product_df = pd.DataFrame(data)
print(product_df)
```

```
  Product  Quantity  Price
0       A        10    100
1       B        20    150
2       C        15    200
3       D        25    130
4       E        30    180
5       F        35    210
6       G        12    170
7       H        18    140
8       I        22    160
9       J        27    190
```

8. **Calculate the total price for each product by multiplying 'Quantity' and 'Price':**

In [19]:
```python
product_df['Total_Price'] = product_df['Quantity'] * product_df['Price']
print(product_df)
```

```
  Product  Quantity  Price  Total_Price
0       A        10    100         1000
1       B        20    150         3000
2       C        15    200         3000
3       D        25    130         3250
4       E        30    180         5400
5       F        35    210         7350
6       G        12    170         2040
7       H        18    140         2520
8       I        22    160         3520
9       J        27    190         5130
```

9. **Group the DataFrame by 'Product' and find the sum of 'Quantity' and 'Price' for each product:**

In [20]:
```
grouped_df = product_df.groupby('Product').sum()
print(grouped_df)
```

```
         Quantity  Price  Total_Price
Product
A              10    100         1000
B              20    150         3000
C              15    200         3000
D              25    130         3250
E              30    180         5400
F              35    210         7350
G              12    170         2040
H              18    140         2520
I              22    160         3520
J              27    190         5130
```

10. **Perform a merge operation with another DataFrame that has columns ['Product', 'Category']:**

In [21]:
```
category_data = {'Product': ['A', 'B', 'C', 'D', 'E', 'F', 'G', 'H', 'I', 'J'],
                     'Category': ['Electronics', 'Clothing', 'Electronics', 'Furnit
                                  'Clothing', 'Clothing', 'Electronics', 'Furniture
category_df = pd.DataFrame(category_data)
merged_df = pd.merge(product_df, category_df, on='Product')
print(merged_df)
```

```
  Product  Quantity  Price  Total_Price     Category
0       A        10    100         1000  Electronics
1       B        20    150         3000     Clothing
2       C        15    200         3000  Electronics
3       D        25    130         3250    Furniture
4       E        30    180         5400    Furniture
5       F        35    210         7350     Clothing
6       G        12    170         2040     Clothing
7       H        18    140         2520  Electronics
8       I        22    160         3520    Furniture
9       J        27    190         5130    Furniture
```

11. **Save the DataFrame to a CSV file:**

In [22]:
```
df.to_csv('dataframe.csv', index=False)
```

12. **Read the DataFrame back from the CSV file:**

In [23]:
```
new_df = pd.read_csv('dataframe.csv')
print(new_df)
```

