

EXPT NO: 1 **A python program to implement univariate regression**
DATE: 23/08/24 **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')

# 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.

```
# 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

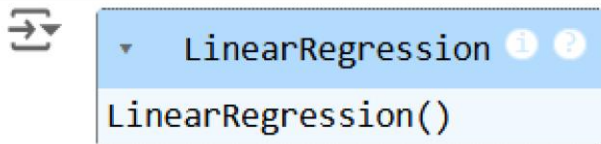
```
X_uni = iris[['sepal_length']]
y_uni = iris['sepal_width']
```

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

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4.2: Split the Data

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



4.4: Make Predictions

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

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

Use the model to make predictions on the test data.

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 :

A screenshot of the output from a Jupyter Notebook cell. On the left, there is a blue icon with a right-pointing arrow. To its right, the output is displayed in a monospaced font. The first line is 'Univariate MSE: 0.13961895650579023' and the second line is 'Univariate R-squared: 0.024098626473972984'.

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

4.6: Visualize the Results

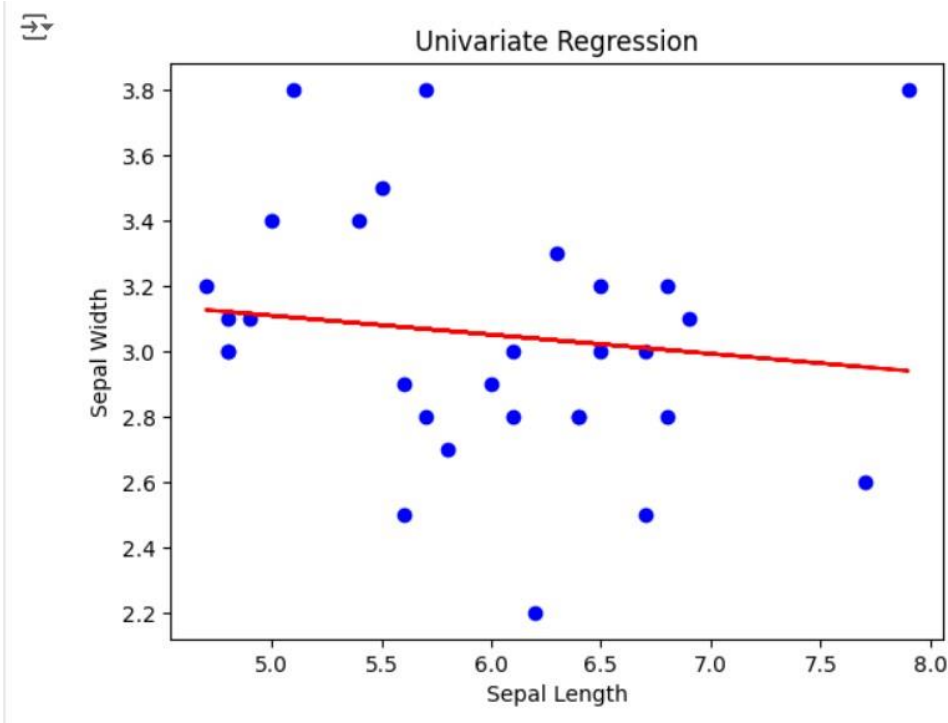
Visualize the relationship between the predictor and the target variable.

```
plt.scatter(X_uni_test, y_uni_test, color='blue')
```

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```
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

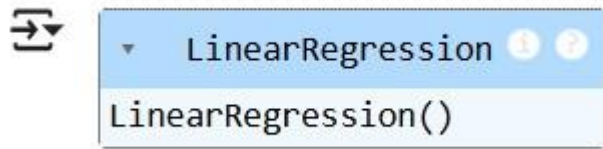
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Fit the linear regression model on the training data.

