Homework 1 Source Code and Results
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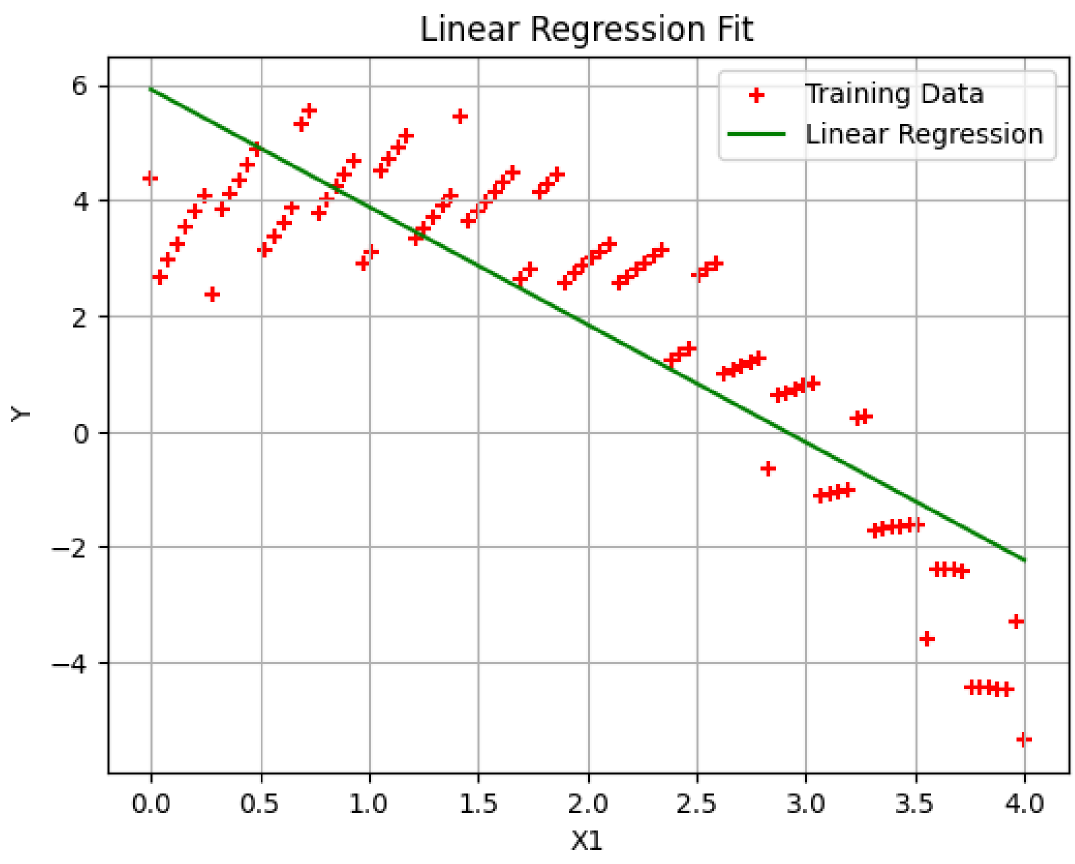
Homework Number: 1
Github Repository: https://github.com/vipravlipare/ECGR-5105-Intro-to-Machine-Learning