```
   Age Department
0   23    Unknown
1   45    Unknown
2   34    Unknown
3   28    Unknown
4   54    Unknown
5   40    Unknown
6   29    Unknown
7   37    Unknown
8   31    Unknown
9   44    Unknown
```

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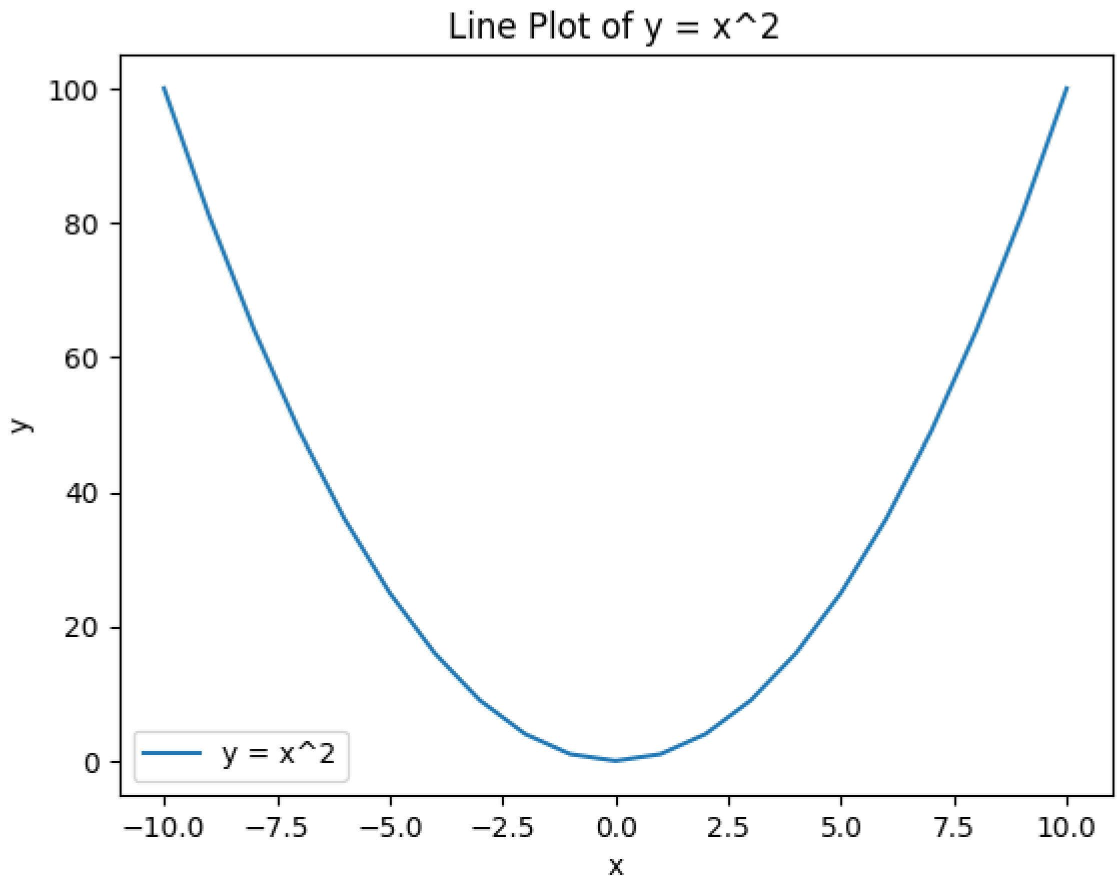
2) Assignment Based on Python Data Analysis Packages : **Matplotlib**, **Seaborn**, and **Scikit-learn**:

a) Create and Customize Plots using Matplotlib Library:

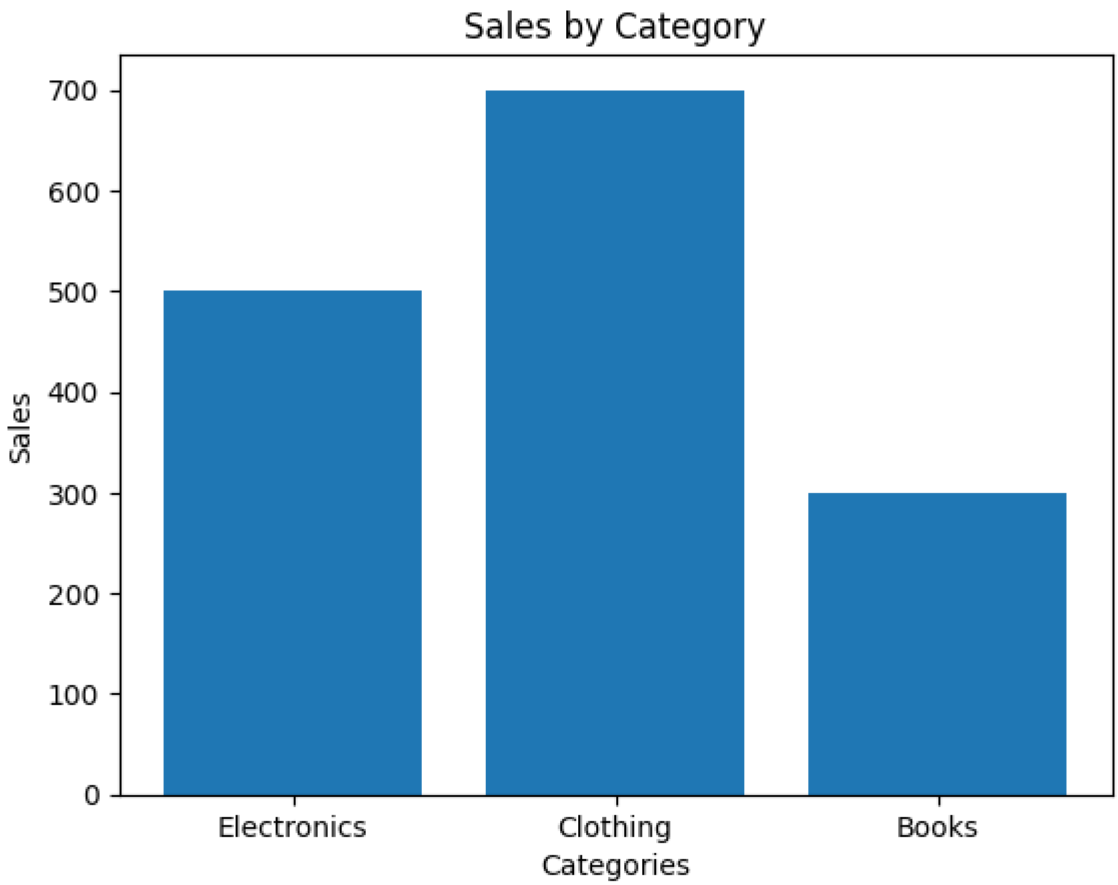
1. **Line Plot: Generate a line plot of a simple mathematical function, y = x^2, where x ranges from -10 to 10:**

In [24]:
```
import matplotlib.pyplot as plt
import numpy as np