```
bi_model = LinearRegression()

bi_model.fit(X_bi_train, y_bi_train)
```

OUTPUT :



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')

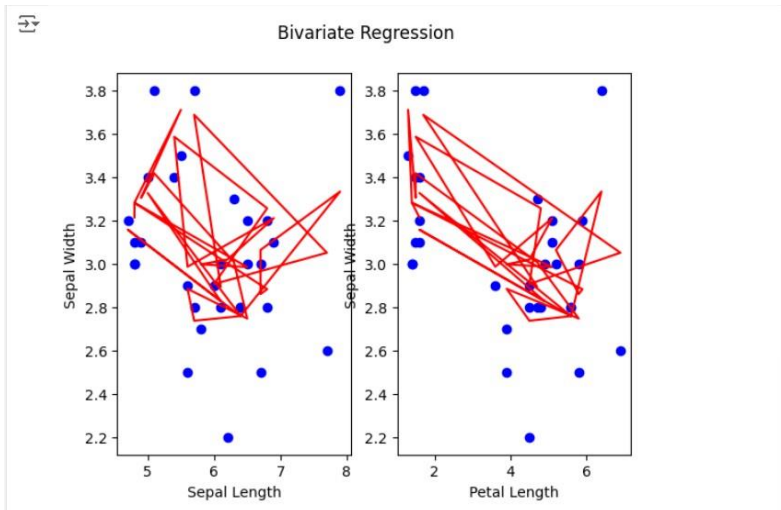
# Petal Length vs Sepal Width
plt.subplot(1, 2, 2)

plt.scatter(X_bi_test['petal_length'], y_bi_test, color='blue')
plt.plot(X_bi_test['petal_length'], y_bi_pred, color='red')
```

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```
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.

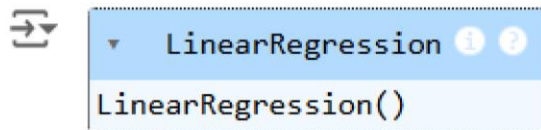
```
X_multi_train, X_multi_test, y_multi_train, y_multi_test =
train_test_split(X_multi,
y_multi, test_size=0.2, random_state=42)
```

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

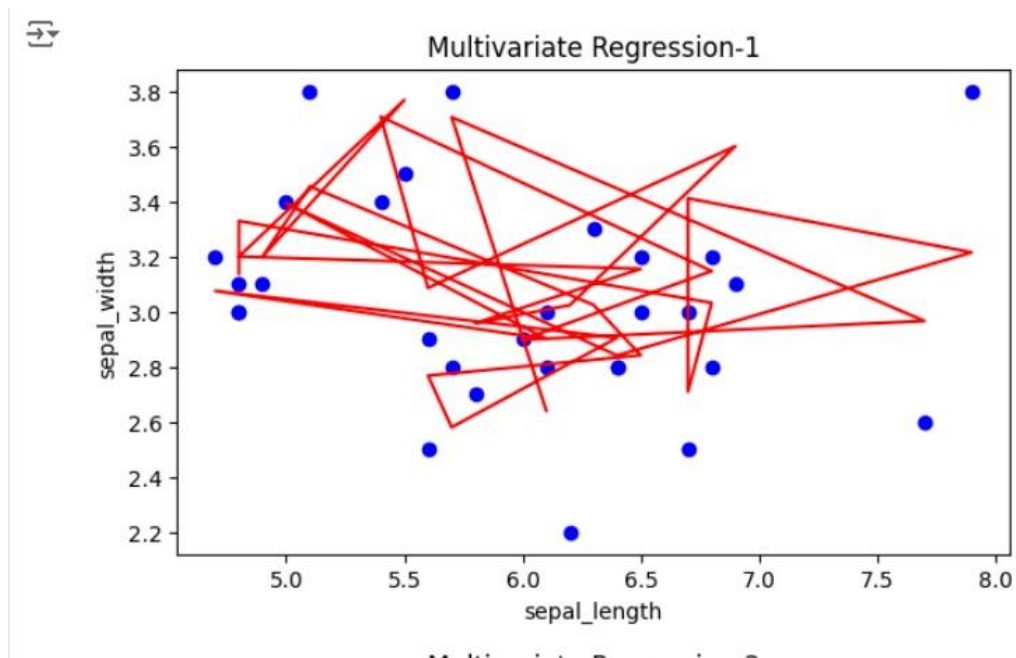
```
plt.figure(figsize=(15,4))
plt.subplot(1, 2, 1)
plt.scatter(X_multi_test['sepal_length'], y_multi_test, color='blue')
plt.plot(X_multi_test['sepal_length'], y_multi_pred, color='red')
plt.xlabel('sepal_length')
plt.ylabel('sepal_width')
plt.title('Multivariate Regression-1')
plt.show()

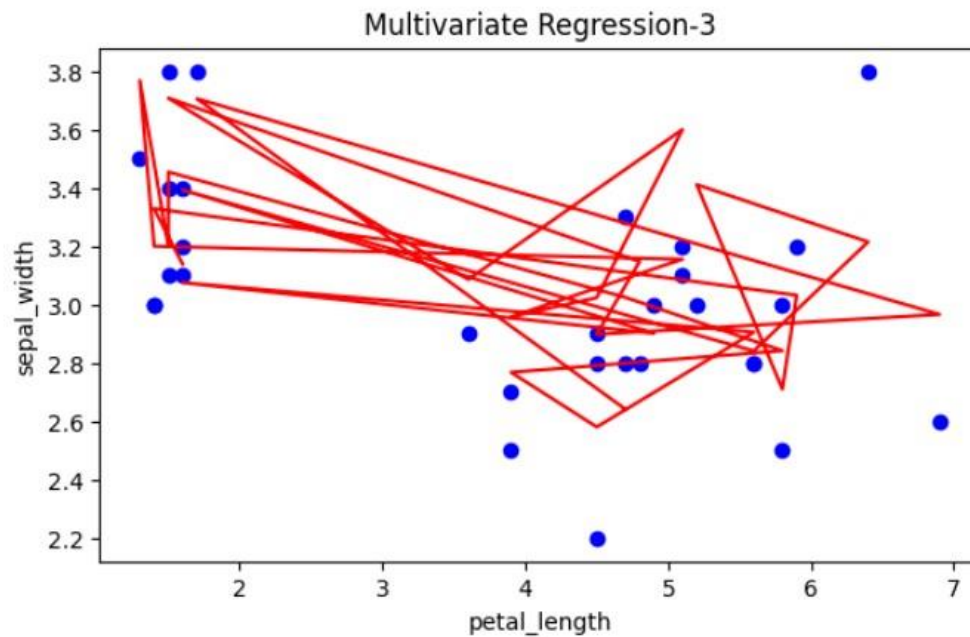
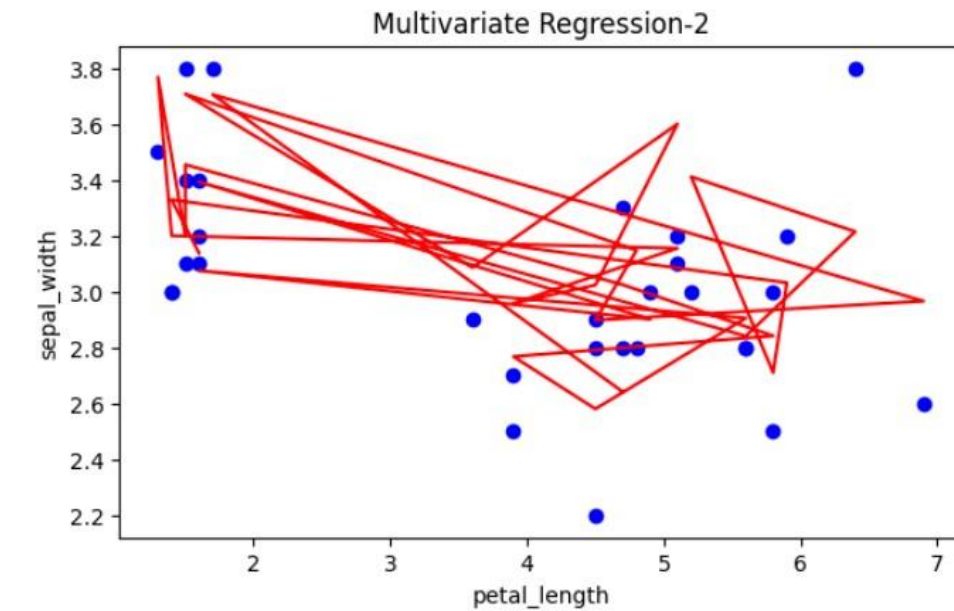
plt.figure(figsize=(15,4))
plt.subplot(1, 2, 1)
plt.scatter(X_multi_test['petal_length'], y_multi_test, color='blue')
plt.plot(X_multi_test['petal_length'], y_multi_pred, color='red')
plt.xlabel('petal_length')
plt.ylabel('sepal_width')
```

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```
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 :





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 :

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```
⇒ 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.