Assignment 1

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```
# import all the necessary libraries here
import pandas as pd
import numpy as np
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
import matplotlib.pyplot as plt

data_df = pd.read_csv('../../dataset/linear-regression.csv')

# Split the dataset into training, validation, and test sets
train_data_df, temp_data_df = train_test_split(data_df, test_size=0.5,
random_state=42)
validation_data_df, test_data_df = train_test_split(temp_data_df,
test_size=0.4, random_state=42)



# Convert DataFrame to numpy arrays
train_data = train_data_df.to_numpy()
validation_data = validation_data_df.to_numpy()
test_data = test_data_df.to_numpy()

# Split data into X and y
X_train = train_data[:, :-1]                    # all rows, all the
features and no labels
y_train = train_data[:, -1]                     # all rows, label
only
X_validation = validation_data[:, :-1]
y_validation = validation_data[:, -1]
X_test = test_data[:, :-1]
y_test = test_data[:, -1]

# Add a column of ones to X for the intercept term
X_train = np.hstack((np.ones((X_train.shape[0], 1)), X_train))
X_validation = np.hstack((np.ones((X_validation.shape[0], 1)),
X_validation))
X_test = np.hstack((np.ones((X_test.shape[0], 1)), X_test))


# Initialize theta
theta = np.zeros(X_train.shape[1])

# Calculating the theta matrix using analytical method
```

```python
# theta = (X^T * X)^-1 * X^T * y
# X^T = transpose of X
# X^-1 = inverse of X
# y = output matrix
# theta = parameter matrix

# X^T * X
X_transpose_X = np.matmul(X_train.T, X_train)

# (X^T * X)^-1
X_transpose_X_inverse = np.linalg.inv(X_transpose_X)

# X^T * y
X_transpose_y = np.matmul(X_train.T, y_train)

# (X^T * X)^-1 * X^T * y
theta = np.matmul(X_transpose_X_inverse, X_transpose_y)


# Predicting the output using the calculated theta matrix
y_pred = np.matmul(X_test, theta)

# Calculating the mean squared error
mse = np.mean((y_pred - y_test) ** 2)

# Calculating the root mean squared error
rmse = np.sqrt(mse)

# Calculating the R2 score
r2_score = 1 - (np.sum((y_test - y_pred) ** 2) / np.sum((y_test -
np.mean(y_test)) ** 2))

# Printing the results for the analytical method
print('Analytical Method')
print('Mean Squared Error: ', mse)
print('Root Mean Squared Error: ', rmse)
print('R2 Score: ', r2_score)
```

```
Analytical Method
Mean Squared Error:  0.4431719294923638
Root Mean Squared Error:  0.6657115963330996
R2 Score:  0.3967805083008594
```

Gradient Descent Method

```python
data_df = pd.read_csv('../../dataset/linear-regression.csv')
```

```python
# Split the dataset into training, validation, and test sets
train_data_df,temp_data_df = train_test_split(data_df, test_size=0.5,
random_state=42)
validation_data_df, test_data_df = train_test_split(temp_data_df,
test_size=0.4, random_state=42)

# Convert DataFrame to numpy arrays
train_data = train_data_df.to_numpy()
validation_data = validation_data_df.to_numpy()
test_data = test_data_df.to_numpy()

# Split data into X and y
X_train = train_data[:, :-1]
y_train = train_data[:, -1]
X_validation = validation_data[:, :-1]
y_validation = validation_data[:, -1]
X_test = test_data[:, :-1]
y_test = test_data[:, -1]

# normalize the data
scaler = StandardScaler()
X_train = scaler.fit_transform(X_train)
X_validation = scaler.transform(X_validation)
X_test = scaler.transform(X_test)

# Add a column of ones to X_train, X_validation, and X_test
X_train = np.hstack((np.ones((X_train.shape[0], 1)), X_train))
X_validation = np.hstack((np.ones((X_validation.shape[0], 1)),
X_validation))
X_test = np.hstack((np.ones((X_test.shape[0], 1)), X_test))



# Initialize thetas for 3 models
theta1 = np.zeros(X_train.shape[1])
theta2= np.zeros(X_train.shape[1])
theta3=np.zeros(X_train.shape[1])


# predictor function after finding theta
def y_predictor(X_test, theta):
    return np.matmul(X_test, theta)

# mean squared error function
def mean_squared_error(y_test, y_pred):
    return np.sum((y_pred - y_test)**2)/y_test.size