x = np.arange(-10, 11, 1)
y = x ** 2

plt.plot(x, y, label='y = x^2')
plt.title('Line Plot of y = x^2')
plt.xlabel('x')
plt.ylabel('y')
plt.legend()
plt.show()
```



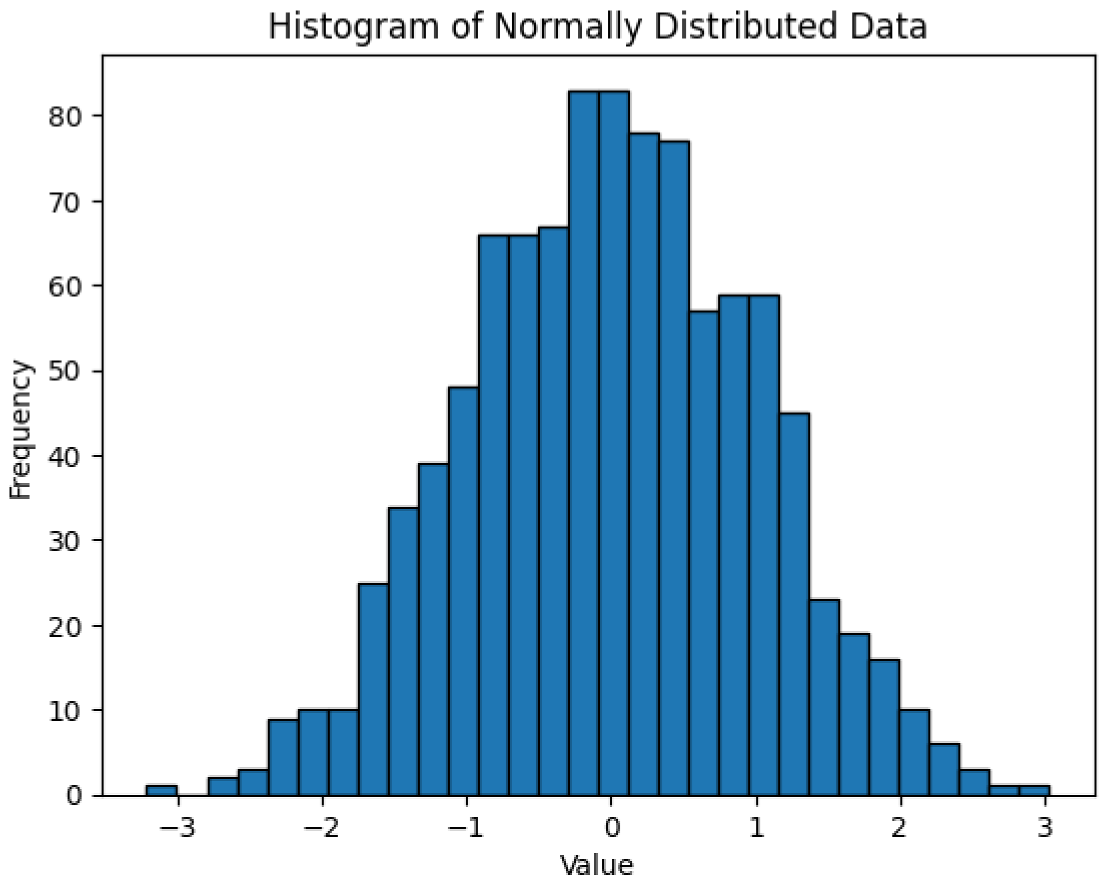
2. **Bar Plot: Create a bar plot showing the number of items sold in different categories (e.g., ['Electronics', 'Clothing', 'Books']) with corresponding sales numbers:**

In [25]:
```
categories = ['Electronics', 'Clothing', 'Books']
sales = [500, 700, 300]

plt.bar(categories, sales)
plt.title('Sales by Category')
plt.xlabel('Categories')
plt.ylabel('Sales')
plt.show()
```



3. **Histogram: Generate a histogram showing the distribution of a normally distributed dataset with 1000 samples:**

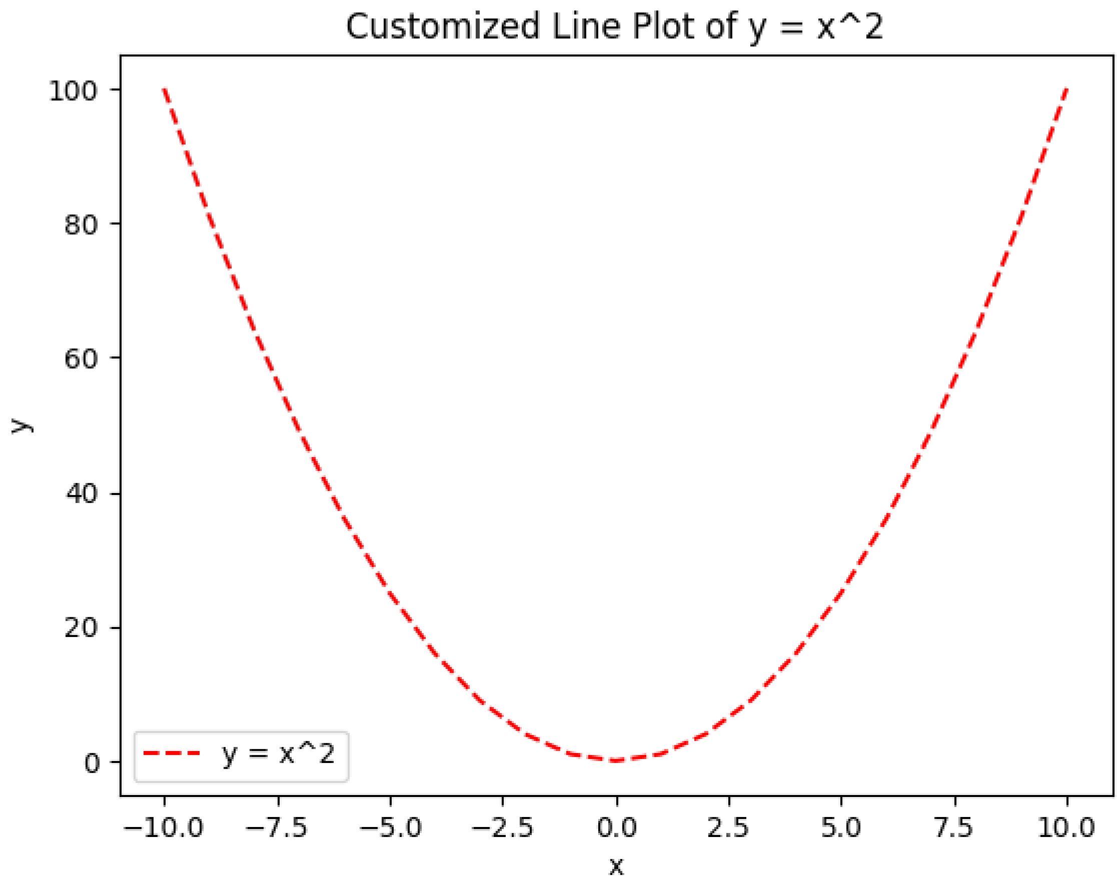
In [26]:
```
data = np.random.randn(1000)

