220962050_Arhaan_Lab05

August 23, 2024

1 Question 1

Create a CSV file for the above training data and write a Python function program to find the fitted linear regression with gradient descent technique. Compare the coefficients obtained from the sklearn model with your program. Compute the error, MSE and RMSE. Plot the graph Daughter height (Y-axis) vs Mother height (X-axis) with blue colour. Also, plot the line of best fit with red colour. Predict her daughterâ€™s height with given a new mother height as 63. Plot the graph of error in y-axis and iteration in x-axis with 4 epochs (6x4=24 iterations).

[ ]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
```

[ ]:
```
data = pd.read_csv('heights.csv')
X = data[['mother_height']].values
y = data['daughter_height'].values

data
```

[ ]:

	mother_height	daughter_height
0	60	62
1	62	64
2	64	66
3	66	68
4	68	70
5	70	72
6	72	74
7	74	76
8	76	78
9	78	80

[ ]:
```
def standardize(X):
    mean = np.mean(X, axis=0)
    std = np.std(X, axis=0)
    X_standardized = (X - mean) / std
    return X_standardized, mean, std

def unstandardize(X_standardized, mean, std):
```

```
    X_unstandardized = X_standardized * std + mean
    return X_unstandardized

X_standardized, X_mean, X_std = standardize(X)
```

[ ]:
```
def train_test_split(X, y, test_size=0.2, random_state=None):
    np.random.seed(random_state)
    indices = np.arange(X.shape[0])
    np.random.shuffle(indices)
    split_index = int(len(X) * (1 - test_size))
    train_indices, test_indices = indices[:split_index], indices[split_index:]
    return X[train_indices], X[test_indices], y[train_indices], y[test_indices]

X_train, X_test, y_train, y_test = train_test_split(X_standardized, y,␣
 ↪test_size=0.2, random_state=42)
```

[ ]:
```
def gradient_descent(X, y, learning_rate=0.001, epochs=1000):
    m = len(y)
    X_b = np.c_[np.ones((m, 1)), X]
    theta = np.random.randn(2, 1)
    y = y.reshape(-1, 1)

    for epoch in range(epochs):
        gradients = 2/m * X_b.T.dot(X_b.dot(theta) - y)
        theta -= learning_rate * gradients

        if np.any(np.isnan(theta)) or np.any(np.isinf(theta)):
            print(f"NaN or Inf detected at epoch {epoch}")
            break

    return theta
```

[ ]:
```
learning_rate = 0.001
epochs = 1000

theta = gradient_descent(X_train, y_train, learning_rate, epochs)
intercept, slope = theta[0][0], theta[1][0]

print(f"Gradient Descent Coefficients:\nIntercept: {intercept}\nSlope: {slope}")
```

