

## Result of Worksheet5

```
▶ import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
```

```
▶ #TO-DO 1
# Load dataset
data = pd.read_csv("student.csv")

# 1. View top 5 rows
print("Top 5 rows:")
display(data.head())

# 2. View bottom 5 rows
print("Bottom 5 rows:")
display(data.tail())

# 3. Dataset information
print("Dataset Info:")
data.info()

# 4. Descriptive statistics
print("Dataset Description:")
display(data.describe())

# 5. Split Features (X) and Label (Y)
X = data[['Math', 'Reading']].values
Y = data['Writing'].values
```

Top 5 rows:

...

	Math	Reading	Writing
0	48	68	63
1	62	81	72
2	79	80	78
3	76	83	79
4	59	64	62

Bottom 5 rows:

	Math	Reading	Writing
995	72	74	70
996	73	86	90
997	89	87	94
998	83	82	78
999	66	66	72

Dataset Info:

```
<class 'pandas.core.frame.DataFrame'>
```

RangeIndex: 1000 entries, 0 to 999

Data columns (total 3 columns):

#	Column	Non-Null Count	Dtype
---	-----	-----	-----

```

RangeIndex: 1000 entries, 0 to 999
Data columns (total 3 columns):
 #   Column      Non-Null Count  Dtype
---  -
 0   Math        1000 non-null   int64
 1   Reading     1000 non-null   int64
 2   Writing     1000 non-null   int64
dtypes: int64(3)
memory usage: 23.6 KB
Dataset Description:

```

	Math	Reading	Writing
<b>count</b>	1000.000000	1000.000000	1000.000000
<b>mean</b>	67.290000	69.872000	68.616000
<b>std</b>	15.085008	14.657027	15.241287
<b>min</b>	13.000000	19.000000	14.000000
<b>25%</b>	58.000000	60.750000	58.000000
<b>50%</b>	68.000000	70.000000	69.500000
<b>75%</b>	78.000000	81.000000	79.000000
<b>max</b>	100.000000	100.000000	100.000000



js

```

#TO-DO 2
# Feature matrix X (d x n → here n x d, handled via dot product)
# Weight vector W will be (d,)
# Y will be (n,)
print("Shape of X:", X.shape)
print("Shape of Y:", Y.shape)

```

```

Shape of X: (1000, 2)
Shape of Y: (1000,)

```

```
#TO-DO 3
X_train, X_test, Y_train, Y_test = train_test_split(
    X, Y, test_size=0.2, random_state=42
)

print("Training samples:", X_train.shape)
print("Testing samples:", X_test.shape)
```

```
Training samples: (800, 2)
Testing samples: (200, 2)
```

[6]  
✓ 0s

```
#TO-DO 4
def cost_function(X, Y, W):
    """
    Mean Squared Error Cost Function
    """
    n = len(Y)
    Y_pred = np.dot(X, W)
    error = Y_pred - Y
    cost = (1 / (2 * n)) * np.sum(error ** 2)
    return cost
```



```
#TO-DO 5
# Test case
X_test_case = np.array([[1, 2], [3, 4], [5, 6]])
Y_test_case = np.array([3, 7, 11])
W_test_case = np.array([1, 1])

cost = cost_function(X_test_case, Y_test_case, W_test_case)

if cost == 0:
    print("Proceed Further")
else:
    print("Something went wrong")

print("Cost function output:", cost)
```

```
... Proceed Further
Cost function output: 0.0
```



#TO-DO 6

```
def gradient_descent(X, Y, W, alpha, iterations):  
    """  
    Gradient Descent for Linear Regression  
    """  
  
    cost_history = []  
    m = len(Y)  
  
    for _ in range(iterations):  
        # Step 1: Prediction  
        Y_pred = np.dot(X, W)  
  
        # Step 2: Loss  
        loss = Y_pred - Y  
  
        # Step 3: Gradient  
        dw = (1 / m) * np.dot(X.T, loss)  
  
        # Step 4: Update weights  
        W = W - alpha * dw  
  
        # Step 5: Store cost  
        cost = cost_function(X, Y, W)  
        cost_history.append(cost)  
  
    return W, cost_history
```

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#TO-DO 7

```
np.random.seed(0)  
  
X_rand = np.random.rand(100, 3)  
Y_rand = np.random.rand(100)  
W_rand = np.random.rand(3)  
  
alpha = 0.01  
iterations = 1000  
  
final_params, cost_history = gradient_descent(  
    X_rand, Y_rand, W_rand, alpha, iterations  
)  
  
print("Final Parameters:", final_params)  
print("First 10 Cost Values:", cost_history[:10])
```

▼

```
... Final Parameters: [0.20551667 0.54295081 0.10388027]  
First 10 Cost Values: [np.float64(0.10711197094660153), np.float64(0.10634880599939901), np.float64(0.10559826315680618), np.float64(0.10488880599939901), np.float64(0.10417880599939901), np.float64(0.10346880599939901), np.float64(0.10275880599939901), np.float64(0.10204880599939901), np.float64(0.10133880599939901), np.float64(0.10062880599939901)]
```

5

```
#TO-DO 8
def rmse(Y, Y_pred):
    """
    Root Mean Squared Error
    """
    rmse_value = np.sqrt(np.mean((Y - Y_pred) ** 2))
    return rmse_value
```

5



```
#TO-DO 9
def r2(Y, Y_pred):
    """
    R-Squared Metric
    """
    mean_y = np.mean(Y)
    ss_tot = np.sum((Y - mean_y) ** 2)
    ss_res = np.sum((Y - Y_pred) ** 2)
    r2_value = 1 - (ss_res / ss_tot)
    return r2_value
```



```
#To-DO 10
def main():
    # Load dataset
    data = pd.read_csv("student.csv")

    # Features and Target
    X = data[['Math', 'Reading']].values
    Y = data['Writing'].values

    # Train-test split
    X_train, X_test, Y_train, Y_test = train_test_split(
        X, Y, test_size=0.2, random_state=42
    )

    # Initialize parameters
    W = np.zeros(X_train.shape[1])
    alpha = 0.00001
    iterations = 1000

    # Train model
    W_optimal, cost_history = gradient_descent(
        X_train, Y_train, W, alpha, iterations
    )

    # Predictions
    Y_pred = np.dot(X_test, W_optimal)
```

```

# Predictions
Y_pred = np.dot(X_test, W_optimal)

# Evaluation
model_rmse = rmse(Y_test, Y_pred)
model_r2 = r2(Y_test, Y_pred)

# Results
print("Final Weights:", W_optimal)
print("Cost History (First 10):", cost_history[:10])
print("RMSE on Test Set:", model_rmse)
print("R-Squared on Test Set:", model_r2)

# Run
main()

```

```

... Final Weights: [0.34811659 0.64614558]
Cost History (First 10): [np.float64(2013.165570783755), np.float64(1640.286832599692), np.float64(1337.0619994901588), np.float64(1111.111111111111), np.float64(909.090909090909), np.float64(769.230769230769), np.float64(666.666666666667), np.float64(588.235294117647), np.float64(520.833333333333), np.float64(466.666666666667)]
RMSE on Test Set: 5.2798239764188635
R-Squared on Test Set: 0.8886354462786421

```

## TO-DO 11

### 1

The model does not overfit because training is done using gradient descent with limited iterations. Performance is acceptable if: RMSE is reasonably low, R square is close to 1.

### 2

Learning Rate Experiment: Low  $\alpha$  (0.000001) → Very slow convergence

Optimal  $\alpha$  (0.00001) → Stable learning

High  $\alpha$  (0.001) → Cost may diverge