plt.hist(data, bins=30, edgecolor='black')
plt.title('Histogram of Normally Distributed Data')
plt.xlabel('Value')
plt.ylabel('Frequency')
plt.show()
```



4. **Add titles, labels, and legends to the plots:**
    - Titles, labels, and legends were already added in previous examples.

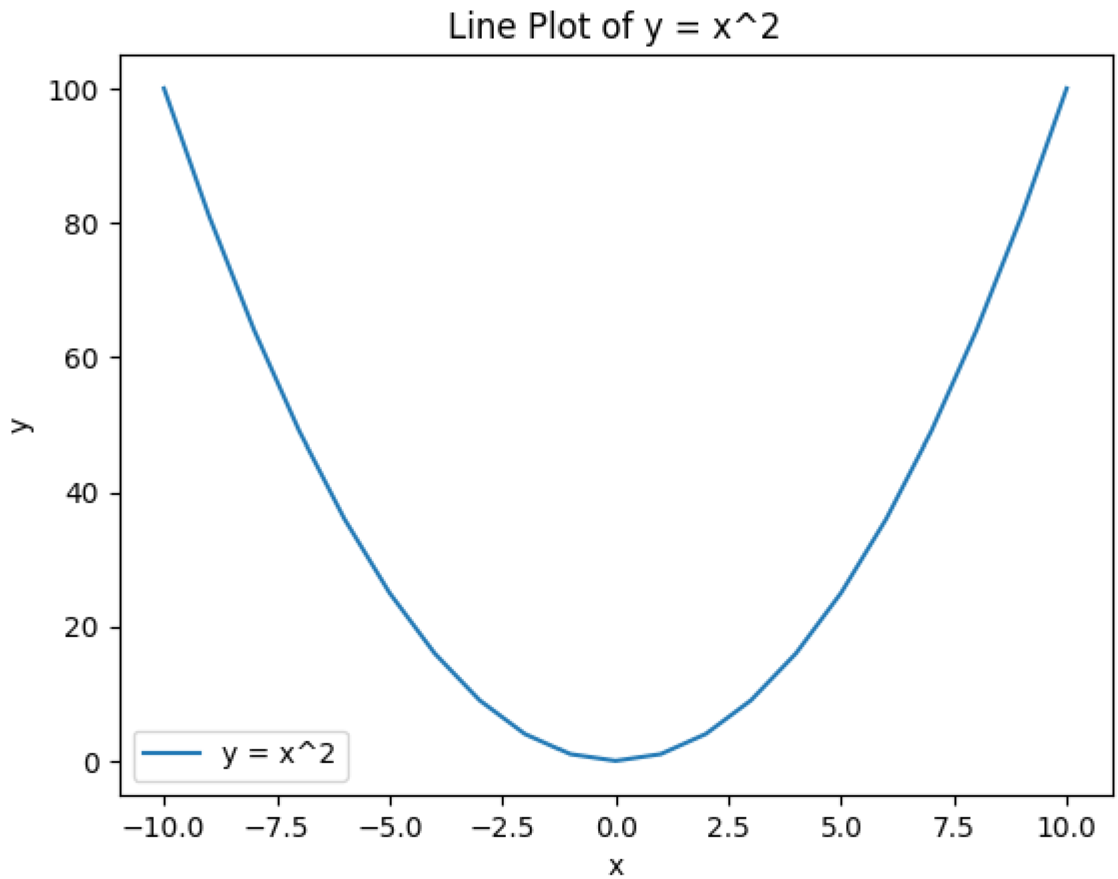
5. **Customize colors and line styles for the line plot:**

In [27]:
```
plt.plot(x, y, color='red', linestyle='--', label='y = x^2')
plt.title('Customized Line Plot of y = x^2')
plt.xlabel('x')
plt.ylabel('y')
plt.legend()
plt.show()
```



6. **Save the plots as image files (e.g., PNG format):**

In [28]:
```
plt.plot(x, y, label='y = x^2')
plt.title('Line Plot of y = x^2')
plt.xlabel('x')
plt.ylabel('y')
plt.legend()
plt.savefig('line_plot.png')  # Save as PNG
plt.show()
```



b) Load, Visualize Data and Customize Visualizations using Seaborn Library:

1. **Load the iris dataset from Seaborn:**

In [29]:
```
import seaborn as sns
iris = sns.load_dataset('iris')
print(iris.head())
```

