EXPT NO: 1 A python program to implement univariate regression

DATE: 16-8-24 bivariate regression and multivariate regression.

AIM:
To write a python program to implement univariate regression, bivariate regression and multivariate regression.

PROCEDURE:
Implementing univariate, bivariate, and multivariate regression using the Iris dataset involve the following steps:

Step 1: Import Necessary Libraries

First, import the libraries that are essential for data manipulation, visualization, and model building.

```
import numpy as np

import pandas as pd

import seaborn as sns

import matplotlib.pyplot as plt

from sklearn.model_selection import train_test_split

from sklearn.linear_model import LinearRegression

from sklearn.metrics import mean_squared_error, r2_score
```

Step 2: Load the Iris Dataset

The Iris dataset can be loaded and display the first few rows of the dataset .

```
# Load the Iris dataset

iris = sns.load_dataset('iris')
```

```python
# Display the first few rows of the dataset

print(iris.head())
```

OUTPUT :

```
   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
```

Step 3: Data Preprocessing

Ensure the data is clean and ready for modeling. Since the Iris dataset is clean, minimal preprocessing is needed.

```python
# Check for missing values
print(iris.isnull().sum())

# Display the basic statistical details
print(iris.describe())
```

OUTPUT :

```
sepal_length    0
sepal_width     0
petal_length    0
petal_width     0
species         0
dtype: int64
       sepal_length  sepal_width  petal_length  petal_width
count    150.000000   150.000000    150.000000   150.000000
mean       5.843333     3.057333      3.758000     1.199333
std        0.828066     0.435866      1.765298     0.762238
min        4.300000     2.000000      1.000000     0.100000
25%        5.100000     2.800000      1.600000     0.300000
50%        5.800000     3.000000      4.350000     1.300000
75%        6.400000     3.300000      5.100000     1.800000
max        7.900000     4.400000      6.900000     2.500000
```

Step 4: Univariate Regression

Univariate regression involves predicting one variable based on a single predictor.

4.1: Select the Features

Choose one feature (e.g., sepal_length) and one target variable (e.g., sepal_width).

```
X_uni = iris[['sepal_length']]
y_uni = iris['sepal_width']
```

4.2: Split the Data

Split the data into training and testing sets.
Fit the linear regression model on the training data.

```
X_uni_train, X_uni_test, y_uni_train, y_uni_test = train_test_split(X_uni,
y_uni,
test_size=0.2, random_state=42)
```

4.3: Train the model

```
uni_model = LinearRegression()
uni_model.fit(X_uni_train, y_uni_train)
```

```
LinearRegression
LinearRegression()
```

4.4: Make Predictions

Use the model to make predictions on the test data.

```
y_uni_pred = uni_model.predict(X_uni_test)
```

4.5: Evaluate the Model

Evaluate the model performance using metrics like Mean Squared Error (MSE) and R-squared.

```
print(f'Univariate MSE: {mean_squared_error(y_uni_test, y_uni_pred)}')
print(f'Univariate R-squared: {r2_score(y_uni_test, y_uni_pred)}')
```

OUTPUT :

