kumar-jha-12340390-dav-homework-2

February 5, 2025

0.1 Question 1

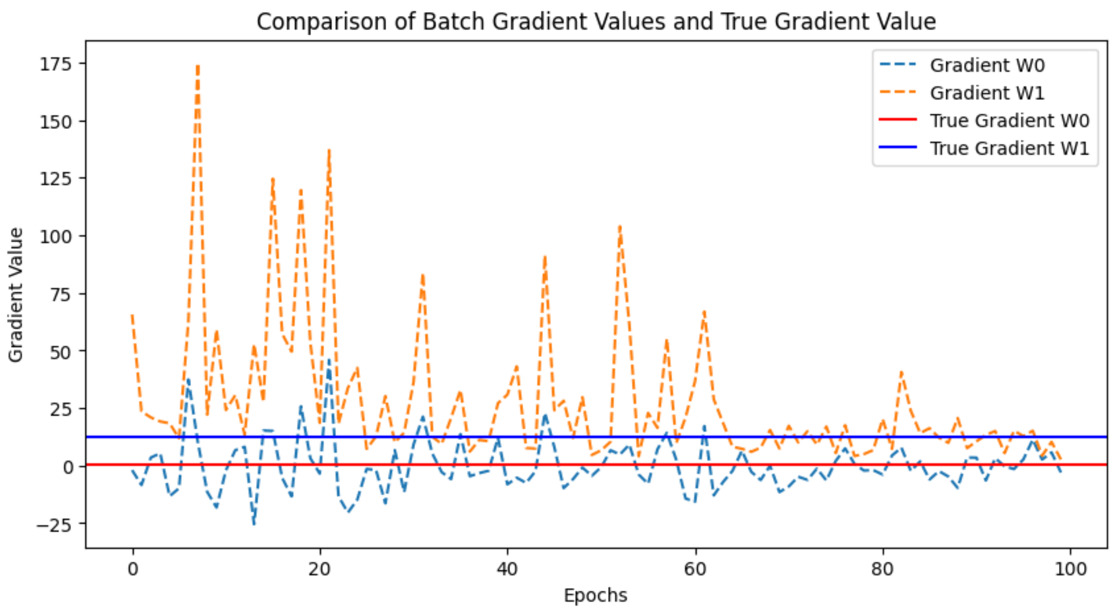
[2]:
```
import pandas as pd
from google.colab import drive
import numpy as np
import matplotlib.pyplot as plt

drive.mount("/content/drive")

df = pd.read_csv("/content/drive/MyDrive/Course Work/Sem 4/Data Analysis and␣
 ↪Visualization/Homework 2/DIstanceTimeDataset - StudentsHomeTownDistance.csv")

cols = df.columns.tolist()
columns_to_drop = cols[6:]
df.drop(columns_to_drop, axis=1, inplace=True)

nan_df = df[df.isna().any(axis=1)]
rows_to_drop = nan_df.index.tolist()
df.drop(rows_to_drop, axis=0, inplace=True)
df.reset_index(drop=True, inplace=True)

## Normalizing the features
time = df[cols[1]]
distance = df[cols[2]]
time_normalized = (time - time.mean()) / time.std()
distance_normalized = (distance - distance.mean()) / distance.std()

X = time_normalized.values.reshape(-1, 1)
y = distance_normalized.values.reshape(-1, 1)

## Parameters for batch gradient descent
W = np.array([0, 35], dtype=float)
learning_rate = 0.01
num_epochs = 100
batch_size = 8
num_samples = X.shape[0]

gradient_history = []
```