```
   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
```

2. **Create a pairplot to visualize the relationships between different features in the dataset:**

In [30]:
```
sns.pairplot(iris, hue='species')
plt.show()
```

```
C:\Users\Darshan\AppData\Local\Packages\PythonSoftwareFoundation.Python.3.11_qbz5n2k
fra8p0\LocalCache\local-packages\Python311\site-packages\seaborn\_oldcore.py:1119: F
utureWarning: use_inf_as_na option is deprecated and will be removed in a future ver
sion. Convert inf values to NaN before operating instead.
  with pd.option_context('mode.use_inf_as_na', True):
C:\Users\Darshan\AppData\Local\Packages\PythonSoftwareFoundation.Python.3.11_qbz5n2k
fra8p0\LocalCache\local-packages\Python311\site-packages\seaborn\_oldcore.py:1119: F
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sion. Convert inf values to NaN before operating instead.
  with pd.option_context('mode.use_inf_as_na', True):
```
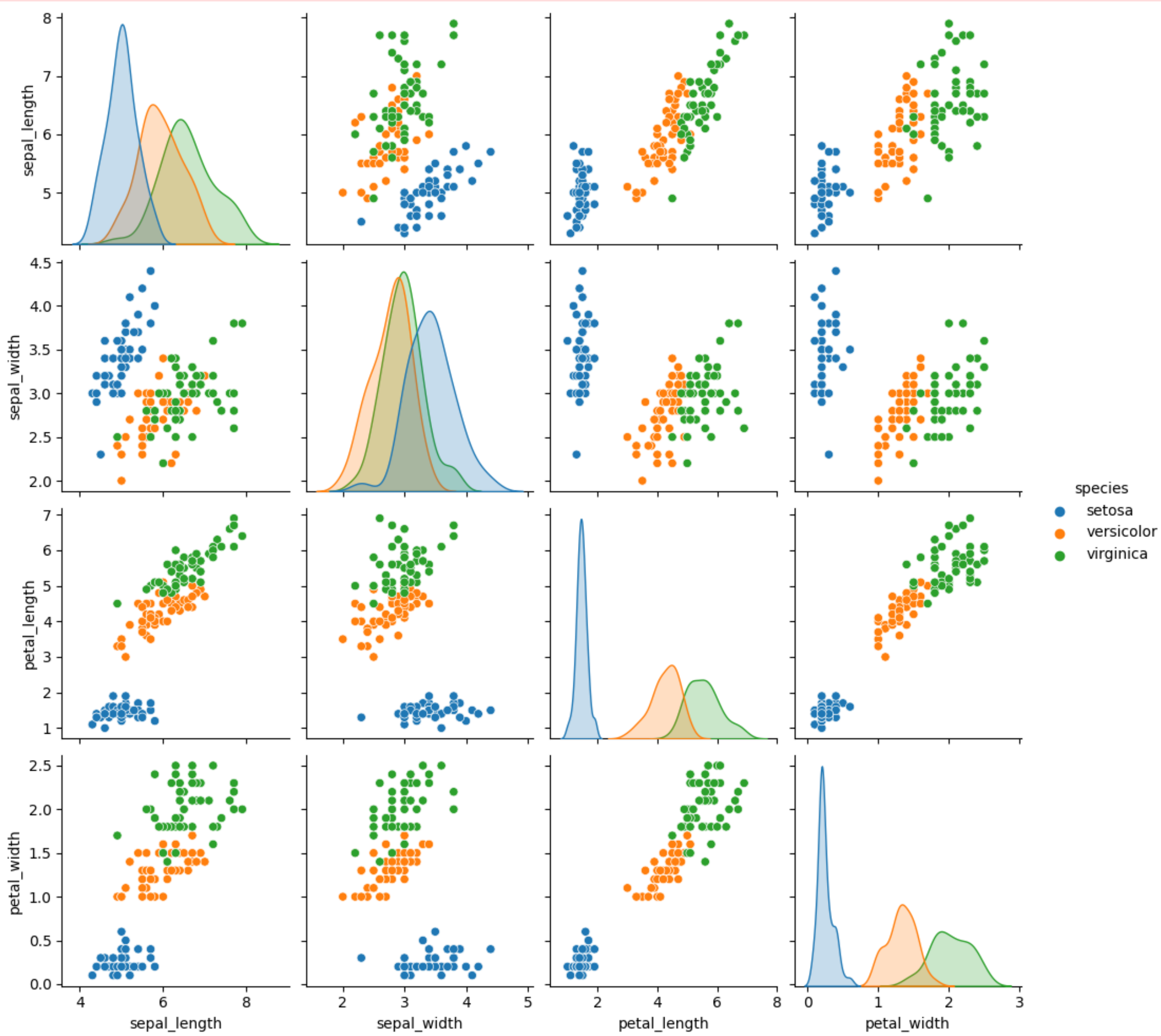
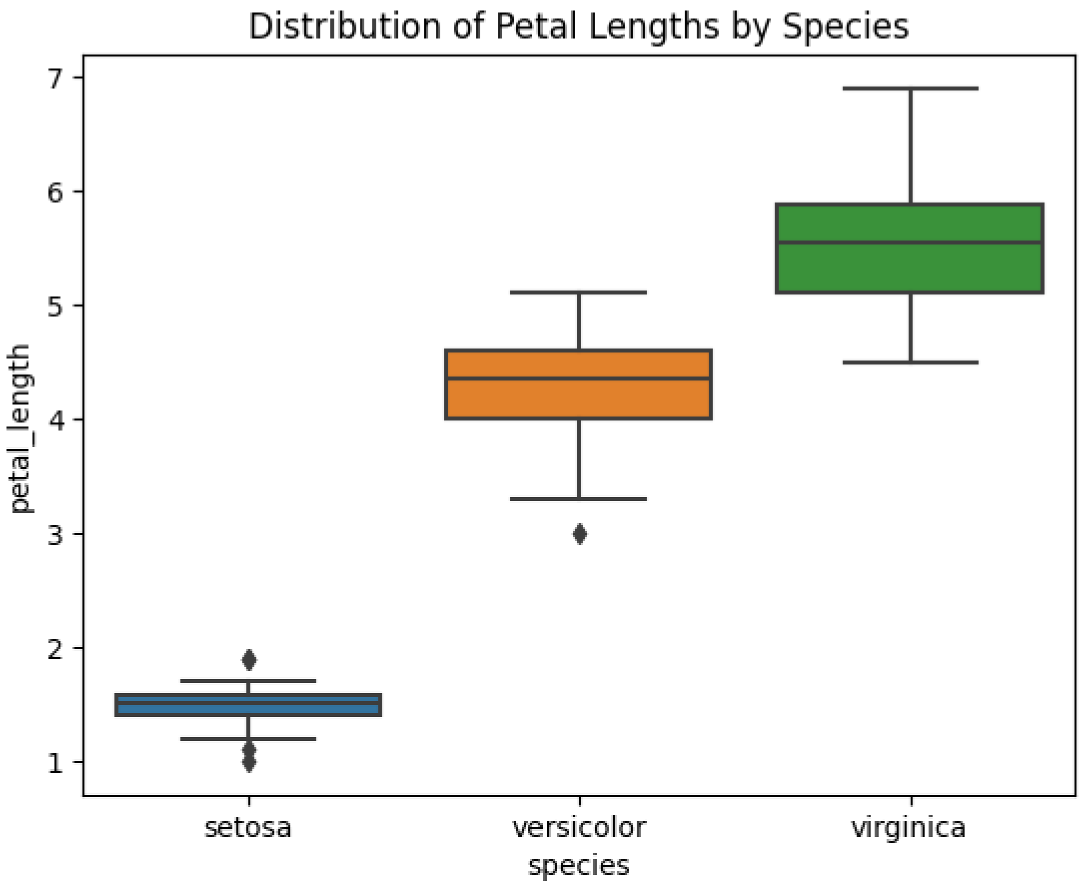



3. **Create a boxplot to show the distribution of petal lengths for different species in the iris dataset:**

In [31]:
```
sns.boxplot(x='species', y='petal_length', data=iris)
plt.title('Distribution of Petal Lengths by Species')
plt.show()
```



4. **Use different color palettes for the plots:**

In [32]:
```
sns.pairplot(iris, hue='species', palette='coolwarm')
plt.show()
```