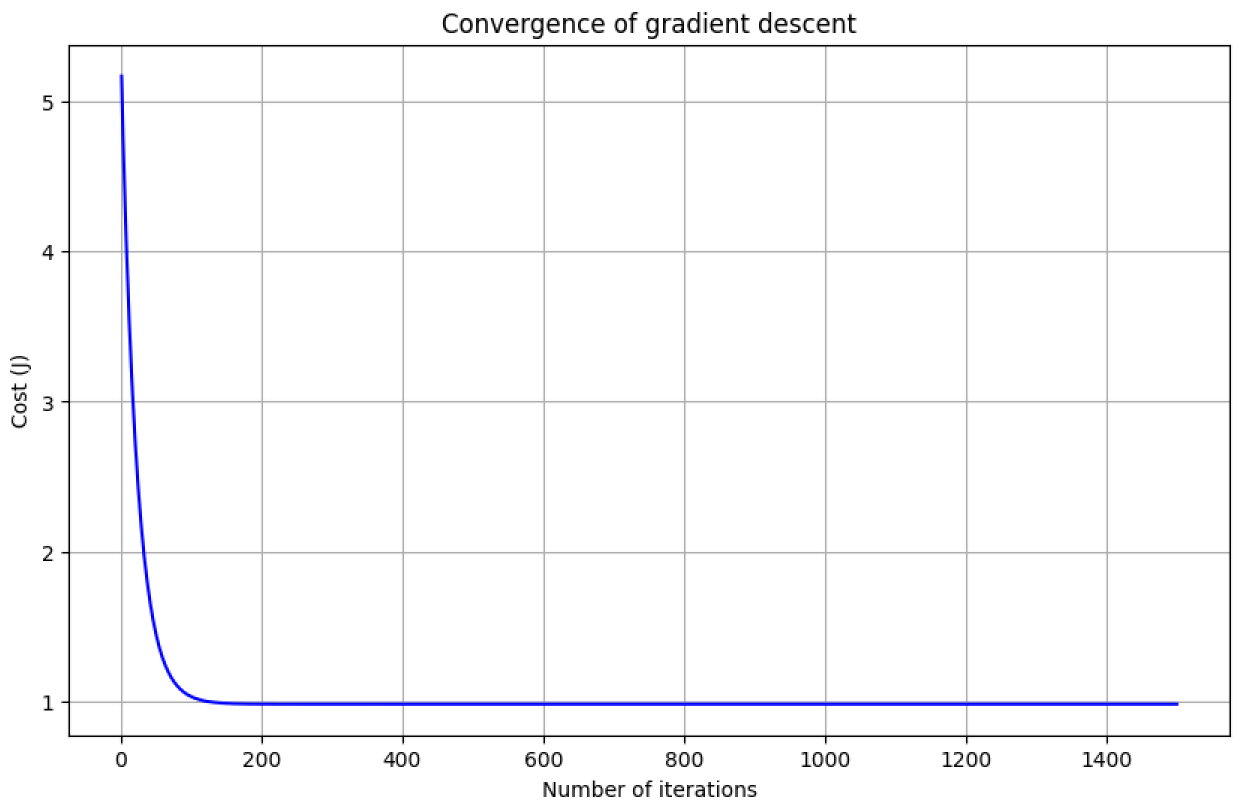
Problem 1

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from google.colab import drive
drive.mount('/content/drive')

file_path = '/content/drive/My Drive/UNCC Notes/Semester 6/Machine
Learning/D3.csv'
sample = pd.DataFrame(pd.read_csv(file_path))

# Separate features and labels
X = sample.values[:, 0]  # get input values from first column -- X is a
list here
y = sample.values[:, 3]  # get output values from second column -- Y is
the list here
m = len(y)  # Number of training examples
n = len(X)  # Number of training examples

# Display first 5 records and the total number of training examples
print('X = ', X[: 5])
print('y = ', y[: 5])
print('m = ', m)
print('n = ', n)

X_0 = np.ones((m, 1))
X_1 = X.reshape(m, 1)
X = np.hstack((X_0, X_1))
X[:5]

theta = np.zeros(2)
theta

def compute_cost(X, y, theta):
    """
    Compute cost for linear regression.
    Parameters:
    X : 2D array where each row represents the training example and each
column represent the feature
        m = number of training examples
        n = number of features (including X_0 column of ones)
    y : 1D array of labels/target values for each training example.
dimension(m)
    theta : 1D array of fitting parameters or weights. Dimension (n)

    Returns:
    J : Scalar value, the cost
    """
    predictions = X.dot(theta)
    errors = np.subtract(predictions, y)
    sqrErrors = np.square(errors)
    J = 1 / (2 * m) * np.sum(sqrErrors)
    return J

# Lets compute the cost for theta values
cost = compute_cost(X, y, theta)
print('The cost for given values of theta_0 and theta_1 =', cost)

def gradient_descent(X, y, theta, alpha, iterations):
    """
    Compute the optimal parameters using gradient descent for linear
regression.