```
Gradient Descent Coefficients:
Intercept: 61.44810748515938
Slope: 5.300439610149634
```

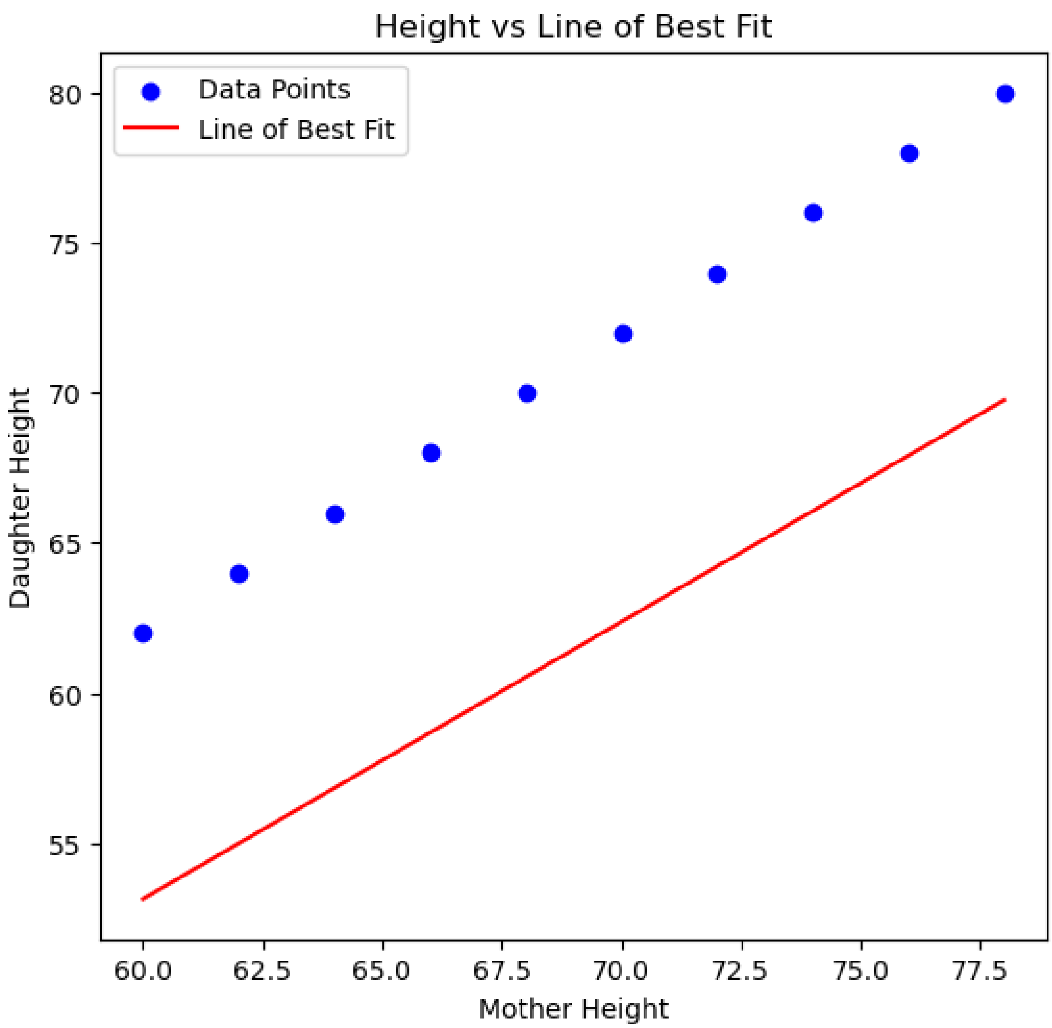
[ ]:
```
X_test_b = np.c_[np.ones((len(X_test), 1)), X_test]
y_test_pred = X_test_b.dot(theta)

mse = np.mean((y_test - y_test_pred.flatten()) ** 2)
```

```python
rmse = np.sqrt(mse)
print(f"Mean Squared Error: {mse}")
print(f"Root Mean Squared Error: {rmse}")
```

```
Mean Squared Error: 91.29244478000933
Root Mean Squared Error: 9.554707990305582
```

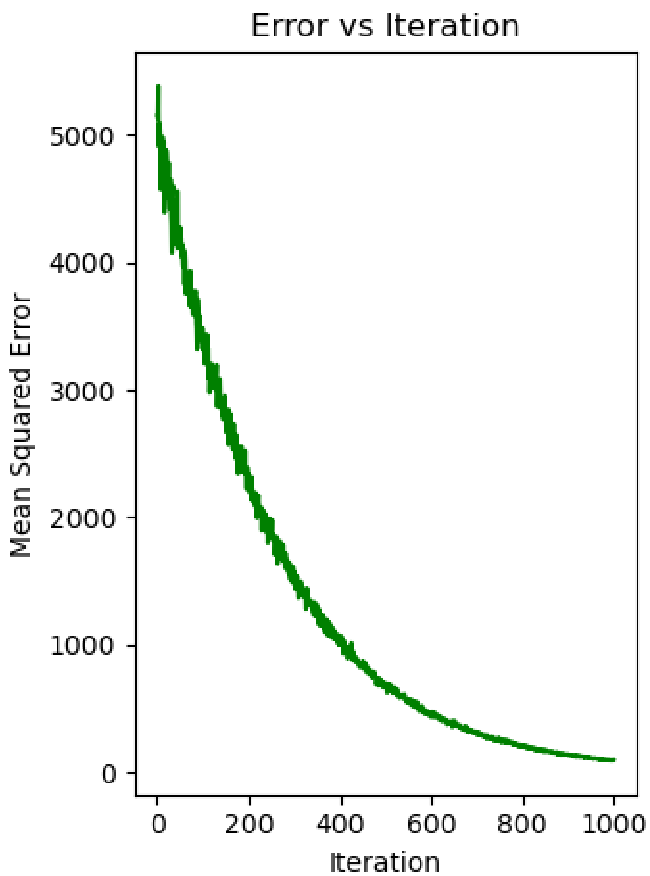
[ ]:
```python
plt.figure(figsize=(14, 6))

plt.subplot(1, 2, 1)
plt.scatter(data['mother_height'], data['daughter_height'], color='blue',␣
 ↪label='Data Points')

X_line = np.linspace(data['mother_height'].min(), data['mother_height'].max(),␣
 ↪100).reshape(-1, 1)
X_line_standardized = (X_line - X_mean) / X_std
X_line_b = np.c_[np.ones((X_line_standardized.shape[0], 1)),␣
 ↪X_line_standardized]

y_line = X_line_b.dot(theta)

plt.plot(X_line, y_line, color='red', label='Line of Best Fit')
plt.xlabel('Mother Height')
plt.ylabel('Daughter Height')
plt.title('Height vs Line of Best Fit')
plt.legend()
```

[ ]:
```
<matplotlib.legend.Legend at 0x706ddf2dbf50>
```



[ ]:
```
errors = []
for epoch in range(1, epochs + 1):
    theta = gradient_descent(X_train, y_train, learning_rate, epoch)
    X_b_train = np.c_[np.ones((len(X_train), 1)), X_train]
    y_pred_train = X_b_train.dot(theta)
    error = np.mean((y_pred_train - y_train.reshape(-1, 1))**2)
    errors.append(error)

plt.subplot(1, 2, 2)
plt.plot(range(1, epochs + 1), errors, color='green')
plt.xlabel('Iteration')
plt.ylabel('Mean Squared Error')
plt.title('Error vs Iteration')

plt.tight_layout()
```

```
plt.show()
```




```
[ ]: new_mother_height = np.array([[63]])
new_mother_height_standardized = (new_mother_height - X_mean) / X_std
new_mother_height_b = np.c_[np.ones((new_mother_height_standardized.shape[0],␣
 ↪1)), new_mother_height_standardized]
predicted_daughter_height = new_mother_height_b.dot(theta)[0][0]
print(f"Predicted Daughter's Height for Mother Height {new_mother_height[0][0]}:
 ↪ {predicted_daughter_height}")
```

```
Predicted Daughter's Height for Mother Height 63: 55.63216772800946
```

2 Question 2

Create a CSV file for the above training data and write a Python function program to find the fitted logistic regression with gradient descent technique. Compare the coefficients obtained from the sklearn model with your program. Compute the predicted y and assign the class label (prediction = 0 IF p(fail) < 0.5 and prediction = 1 IF p(pass) >= 0.5) and compute the accuracy. Find the error for each iteration and predict the probability that a student will pass the exam if they study for a) 3.5 hours b) 7.5 hours. Plot the graph of error in y-axis and iteration in x-axis with 3 epochs (8x3=24 iterations).

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

[ ]:
```
hours_of_study = np.array([1, 2, 3, 4, 5, 6, 7, 8]).reshape(-1, 1)
pass_status = np.array([0, 0, 0, 0, 1, 1, 1, 1])
```

[ ]:
```
def sigmoid(z):
    return 1 / (1 + np.exp(-z))

def gradient_descent(X, y, alpha, epochs):
    m = len(y)
    theta = np.zeros(X.shape[1])
    intercept = 0
    errors = []

    for epoch in range(epochs):
        z = np.dot(X, theta) + intercept
        predictions = sigmoid(z)
        error = - (1/m) * np.sum(y * np.log(predictions + 1e-10) + (1 - y) * np.
 ↪log(1 - predictions + 1e-10))
        errors.append(error)
        gradient_theta = (1/m) * np.dot(X.T, (predictions - y))
        gradient_intercept = (1/m) * np.sum(predictions - y)
        theta -= alpha * gradient_theta
        intercept -= alpha * gradient_intercept
    return theta, intercept, errors
```

[ ]:
```
from sklearn.preprocessing import StandardScaler

scaler = StandardScaler()
X_scaled = scaler.fit_transform(hours_of_study)
```

[ ]:
```
alpha = 0.1
epochs = 24
theta, intercept, errors = gradient_descent(X_scaled, pass_status, alpha,␣
 ↪epochs)
```

[ ]:
```
print("Gradient Descent Coefficients:", theta)
print("Gradient Descent Intercept:", intercept)
```

```
Gradient Descent Coefficients: [0.80521209]
Gradient Descent Intercept: 8.326672684688675e-18
```

[ ]:
```
def predict_probabilities(X, theta, intercept):
    z = np.dot(X, theta) + intercept
```