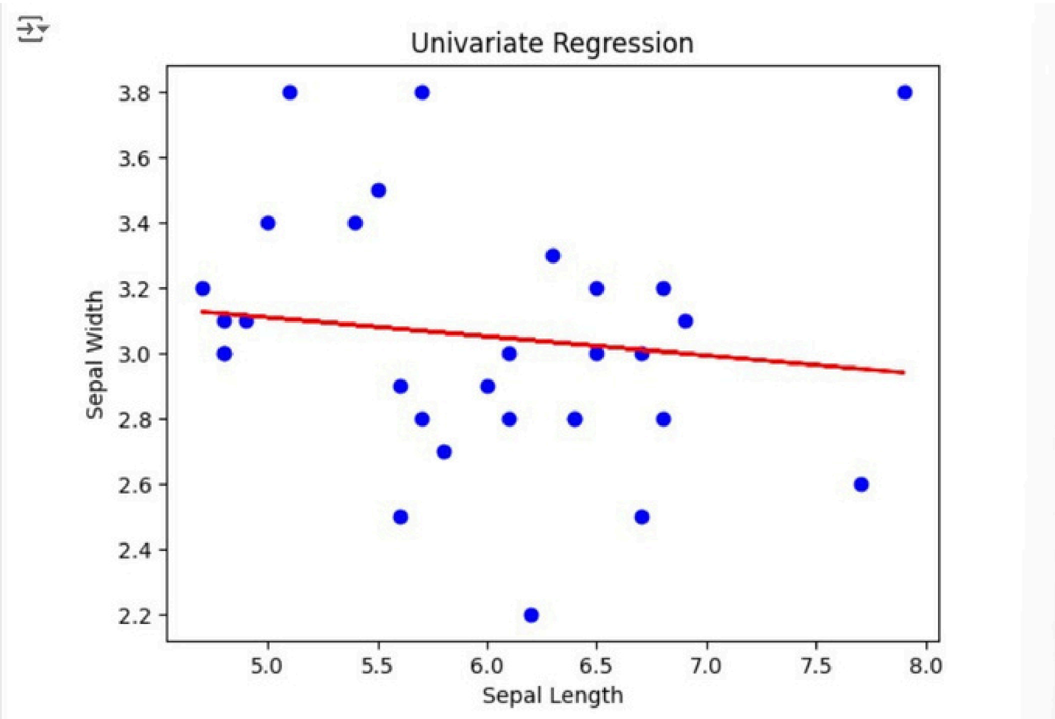
```
Univariate MSE: 0.13961895650579023
Univariate R-squared: 0.024098626473972984
```

4.6: Visualize the Results

Visualize the relationship between the predictor and the target variable.

```
plt.scatter(X_uni_test, y_uni_test, color='blue')
plt.plot(X_uni_test, y_uni_pred, color='red')
plt.xlabel('Sepal Length')
plt.ylabel('Sepal Width')
plt.title('Univariate Regression')
plt.show()
```

OUTPUT :



Step 5 : Bivariate Regression

Bivariate regression involves predicting one variable based on two predictors.

5.1: Select the Features

Choose two features (e.g., sepal_length, petal_length) and one target variable (e.g., sepal_width).

```
X_bi = iris[['sepal_length', 'petal_length']]

y_bi = iris['sepal_width']
```

5.2: Split the Data

Split the data into training and testing sets.

```
X_bi_train, X_bi_test, y_bi_train, y_bi_test = train_test_split(X_bi, y_bi,

test_size=0.2, random_state=42)
```

5.3: Train the Model

Fit the linear regression model on the training data.

```
bi_model = LinearRegression()

bi_model.fit(X_bi_train, y_bi_train)
```

OUTPUT :

```
LinearRegression
LinearRegression()
```

5.4: Make Predictions

Use the model to make predictions on the test data.

```
y_bi_pred = bi_model.predict(X_bi_test)
```

5.5: Evaluate the Model

Evaluate the model performance using metrics like MSE and R-squared.

```
print(f'Bivariate MSE: {mean_squared_error(y_bi_test, y_bi_pred)}')
print(f'Bivariate R-squared: {r2_score(y_bi_test, y_bi_pred)}')
```

OUTPUT :