```
C:\Users\Darshan\AppData\Local\Packages\PythonSoftwareFoundation.Python.3.11_qbz5n2k
fra8p0\LocalCache\local-packages\Python311\site-packages\seaborn\_oldcore.py:1119: F
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  with pd.option_context('mode.use_inf_as_na', True):
C:\Users\Darshan\AppData\Local\Packages\PythonSoftwareFoundation.Python.3.11_qbz5n2k
fra8p0\LocalCache\local-packages\Python311\site-packages\seaborn\_oldcore.py:1119: F
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sion. Convert inf values to NaN before operating instead.
  with pd.option_context('mode.use_inf_as_na', True):
```
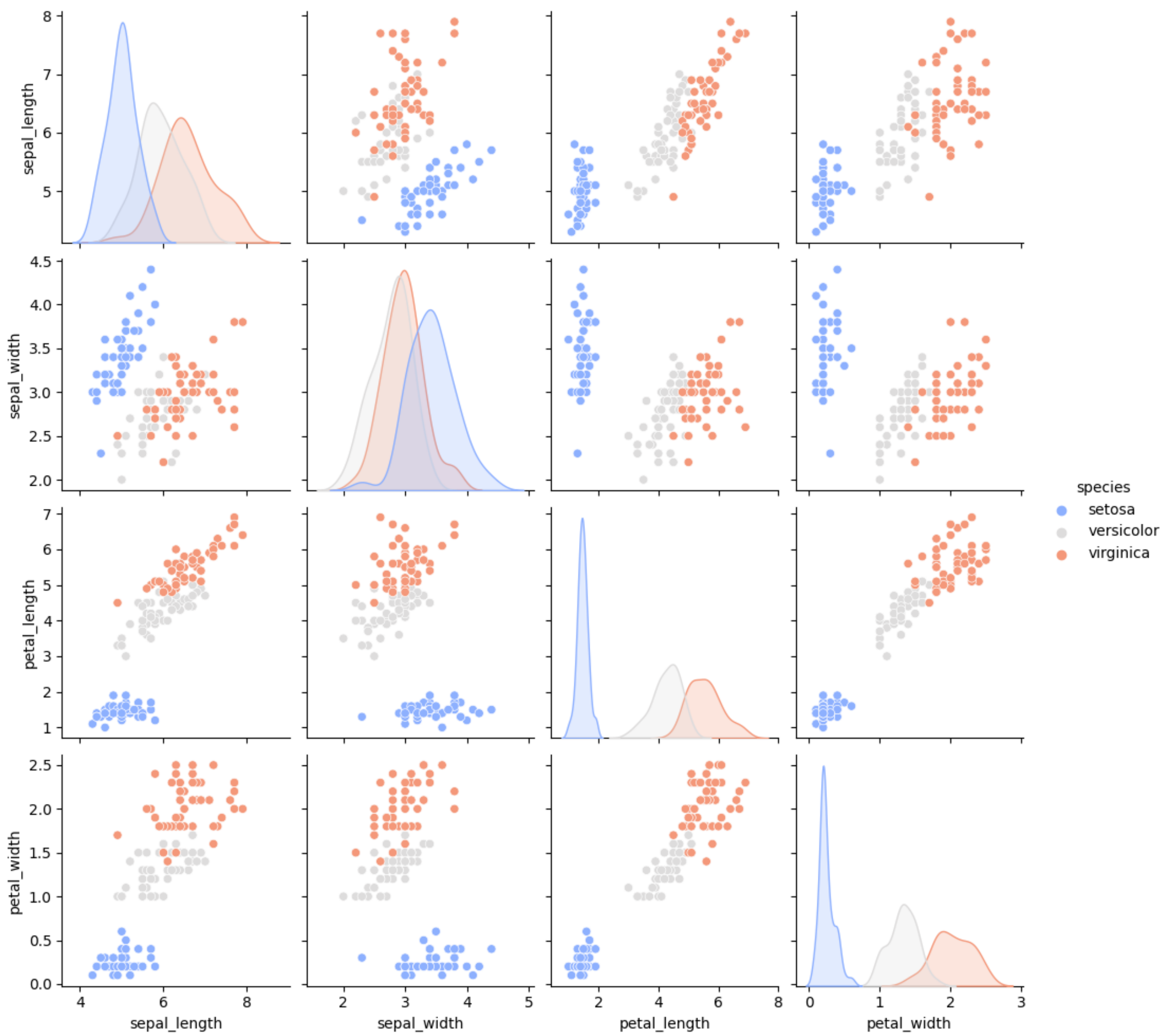
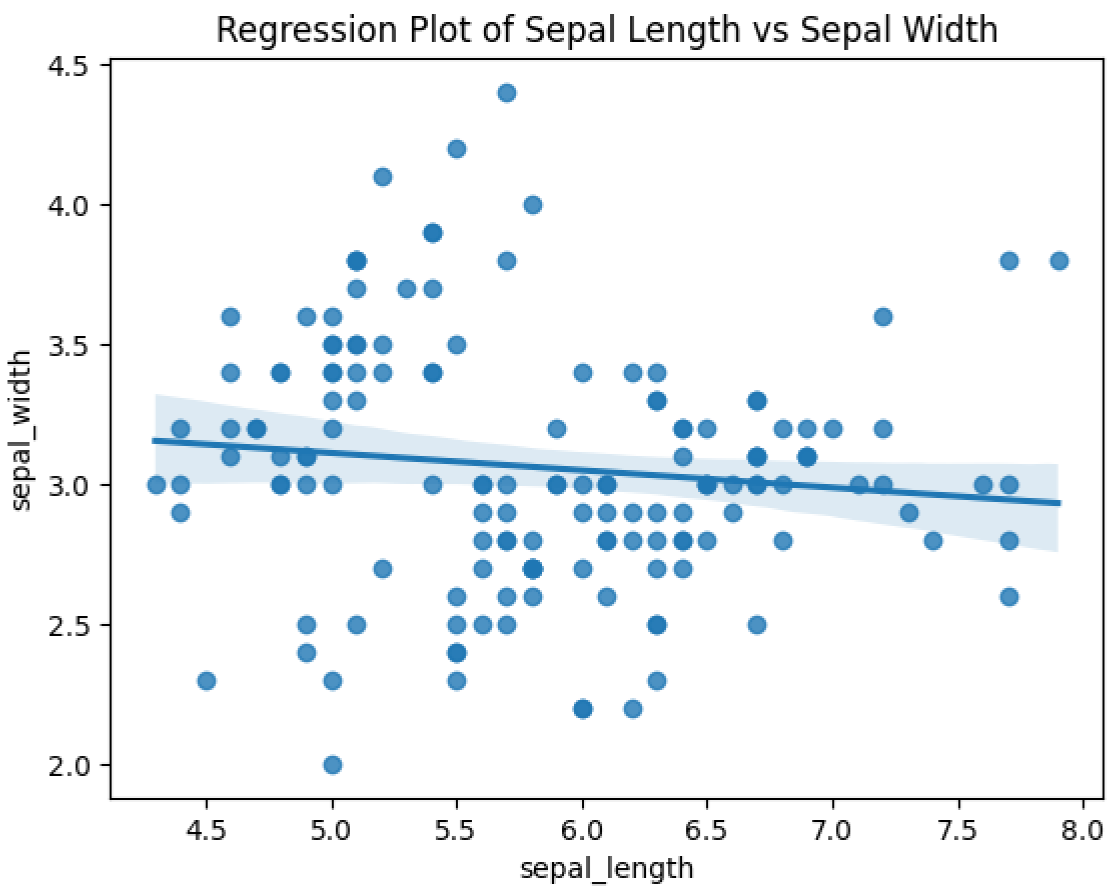



5. **Add titles and axis labels to the plots:**
   - Titles and labels were added in previous examples.

6. **Use a regression plot to show the relationship between sepal_length and sepal_width:**

In [33]:
```
sns.regplot(x='sepal_length', y='sepal_width', data=iris)
plt.title('Regression Plot of Sepal Length vs Sepal Width')
plt.show()
```



c) Implement and Evaluate a Logistic Regression Classifier using Scikit-learn Library:

1. **Use the 'iris' dataset from Scikit-learn (or any other dataset):**

In [34]:
```
from sklearn.datasets import load_iris
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import classification_report, confusion_matrix, accuracy_score