```
    return sigmoid(z)

def predict_class(probabilities):
    return (probabilities >= 0.5).astype(int)

probabilities = predict_probabilities(X_scaled, theta, intercept)
predictions = predict_class(probabilities)
```

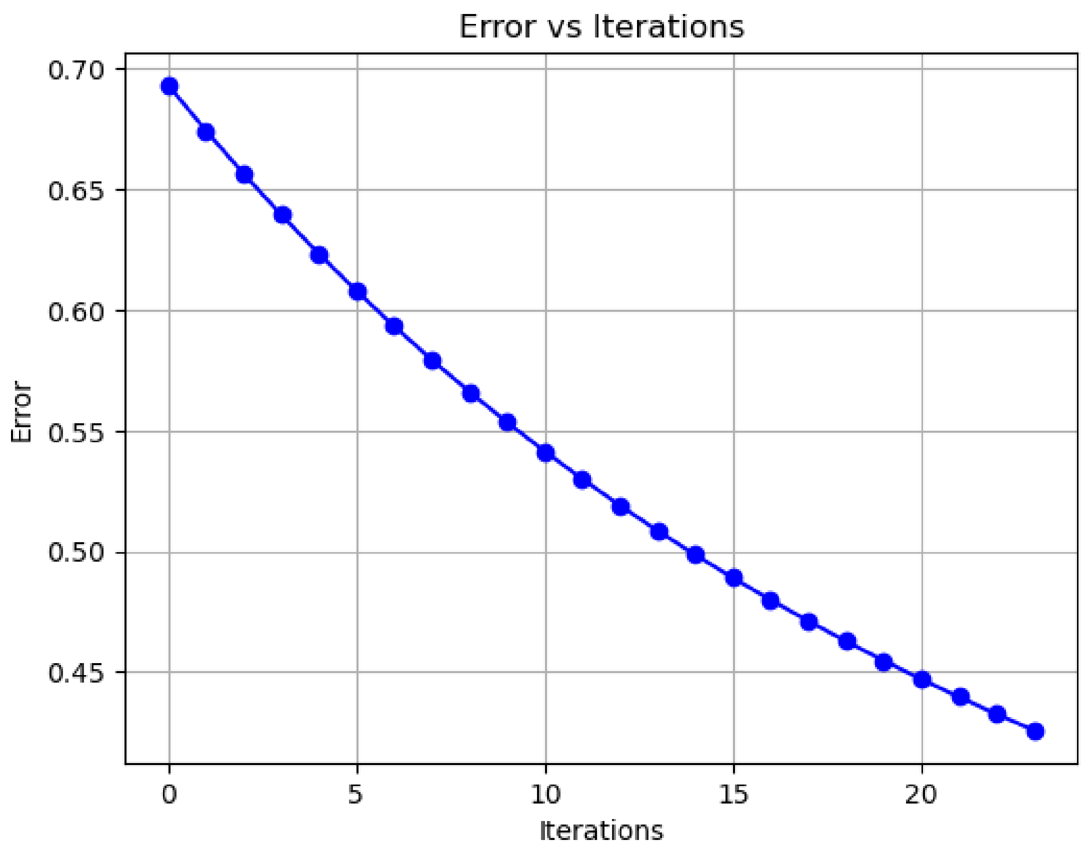
[ ]:
```
accuracy = np.mean(predictions == pass_status)
print("Accuracy:", accuracy)
```

```
Accuracy: 1.0
```

[ ]:
```
test_hours = np.array([3.5, 7.5]).reshape(-1, 1)
test_hours_scaled = scaler.transform(test_hours)
test_probabilities = predict_probabilities(test_hours_scaled, theta, intercept)
print("Probability of passing with 3.5 hours:", test_probabilities[0])
print("Probability of passing with 7.5 hours:", test_probabilities[1])
```

```
Probability of passing with 3.5 hours: 0.4130373007834765
Probability of passing with 7.5 hours: 0.7415940326348259
```

[ ]:
```
plt.plot(range(epochs), errors, color='blue', marker='o')
plt.xlabel('Iterations')
plt.ylabel('Error')
plt.title('Error vs Iterations')
plt.grid(True)
plt.show()
```



3 Question 3

Consider the above dataset with two independent variables (X1 and X2) and a dependent variable (Y). Implement in python, how you can perform the logistic regression to model the relationship between the independent variables and the dependent variable.

[ ]:
```
import numpy as np
from scipy.special import expit
```

[ ]:
```
X1 = np.array([[4, 1], [8, -14], [1, 0], [3, 2], [1, 4], [6, 7]])
y1 = np.array([1, 0, 1, 0, 0, 0])
```

[ ]:
```
def sigmoid(z1):
    return expit(z1)
```

[ ]:
```
def cost_function(X1, y1, theta, intercept):
    m1 = len(y1)
    z1 = np.dot(X1, theta) + intercept
    predictions = sigmoid(z1)
```

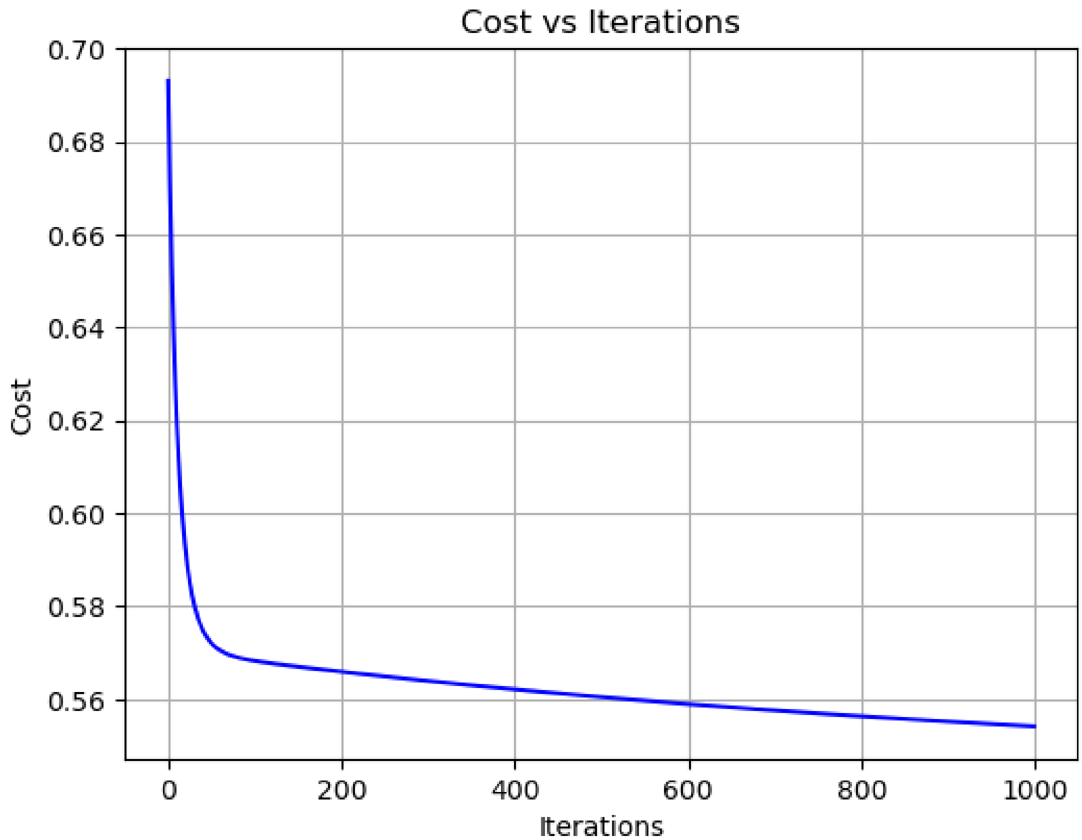
```
    cost = - (1/m1) * np.sum(y1 * np.log(predictions + 1e-10) + (1 - y1) * np.
↪log(1 - predictions + 1e-10))
    return cost
```

[ ]:
```
def gradient_descent(X1, y1, alpha, epochs):
    m1, n1 = X.shape
    theta1 = np.zeros(n1)
    intercept = 0
    costs = []

    for _ in range(epochs):
        z1 = np.dot(X1, theta1) + intercept
        predictions = sigmoid(z1)
        error = predictions - y1
        cost = cost_function(X1, y1, theta1, intercept)
        costs.append(cost)
        gradient_theta = (1/m1) * np.dot(X1.T, error)
        gradient_intercept = (1/m1) * np.sum(error)
        theta1 -= alpha * gradient_theta
        intercept -= alpha * gradient_intercept
    return theta1, intercept, costs
```

[ ]:
```
alpha = 0.01
epochs = 1000
theta1, intercept, costs = gradient_descent(X1, y1, alpha, epochs)
print("Custom Logistic Regression Coefficients:", theta1)
print("Custom Logistic Regression Intercept:", intercept)
```

```
Custom Logistic Regression Coefficients: [-0.33142516 -0.05538593]
Custom Logistic Regression Intercept: 0.3366451923042207
```

[ ]:
```
import matplotlib.pyplot as plt
plt.plot(range(epochs), costs, color='blue')
plt.xlabel('Iterations')
plt.ylabel('Cost')
plt.title('Cost vs Iterations')
plt.grid(True)
plt.show()
```


Cost vs Iterations
0.70
0.68
0.66
0.64
0.62
0.60
0.58
0.56
Cost
0
200
400
600
800
1000
Iterations