# root mean squared error function
def root_mean_squared_error(y_test, y_pred):
    return np.sqrt(np.mean((y_pred - y_test)**2))
```

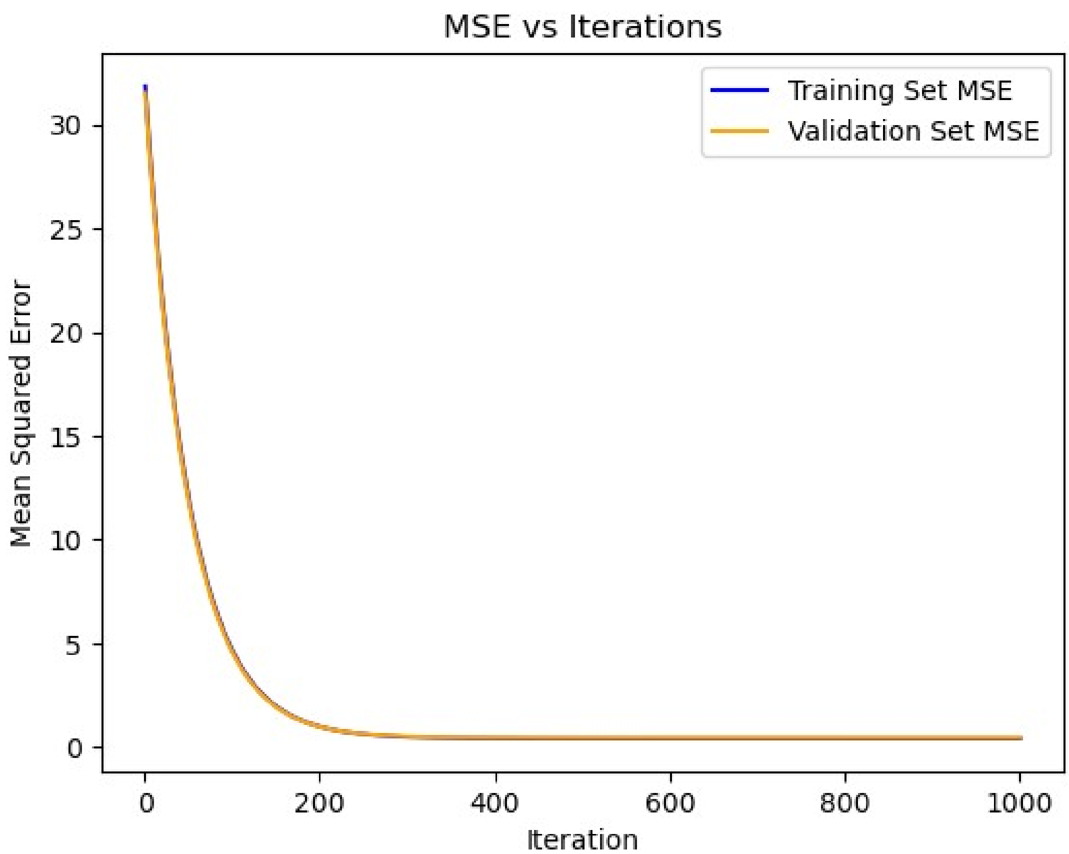
```
# r2 score function
def r2_score_error(y_test, y_pred):
    return 1 - (np.sum((y_test - y_pred) ** 2) / np.sum((y_test -
np.mean(y_test)) ** 2))

# gradient descent function
def gradient_descent(X_train, y_train, theta, alpha, iterations,
iteration, validation_mse,training_mse):
    for i in range(iterations):

        # calculating the gradient term as an (n+1 X 1) matrix
        # gradient matrix= (X^T)*(X*theta-Y)

        # loss matrix=(X*theta-Y)
        loss=np.dot( X_train, theta) - y_train

        # X^T*loss
        gradient=np.dot(X_train.T,loss)/y_train.size

        # Directly repeating theta=theta-(alpha)gradient until
convergence
        theta = theta - alpha * gradient

        # storing values of mse vs iteration for plotting the graph
        iteration.append(i+1)
        training_mse.append(mean_squared_error(y_train,
np.dot(X_train, theta)))
        validation_mse.append(mean_squared_error(y_validation,
np.dot(X_validation,theta)))

    return theta
```

First Model

```
# Set hyperparameters
alpha = 0.01
iterations = 1000

# Initializing lists to store the mse and iteration values for the
plot
validation_mse1 = []
training_mse1=[]
iteration1 = []


# Perform gradient descent to learn theta
theta1 = gradient_descent(X_train, y_train, theta1, alpha,
                          iterations,
```

```
iteration1,validation_mse1,training_mse1)

# Predicting the output using the calculated theta matrix and
evaluating errors for validation set data
y_pred = y_predictor(X_validation, theta1)

# Calculating the mean squared error
mse = mean_squared_error(y_validation, y_pred)


# Calculating the root mean squared error
rmse = root_mean_squared_error(y_validation, y_pred)

# Calculating the R2 score
r2_score = r2_score_error(y_validation, y_pred)

# Printing theta, rmse, and r2_score
print('theta matrix: ',theta1)
print('Mean Squared Error1: ', mse)
print('Root Mean Squared Error1: ', rmse)
print('R2 Score1: ', r2_score)


# Plotting the predicted values against the actual values
plt.plot(iteration1, training_mse1, label='Training Set MSE',
color='blue')
plt.plot(iteration1, validation_mse1, label='Validation Set MSE',
color='orange')


plt.xlabel('Iteration')
plt.ylabel('Mean Squared Error')
plt.title('MSE vs Iterations')
plt.legend()
plt.show()
```

```
theta matrix:  [ 5.6430605   0.03556461 -0.215944   -0.04556511
0.03454144 -0.08419887
  0.03180185 -0.10097283 -0.04565794 -0.0080804   0.12436804
0.29577867]
Mean Squared Error1:  0.4414484382303795
Root Mean Squared Error1:  0.6644158624162878
R2 Score1:  0.27795802924608537
```



We can see that this model with hyperparameters (alpha=0.01,iterations=1000) is working fine as the r2_score is between [0,1] and the mse value is also close to zero

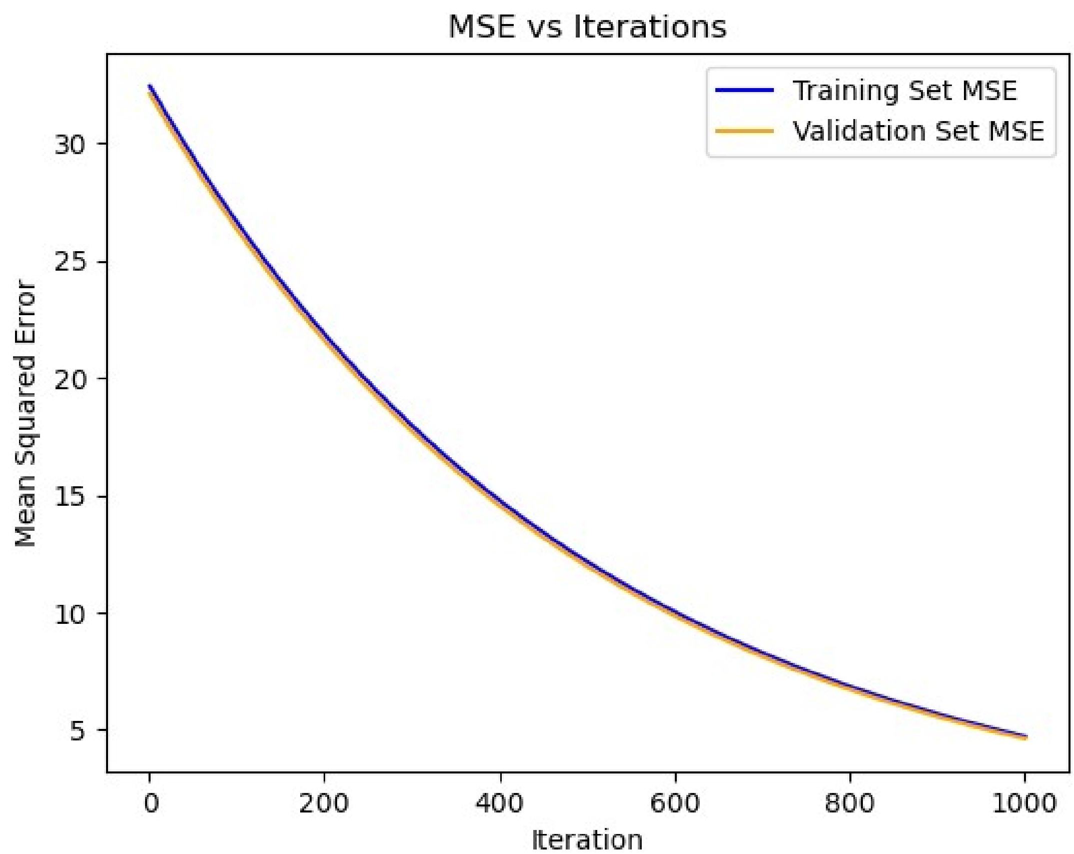
It can be seen that there isnt much overfitting too as the plots for both the training and the validation data set are almost coinciding.

Second model

```
# Set hyperparameters2
alpha = 0.001
iterations = 1000


# Initializing lists to store the mse and iteration values for the
plot
validation_mse2 = []
training_mse2=[]
iteration2 = []
```

```python
# Perform gradient descent to learn theta
theta2 = gradient_descent(X_train, y_train, theta2, alpha,
                          iterations, iteration2,
validation_mse2,training_mse2)

# Predicting the output using the calculated theta matrix on
validation set
y_pred = y_predictor(X_validation, theta2)

# Calculating the mean squared error
mse = mean_squared_error(y_validation, y_pred)


# Calculating the root mean squared error
rmse = root_mean_squared_error(y_validation, y_pred)

# Calculating the R2 score
r2_score = r2_score_error(y_validation, y_pred)

# Print theta, rmse, and r2_score

print('theta matrix: ',theta2)
print('Mean Squared Error2: ', mse)
print('Root Mean Squared Error2: ', rmse)
print('R2 Score2: ', r2_score)



# Plotting the predicted values against the actual values
plt.plot(iteration2, training_mse2, label='Training Set MSE',
color='blue')
plt.plot(iteration2, validation_mse2, label='Validation Set MSE',
color='orange')


plt.xlabel('Iteration')
plt.ylabel('Mean Squared Error')
plt.title('MSE vs Iterations')
plt.legend()
plt.show()
```

```
theta matrix:  [ 3.56828702e+00  2.58132362e-02 -1.49289870e-01
4.27779059e-02
  2.12870069e-02 -6.29974361e-02 -3.03403624e-03 -7.16809247e-02
 -7.65596010e-02  1.24433361e-02  8.53388269e-02  2.07996712e-01]
Mean Squared Error2:  4.632374444268015
Root Mean Squared Error2:  2.1522951573304288
R2 Score2:  -6.576805088307521
```



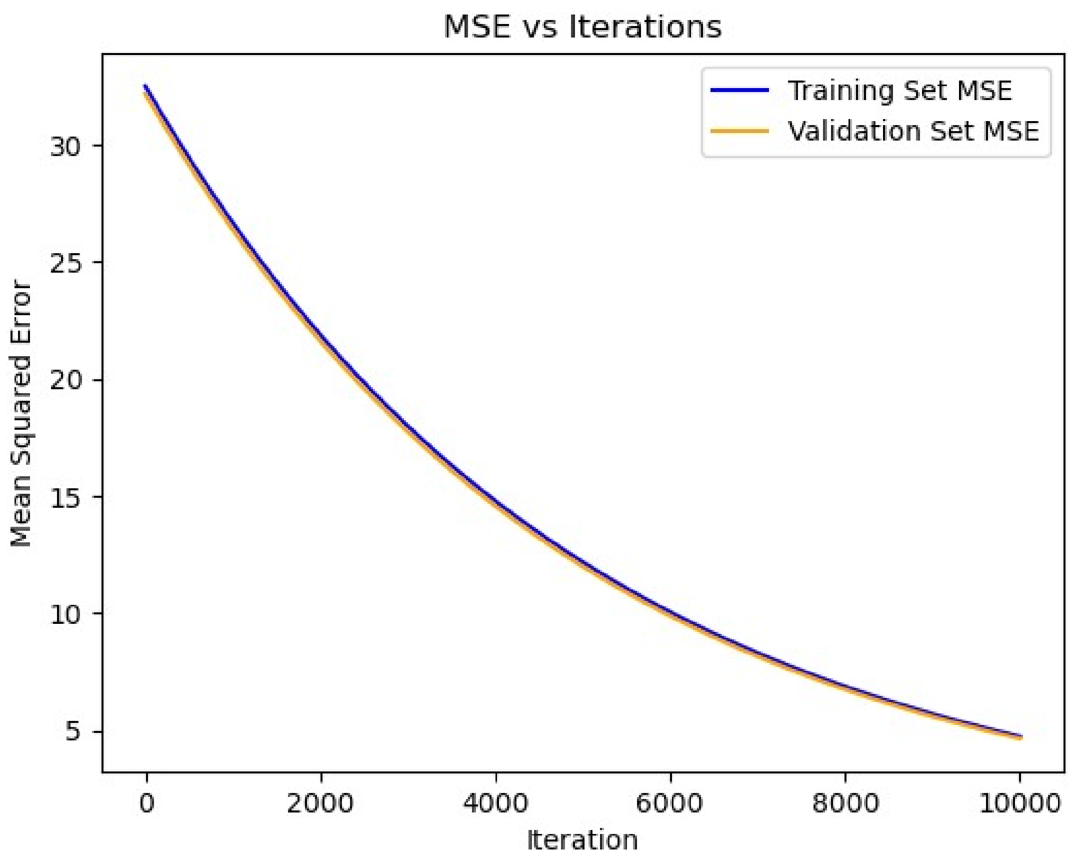
we can see that for the hyperparameters (alpha=0.001,iterations=1000) the iterations are not sufficient for convergence as the r2_score is becoming negative.The mse error is also larger when compared to the the previous case.

Third Model

```
# Set hyperparameters3
alpha = 0.0001
iterations = 10000

# Initialize theta
theta3 = np.zeros(X_train.shape[1])

# Initializing lists to store the mse and iteration values for the plot
validation_mse3 = []
training_mse3=[]
iteration3 = []
```

```python
# Perform gradient descent to learn theta
theta3 = gradient_descent(X_train, y_train, theta3, alpha,iterations,
iteration3, validation_mse3,training_mse3)

# Predicting the output using the calculated theta matrix for the
validation set
y_pred = y_predictor(X_validation, theta3)

# Calculating the mean squared error
mse = mean_squared_error(y_validation, y_pred)

# Calculating the root mean squared error
rmse = root_mean_squared_error(y_validation, y_pred)

# Calculating the R2 score
r2_score = r2_score_error(y_validation, y_pred)

# Print theta, rmse, and r2_score
print('theta matrix: ',theta3)
print('Mean Squared Error2: ', mse)
print('Root Mean Squared Error2: ', rmse)
print('R2 Score2: ', r2_score)



# Plotting the predicted values against the actual values
plt.plot(iteration3, training_mse3, label='Training Set MSE',
color='blue')
plt.plot(iteration3, validation_mse3, label='Validation Set MSE',
color='orange')


plt.xlabel('Iteration')
plt.ylabel('Mean Squared Error')
plt.title('MSE vs Iterations')
plt.legend()
plt.show()
```

```
theta matrix:  [ 3.56735237e+00  2.58088217e-02 -1.49249180e-01
4.27603488e-02
  2.12819174e-02 -6.29796589e-02 -3.03138181e-03 -7.16627296e-02
 -7.65332887e-02  1.24369437e-02  8.53172070e-02  2.07938771e-01]
Mean Squared Error2:  4.636207974499204
Root Mean Squared Error2:  2.153185541122549
R2 Score2:  -6.583075287686112
```



The same result as we have seen before.we can see that for the hyperparameters (alpha=0.0001,iterations=10000), the no of iterations are not sufficient for convergence as the r2_score is becoming negative.The mse error is also larger when compared to the original model.

Hence we can proceed with the first model for calculating the final errors on the testing data set.

```
# using the first model to predict the values of the testing data set
y_pred = y_predictor(X_test, theta1)

# Calculating the mean squared error
mse = mean_squared_error(y_test, y_pred)


# Calculating the root mean squared error
rmse = root_mean_squared_error(y_test, y_pred)

# Calculating the R2 score
r2_score = r2_score_error(y_test, y_pred)

# Printi, rmse, and r2_score
print('Gradient Descent Model:')
print('Mean Squared Error: ', mse)
```

```
print('Root Mean Squared Error: ', rmse)
print('R2 Score: ', r2_score)
```

```
Gradient Descent Model:
Mean Squared Error:  0.4436561528393705
Root Mean Squared Error:  0.6660751855754502
R2 Score:  0.3961214120408936
```