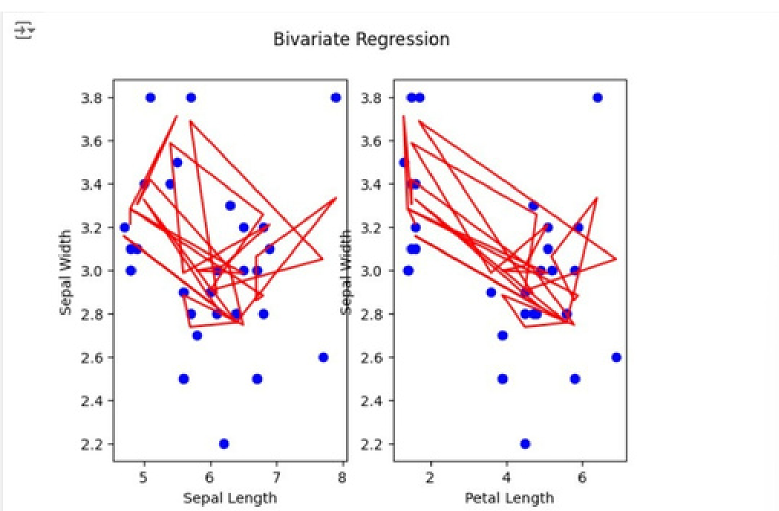
```
Bivariate MSE: 0.08308605032913309
Bivariate R-squared: 0.4192494152204116
```

5.6: Visualize the Results

Since visualizing in 3D is challenging, we can plot the relationships between the target and each predictor separately.

```
# Sepal Length vs Sepal Width


plt.subplot(1, 2, 1)

plt.scatter(X_bi_test['sepal_length'], y_bi_test, color='blue')

plt.plot(X_bi_test['sepal_length'], y_bi_pred, color='red')

plt.xlabel('Sepal Length')

plt.ylabel('Sepal Width')

# Petal Length vs Sepal Width

plt.subplot(1, 2, 2)

plt.scatter(X_bi_test['petal_length'], y_bi_test, color='blue')

plt.plot(X_bi_test['petal_length'], y_bi_pred, color='red')

plt.xlabel('Petal Length')

plt.ylabel('Sepal Width')

plt.suptitle('Bivariate Regression')

plt.show()
```

OUTPUT :



Step 6: Multivariate Regression

Multivariate regression involves predicting one variable based on multiple predictors.

6.1: Select the Features

Choose multiple features (e.g., sepal_length, petal_length, petal_width) and one target variable (e.g., sepal_width).

```
X_multi = iris[['sepal_length', 'petal_length', 'petal_width']]

y_multi = iris['sepal_width']
```

6.2: Split the Data

Split the data into training and testing sets.

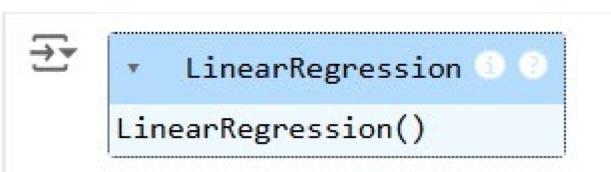
```
X_multi_train, X_multi_test, y_multi_train, y_multi_test =
train_test_split(X_multi,

y_multi, test_size=0.2, random_state=42)
```

6.3: Train the Model

Fit the linear regression model on the training data.

```
multi_model = LinearRegression()
multi_model.fit(X_multi_train, y_multi_train)
```

OUTPUT :



6.4: Make Predictions

Use the model to make predictions on the test data.

```
y_multi_pred = multi_model.predict(X_multi_test)
```

6.5: Evaluate the Model

Evaluate the model performance using metrics like MSE and R-squared.

```
print(f'Multivariate MSE: {mean_squared_error(y_multi_test, y_multi_pred)}')
print(f'Multivariate R-squared: {r2_score(y_multi_test, y_multi_pred)}')
```

OUTPUT :