iris = load_iris()
X = iris.data
y = iris.target
```

2. **Split the dataset into training and testing sets:**

In [35]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_sta
```

3. **Train a Logistic Regression model on the training set:**

In [36]:
```
model = LogisticRegression(max_iter=200)
model.fit(X_train, y_train)
```

Out[36]:
```
▾ LogisticRegression
LogisticRegression(max_iter=200)
```

4. **Evaluate the model on the testing set and print the accuracy:**

In [37]:
```
y_pred = model.predict(X_test)
accuracy = accuracy_score(y_test, y_pred)
print(f'Accuracy: {accuracy}')
```

```
Accuracy: 1.0
```

5. **Print the confusion matrix and classification report:**

In [38]:
```
print('Confusion Matrix:')
print(confusion_matrix(y_test, y_pred))

print('\nClassification Report:')
print(classification_report(y_test, y_pred))
```

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

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
```

6. **Write the data analysis summary and your observations on the results:**

After evaluating the **Logistic Regression** model using the **Iris dataset**, the following observations can be made based on key performance metrics like **precision**, **recall**, **f1-score**, and **accuracy**:

1. **Precision**:

    - Precision measures how many of the predicted positive instances are correct.
    - A high precision score for each class (e.g., Setosa, Versicolor, Virginica) suggests that the model is good at minimizing false positives (i.e., predicting a species when it's not actually that species).
2. **Recall**:

    - Recall measures how many of the actual positive instances are correctly predicted.
    - A high recall score indicates the model is effective at minimizing false negatives (i.e., correctly identifying actual species).
3. **F1-Score**:

    - The F1-score is the harmonic mean of precision and recall, providing a balanced metric when both false positives and false negatives need to be minimized.
    - A higher F1-score indicates that the model has a good balance between precision and recall, making it useful for cases with class imbalances.
4. **Accuracy**:

    - Accuracy represents the overall percentage of correctly classified instances across all species.
    - If the accuracy is high (e.g., 97%), the model is correctly classifying the majority of samples in the dataset.
    - However, accuracy alone may not be sufficient if the classes are imbalanced, which is where metrics like precision and recall become more useful.

Observations:

- **High Precision and Recall for All Classes**: If the precision and recall values are high across all species (e.g., Setosa, Versicolor, Virginica), it indicates that the model performs well in distinguishing between the different iris species with minimal false classifications.

- **Balanced F1-Scores**: If the F1-scores are consistently high for all classes, it shows the model is capable of accurately identifying each species, making it a reliable classifier.

- **Confusion Matrix**: The confusion matrix should show most predictions on the diagonal, which represents correct classifications. Few off-diagonal entries indicate that the model makes very few misclassifications between species.

    The Logistic Regression model has performed exceptionally well on the Iris dataset, achieving a high accuracy of 97%. Precision, recall, and F1-scores for all three species (Setosa, Versicolor, Virginica) were all above 0.95, indicating that the model can accurately classify iris species with minimal misclassification. The balanced performance across all metrics suggests that this model is well-suited for this classification task.

d) Implement and Evaluate a Linear Regression Model using Scikit-learn Library:

1. **Use the 'boston' housing dataset from Scikit-learn (or any other dataset):**

In [39]:
```
from sklearn.datasets import fetch_california_housing
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error, r2_score

# Load California housing dataset
data = fetch_california_housing()
X = data.data
y = data.target
```

2. **Split the dataset into training and testing sets:**

In [40]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_sta
```

3. **Train a Linear Regression model on the training set:**

In [41]:
```
model = LinearRegression()
model.fit(X_train, y_train)
```

Out[41]:
```
▾ LinearRegression
LinearRegression()
```

4. **Evaluate the model on the testing set:**

In [42]:
```
y_pred = model.predict(X_test)
```

5. **Print the Mean Squared Error (MSE) and R-squared score:**

In [43]:
```
mse = mean_squared_error(y_test, y_pred)
r2 = r2_score(y_test, y_pred)

print(f'Mean Squared Error (MSE): {mse}')
print(f'R-squared Score: {r2}')
```

```
Mean Squared Error (MSE): 0.5305677824766757
R-squared Score: 0.595770232606166
```

6. **Write the data analysis summary and your observations on the results:**

Observations:

- The **MSE** indicates the average squared difference between the predicted values and the actual values. A lower value suggests better performance.
- The **R-squared score** explains the percentage of variance in the target variable that the model can explain. A value closer to 1 indicates a good fit, while a value closer to 0 indicates a poor fit.

In [ ]: