LAB ASSIGNMENT 3

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Roll No.:	21BCP359	**Date:**	05-08-24	**Batch:**	G11
Aim:	Implement simple and multi-linear regression to predict profits for a food truck. Compare the performance of the model on linear and multi-linear regression.				

Objective

The objective of this lab assignment is to implement simple and multi-linear regression models to predict profits for a food truck business. By comparing the performance of these two regression models, you will gain insights into when and how to use simple and multi-linear regression techniques.

Steps

1. **Data Preparation**:

   - Construct a numpy array containing both features (Population, Years in Business) and the target variable (Profit).
   - Separate the data into feature set XXX and target variable yyy.
   - Address any missing values in yyy by substituting NaN with the average of yyy.

2. **Simple Linear Regression**:

   - Develop a function called simple_linear_regression to compute the coefficients (β0\beta_0β0, β1\beta_1β1), make predictions, and calculate the mean squared error (MSE) for a single feature (Years in Business).
   - Extract the Years in Business as X_simple and apply the simple linear regression model.

3. **Multiple Linear Regression**:

   - Create a function named multi_linear_regression to determine coefficients, predictions, and MSE using all features.
   - Prepare the feature set X_multi by adding a column of ones for the intercept term and then perform the multiple linear regression analysis.

4. **Plotting**:

   - Generate two subplots:
     - The first subplot will display the results of the simple linear regression (Years in Business vs. Profit).
     - The second subplot will illustrate the results of the multiple linear regression (Population vs. Profit).
   - Show both actual and predicted values in these plots.

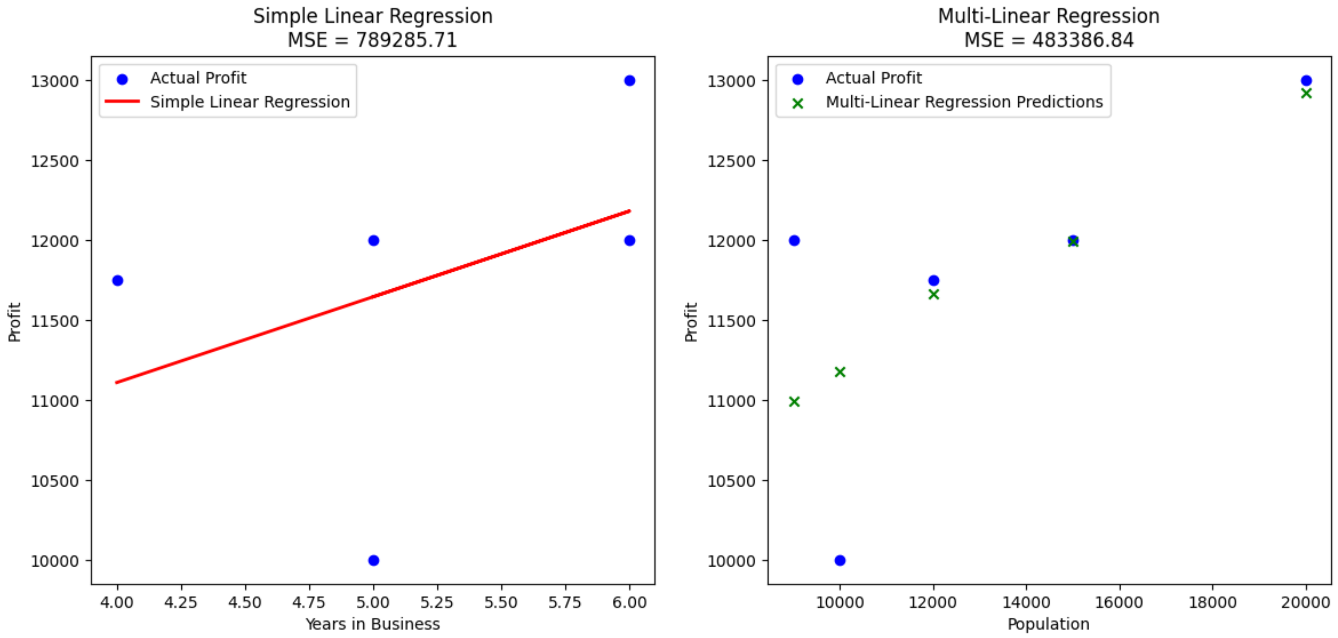
5. **Print Results**:

   - Print out the coefficients, intercepts, and MSE for both the simple and multiple linear regression models.

Code

```
import numpy as np
import matplotlib.pyplot as plt

data = np.array(
    [
        [10000, 5, 10000],
        [15000, 6, 12000],
        [20000, 6, 13000],
        [9000, 5, 12000],
        [12000, 4, np.nan],
    ]
)
X = data[:, :-1]
y = data[:, -1]

mean_y = np.nanmean(y)
y[np.isnan(y)] = mean_y


def simple_linear_regression(X_simple, y):
    X_simple_mean = np.mean(X_simple)
    y_mean = np.mean(y)
    beta1 = np.sum((X_simple - X_simple_mean) * (y - y_mean)) / np.sum(
        (X_simple - X_simple_mean) ** 2
    )
    beta0 = y_mean - beta1 * X_simple_mean
    y_pred = beta0 + beta1 * X_simple
    mse = np.mean((y - y_pred) ** 2)
    return beta0, beta1, y_pred, mse

def multi_linear_regression(X_multi, y):
    XTX = np.dot(X_multi.T, X_multi)
    XTX_inv = np.linalg.inv(XTX)
    XTy = np.dot(X_multi.T, y)
    beta = np.dot(XTX_inv, XTy)
    y_pred = np.dot(X_multi, beta)
    mse = np.mean((y - y_pred) ** 2)
    return beta, y_pred, mse


X_simple = X[:, 1]
beta0, beta1, y_pred_simple, mse_simple = simple_linear_regression(X_simple, y)
X_multi = np.hstack([np.ones((X.shape[0], 1)), X])
beta_multi, y_pred_multi, mse_multi = multi_linear_regression(X_multi, y)

plt.figure(figsize=(14, 6))

plt.subplot(1, 2, 1)
plt.scatter(X_simple, y, color="blue", label="Actual Profit")
```

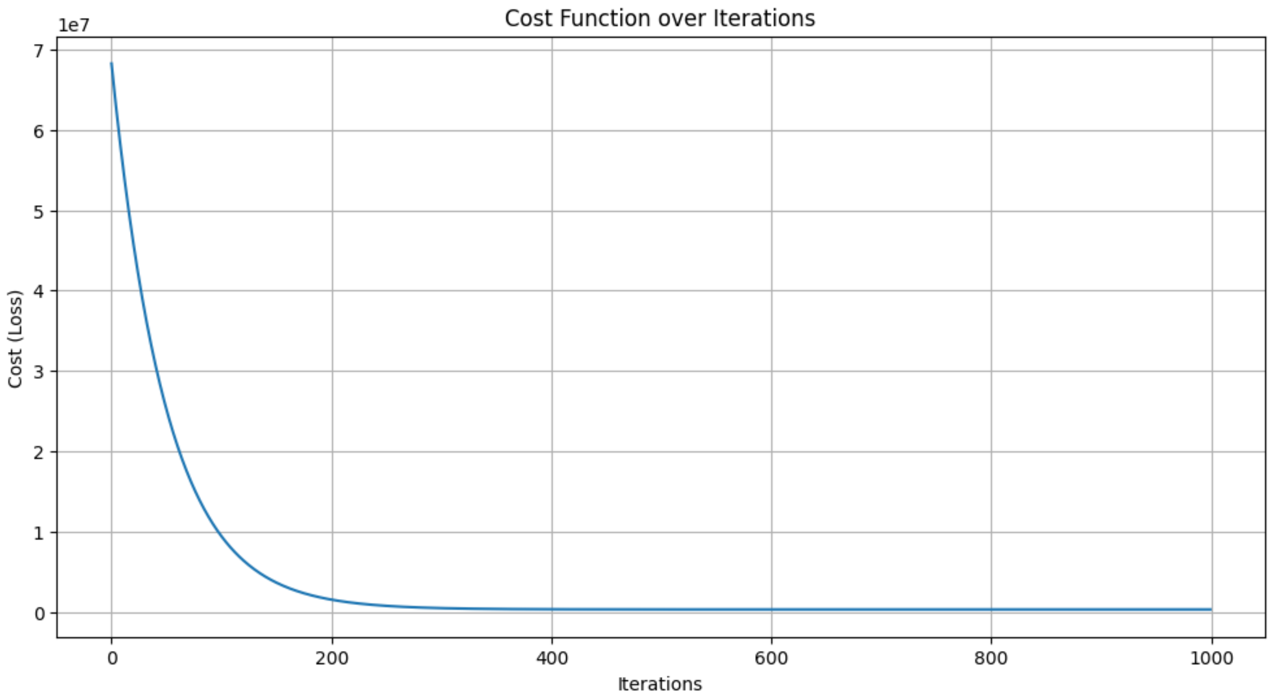
```
plt.plot(
    X_simple, y_pred_simple, color="red", linewidth=2, label="Simple Linear Regression"
)
plt.xlabel("Years in Business")
plt.ylabel("Profit")
plt.title(f"Simple Linear Regression\nMSE = {mse_simple:.2f}")
plt.legend()

plt.subplot(1, 2, 2)
X_population = X[:, 0]
plt.scatter(X_population, y, color="blue", label="Actual Profit")
plt.scatter(
    X_population,
    y_pred_multi,
    color="green",
    marker="x",
    label="Multi-Linear Regression Predictions",
)
plt.xlabel("Population")
plt.ylabel("Profit")
plt.title(f"Multi-Linear Regression\nMSE = {mse_multi:.2f}")
plt.legend()
plt.show()
```




```
X = np.array([[10000], [15000], [20000], [9000]])
y = np.array([10000, 12000, 13000, 12000])

Population_mean = X.mean()
Population_std = X.std()
Population_normalized = (X - Population_mean) / Population_std
```

```
X = np.hstack((np.ones((X.shape[0], 1)), Population_normalized))
y = y

w = np.zeros(X.shape[1])

learning_rate = 0.01
n_iterations = 1000


def predict(X, w):
    return X.dot(w)

def compute_cost(X, y, w):
    m = len(y)
    predictions = predict(X, w)
    cost = (1 / (2 * m)) * np.sum((predictions - y) ** 2)
    return cost

def gradient_descent(X, y, w, learning_rate, n_iterations):
    m = len(y)
    cost_history = []

    for i in range(n_iterations):
        predictions = predict(X, w)
        errors = predictions - y
        gradients = (1 / m) * X.T.dot(errors)
        w -= learning_rate * gradients

        cost = compute_cost(X, y, w)
        cost_history.append(cost)

    return w, cost_history


w, cost_history = gradient_descent(X, y, w, learning_rate, n_iterations)

print(f"Final weights: {w}")

plt.figure(figsize=(12, 6))

plt.plot(range(len(cost_history)), cost_history)
plt.xlabel("Iterations")
plt.ylabel("Cost (Loss)")
plt.title("Cost Function over Iterations")
plt.grid(True)
plt.show()
```

Final weights: [11749.49273784   769.20068232]


Cost Function over Iterations
1e7
7
6
5
4
3
2
1
0
Cost (Loss)
0
200
400
600
800
1000
Iterations