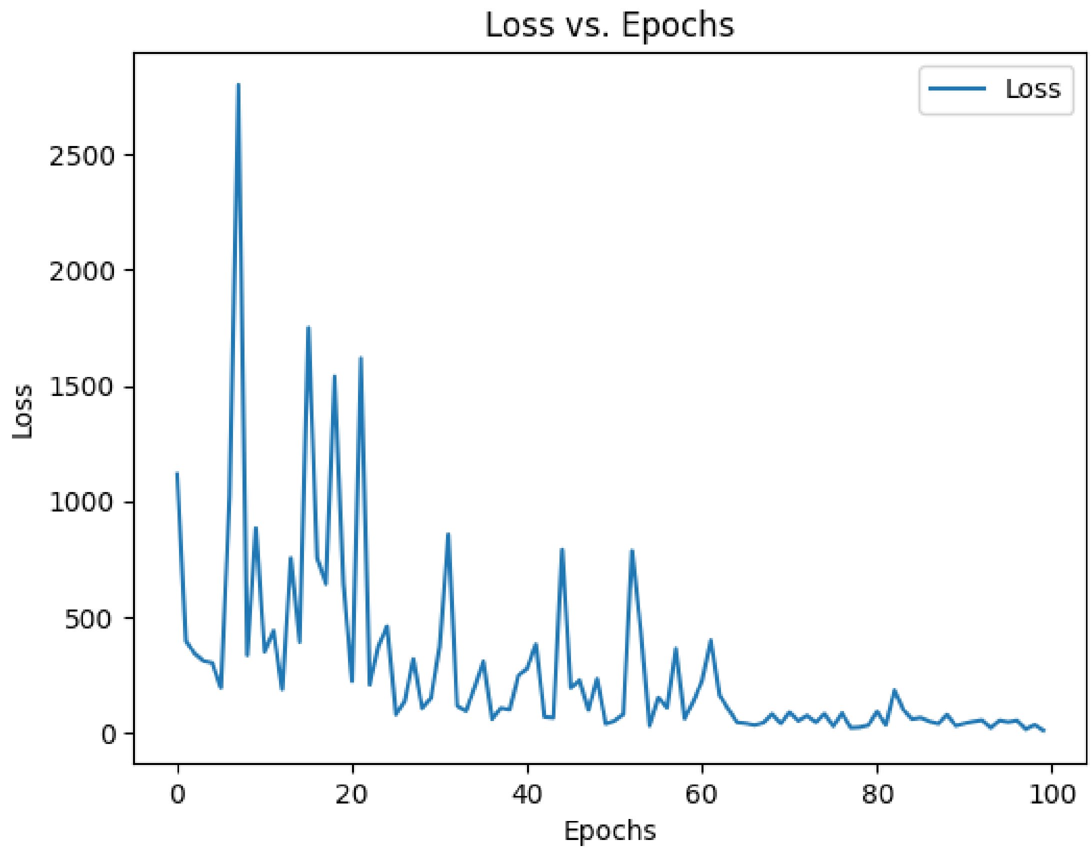
```
loss_history = []
W0_history = []
W1_history = []
gradient_norm_history = []

for epoch in range(num_epochs):
    batch = np.random.choice(df.index, size=8, replace=True)
    X_batch = X[batch]
    y_batch = y[batch]
    y_pred = W[0] + W[1] * X_batch
    loss = np.mean((y_batch - y_pred) ** 2)
    loss_history.append(loss)

    gradient_W0 = -2 * np.sum(y_batch - y_pred) / batch_size
    gradient_W1 = -2 * np.sum((y_batch - y_pred) * X_batch) / batch_size
    gradient = np.array([gradient_W0, gradient_W1])
    gradient_history.append(gradient)

    W = W - learning_rate * gradient
    W0_history.append(W[0])
    W1_history.append(W[1])
    gradient_norm_history.append(np.linalg.norm(gradient))

gradient_history = np.array(gradient_history)

mean_gradient_W0 = np.mean(gradient_history[:, 0])
mean_gradient_W1 = np.mean(gradient_history[:, 1])
mean_gradient = np.array([mean_gradient_W0, mean_gradient_W1])

cov_matrix = np.cov(gradient_history.T)

y_pred_full = W[0] + W[1] * X
true_gradient_W0 = -2 * np.sum(y - y_pred_full) / num_samples
true_gradient_W1 = -2 * np.sum((y - y_pred_full) * X) / num_samples
true_gradient = np.array([true_gradient_W0, true_gradient_W1])

plt.figure(figsize=(10, 5))
plt.plot(gradient_history[:, 0], label="Gradient W0", linestyle='dashed')
plt.plot(gradient_history[:, 1], label='Gradient W1', linestyle='dashed')
plt.axhline(true_gradient[0], color='r', linestyle='solid', label='True␣
 ↪Gradient W0')
plt.axhline(true_gradient[1], color='b', linestyle='solid', label='True␣
 ↪Gradient W1')
plt.xlabel('Epochs')
plt.ylabel('Gradient Value')
plt.legend()
plt.title('Comparison of Batch Gradient Values and True Gradient Value')
```