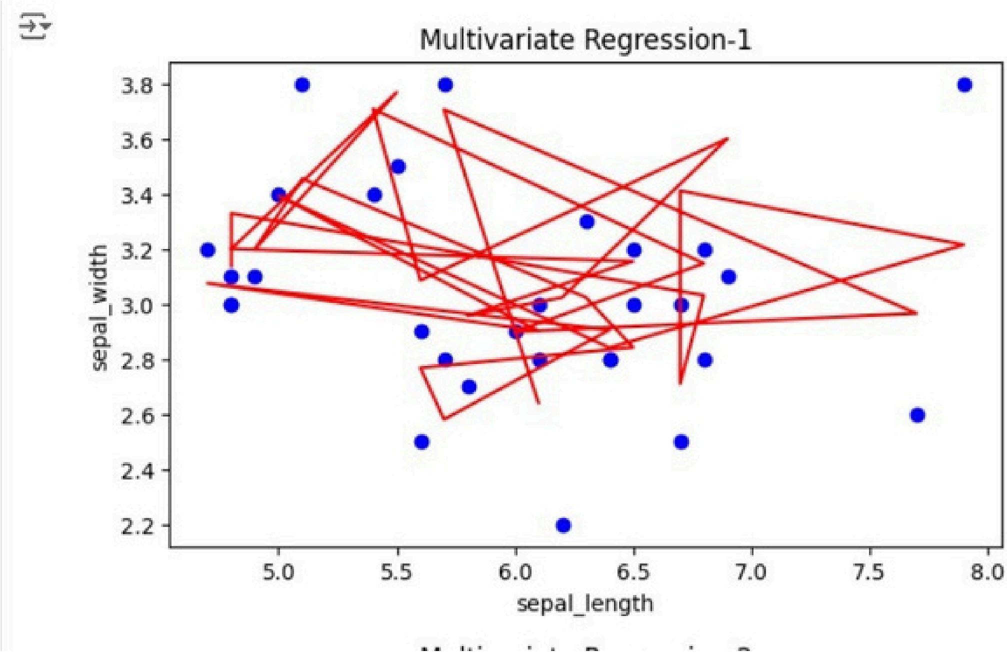
```
Multivariate MSE: 0.0868353771078583
Multivariate R-squared: 0.39304256448374897
```

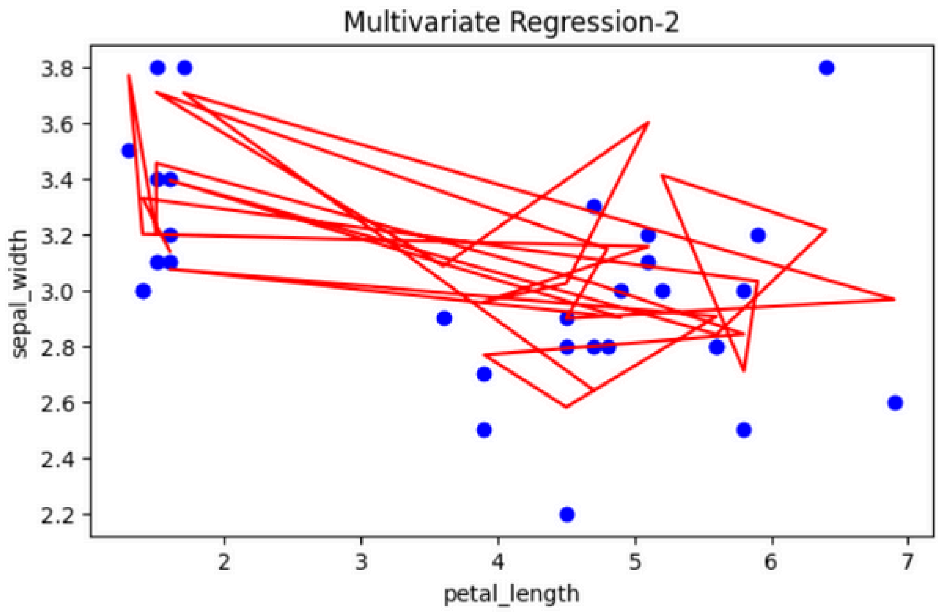
Step 7: Visualize the multivariate regression