    Parameters:
    X : 2D array where each row represents the training example and each
column represents the feature
        m = number of training examples
        n = number of features (including X_0 column of ones)
    y : 1D array of labels/target values for each training example.
dimension(m)
    theta : 1D array of fitting parameters or weights. Dimension (n)
    alpha : Learning rate (scalar)
    iterations : Number of iterations (scalar)

    Returns:
```

```
    theta : Updated values of fitting parameters or weights after
'iterations' iterations. Dimension (n)
    cost_history : Array containing the cost for each iteration. Dimension
(iterations)
    """

    m = len(y)  # Number of training examples
    cost_history = np.zeros(iterations)

    for i in range(iterations):
        predictions = X.dot(theta)
        errors = np.subtract(predictions, y)
        sum_delta = (alpha / m) * X.transpose().dot(errors)
        theta -= sum_delta
        cost_history[i] = compute_cost(X, y, theta)

    return theta, cost_history

theta = [0., 0.]
iterations = 1500
alpha = 0.1

theta, cost_history = gradient_descent(X, y, theta, alpha, iterations)
print('Final value of theta =', theta)
print('cost_history =', cost_history)

# Scatter plot for the training data
plt.scatter(X[:, 1], y, color='red', marker='+', label='Training Data')

# Line plot for the linear regression model
plt.plot(X[:, 1], X.dot(theta), color='green', label='Linear Regression')

# Plot customizations
plt.rcParams["figure.figsize"] = (10, 6)
plt.grid(True)
plt.xlabel('Population of City in 10,000s')
plt.ylabel('Profit in $10,000s')
plt.title('Linear Regression Fit')
plt.legend()
```

```
# Show the plot
plt.show()

plt.plot(range(1, iterations + 1), cost_history, color='blue')
plt.rcParams["figure.figsize"] = (10, 6)
plt.grid(True)

plt.xlabel('Number of iterations')
plt.ylabel('Cost (J)')
plt.title('Convergence of gradient descent')

# Show the plot
plt.show()

# Gets linear model for X1, X2, and X3
print(f"Linear model: y = {theta[0]} + {theta[1]}*X1")
```





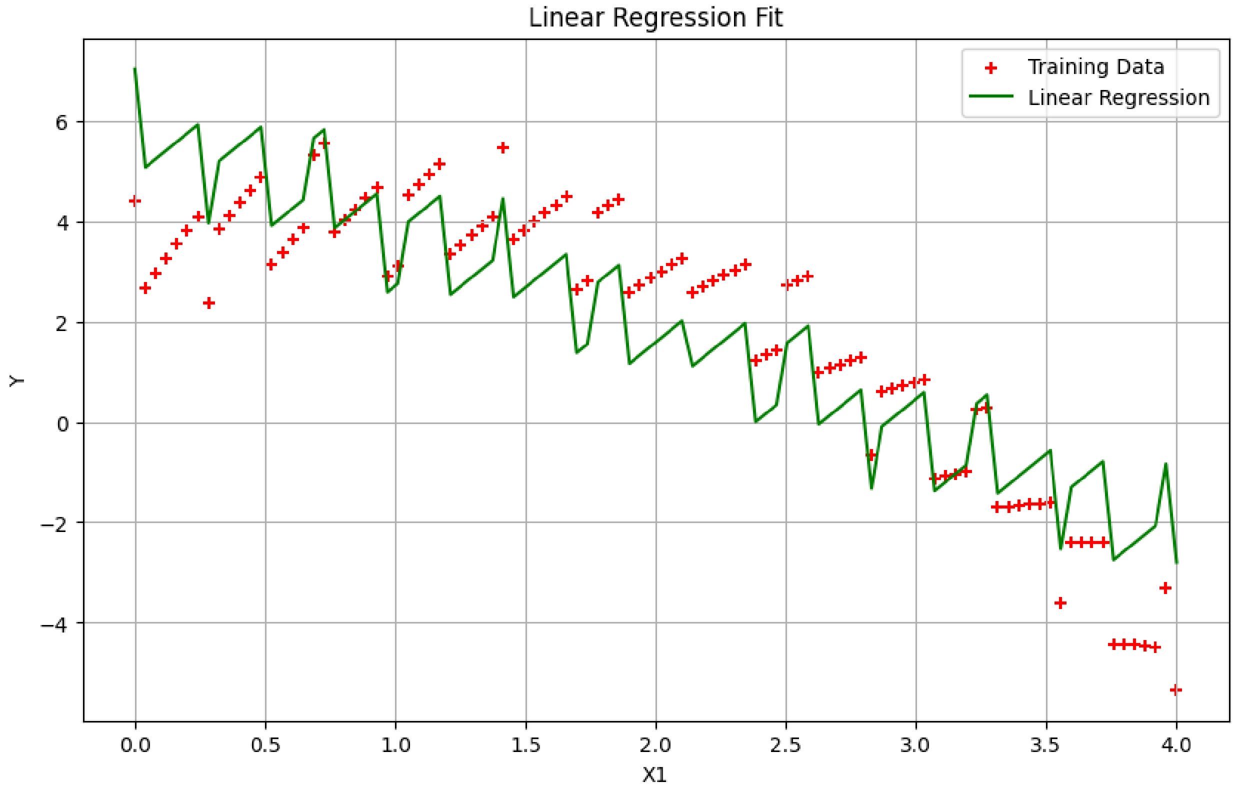
Problem 2

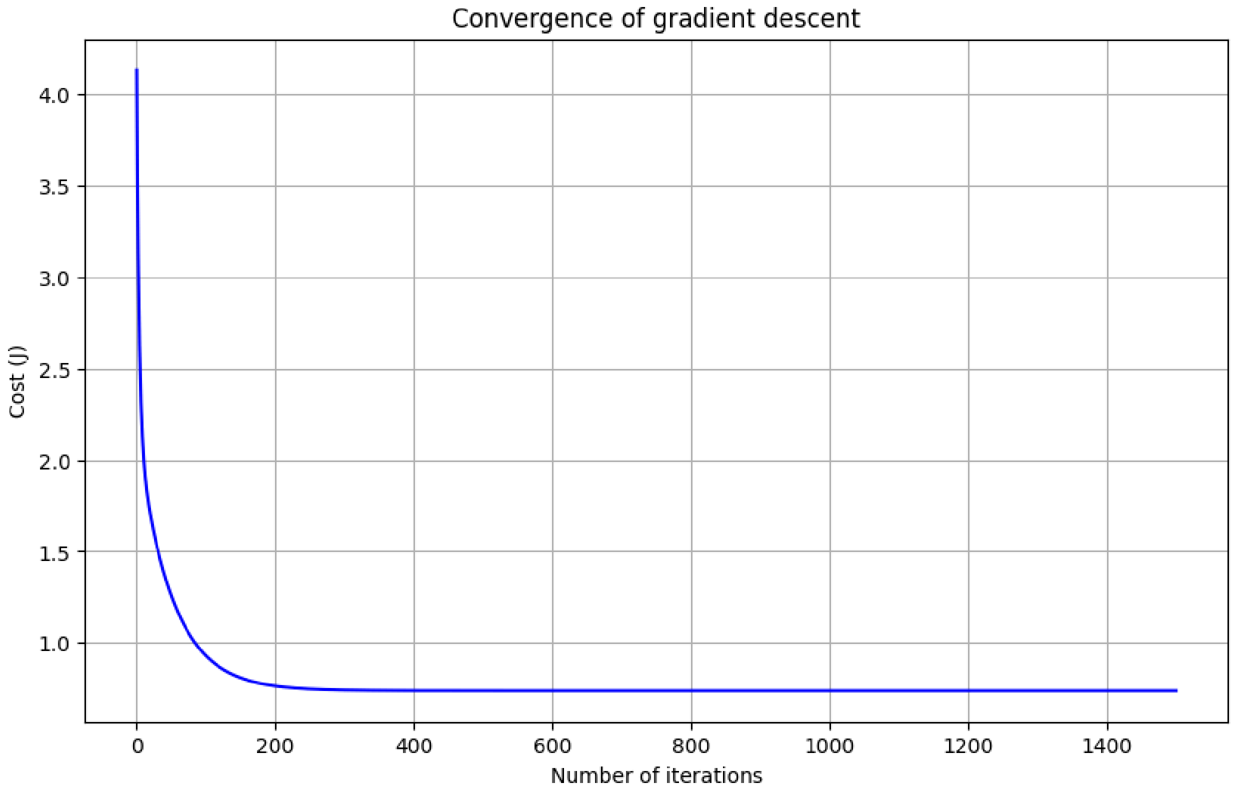
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from google.colab import drive
drive.mount('/content/drive')
file_path = '/content/drive/My Drive/UNCC Notes/Semester 6/Machine
Learning/D3.csv'
sample = pd.DataFrame(pd.read_csv(file_path))

# Separate features and labels
X = sample.values[:, 0:3]  # get input values from first column -- X is a
list here
y = sample.values[:, 3]  # get output values from second column -- Y is
the list here
m = len(y)  # Number of training examples
n = len(X)  # Number of training examples

# Display first 5 records and the total number of training examples
```

```
print('X = ', X[: 5])
print('y = ', y[: 5])
print('m = ', m)
print('n = ', n)

X_0 = np.ones((m, 1))
X = np.hstack((X_0, X))

theta = np.zeros(4)
theta

def compute_cost(X, y, theta):
    """
    Compute cost for linear regression.

    Parameters:
    X : 2D array where each row represents the training example and each
column represent the feature
        m = number of training examples
        n = number of features (including X_0 column of ones)
    y : 1D array of labels/target values for each training example.
dimension(m)
    theta : 1D array of fitting parameters or weights. Dimension (n)

    Returns:
    J : Scalar value, the cost
    """
    predictions = X.dot(theta)
    errors = np.subtract(predictions, y)
    sqrErrors = np.square(errors)
    J = 1 / (2 * m) * np.sum(sqrErrors)
    return J

# Lets compute the cost for theta values
cost = compute_cost(X, y, theta)
print('The cost for given values of theta_0 and theta_1 =', cost)

def gradient_descent(X, y, theta, alpha, iterations):
    """
    Compute the optimal parameters using gradient descent for linear
regression.

    Parameters:
    X : 2D array where each row represents the training example and each
column represents the feature
        m = number of training examples
        n = number of features (including X_0 column of ones)
    y : 1D array of labels/target values for each training example.
dimension(m)
    theta : 1D array of fitting parameters or weights. Dimension (n)
    alpha : Learning rate (scalar)
    iterations : Number of iterations (scalar)

    Returns:
    theta : Updated values of fitting parameters or weights after
'iterations' iterations. Dimension (n)
    cost_history : Array containing the cost for each iteration. Dimension
(iterations)
    """

    m = len(y)  # Number of training examples
    cost_history = np.zeros(iterations)

    for i in range(iterations):
        predictions = X.dot(theta)
        errors = np.subtract(predictions, y)
        sum_delta = (alpha / m) * X.transpose().dot(errors)
        theta -= sum_delta
        cost_history[i] = compute_cost(X, y, theta)

    return theta, cost_history

theta = np.zeros(4)
iterations = 1500
alpha = 0.1

theta, cost_history = gradient_descent(X, y, theta, alpha, iterations)
print('Final value of theta =', theta)
print('cost_history =', cost_history)
```

```
# Final model
print('Final theta:', theta)

# Scatter plot for the training data
plt.scatter(X[:, 1], y, color='red', marker='+', label='Training Data')

# Line plot for the linear regression model
plt.plot(X[:, 1], X.dot(theta), color='green', label='Linear Regression')

# Plot customizations
plt.rcParams["figure.figsize"] = (10, 6)
plt.grid(True)
plt.xlabel('X1')
plt.ylabel('Y')
plt.title('Linear Regression Fit')
plt.legend()

# Show the plot
plt.show()

plt.plot(range(1, iterations + 1), cost_history, color='blue')
plt.rcParams["figure.figsize"] = (10, 6)
plt.grid(True)

plt.xlabel('Number of iterations')
plt.ylabel('Cost (J)')
plt.title('Convergence of gradient descent')

# Show the plot
plt.show()

# Predict new values
newXValues = np.array([[1, 1, 1],
                       [2, 0, 4],
                       [3, 2, 1]])
newXValues = np.hstack((np.ones((newXValues.shape[0], 1)), newXValues))
newYValues = newXValues.dot(theta)
print('Y values for new X values =', newYValues)

# Gets linear model for X1, X2, and X3
```

```
print(f"Linear model: y = {theta[0]} + {theta[1]}*X1 + {theta[2]}*X2 +
{theta[3]}*X3")
```


Linear Regression Fit
Training Data
Linear Regression
Y
X1


Convergence of gradient descent
Cost (J)
Number of iterations