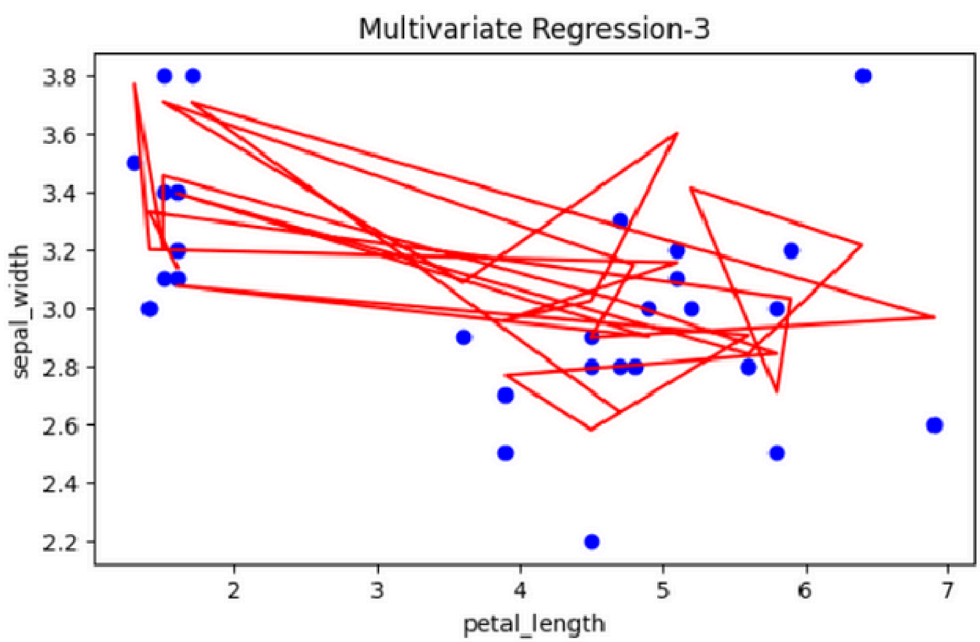
```
plt.figure(figsize=(15,4))

plt.subplot(1, 2, 1)

plt.scatter(X_multi_test['sepal_length'], y_multi_test, color='blue')

plt.plot(X_multi_test['sepal_length'], y_multi_pred, color='red')

plt.xlabel('sepal_length')

plt.ylabel('sepal_width')

plt.title('Multivariate Regression-1')

plt.show()

plt.figure(figsize=(15,4))

plt.subplot(1, 2, 1)

plt.scatter(X_multi_test['petal_length'], y_multi_test, color='blue')

plt.plot(X_multi_test['petal_length'], y_multi_pred, color='red')

plt.xlabel('petal_length')

plt.ylabel('sepal_width')

plt.title('Multivariate Regression-2')

plt.show()
```

```
plt.figure(figsize=(15,4))

plt.subplot(1, 2, 2 )

plt.scatter(X_multi_test['petal_length'], y_multi_test, color='blue')

plt.plot(X_multi_test['petal_length'], y_multi_pred, color='red')

plt.xlabel('petal_length')

plt.ylabel('sepal_width')

plt.title('Multivariate Regression-3')

plt.show()
```

OUTPUT :




Multivariate Regression-2
sepal_width
3.8
3.6
3.4
3.2
3.0
2.8
2.6
2.4
2.2
2
3
4
5
6
7
petal_length


Multivariate Regression-3
sepal_width
3.8
3.6
3.4
3.2
3.0
2.8
2.6
2.4
2.2
2
3
4
5
6
7
petal_length

Step 8: Interpret the Results

After implementing and evaluating the models, interpret the coefficients to understand the influence of each predictor on the target variable.

```
print('Univariate Coefficients:', uni_model.coef_)
print('Bivariate Coefficients:', bi_model.coef_)
print('Multivariate Coefficients:', multi_model.coef_)
```

OUTPUT :

```
Univariate Coefficients: [-0.05829418]
Bivariate Coefficients: [ 0.56420418 -0.33942806]
Multivariate Coefficients: [ 0.62934965 -0.63196673  0.6440201 ]
```

RESULT:

This step-by-step process will help us to implement univariate, bivariate, and multivariate regression models using the Iris dataset and analyze their performance.