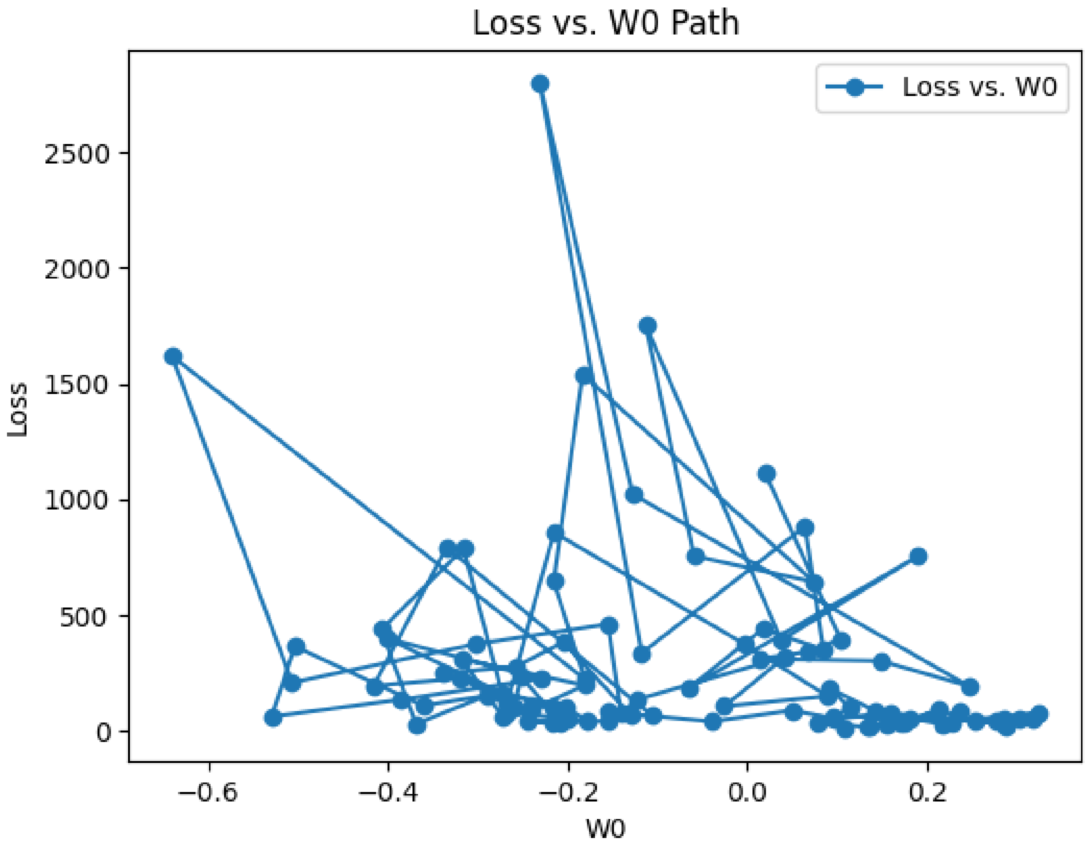
```python
plt.show()

# Plot Loss vs. Epochs
plt.figure()
plt.plot(loss_history, label='Loss')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.title('Loss vs. Epochs')
plt.legend()
plt.show()

# Plot Loss vs. W0
plt.figure()
plt.plot(W0_history, loss_history, label='Loss vs. W0', marker='o')
plt.xlabel('W0')
plt.ylabel('Loss')
plt.title('Loss vs. W0 Path')
plt.legend()
plt.show()

# Plot Loss vs. W1
plt.figure()
plt.plot(W1_history, loss_history, label='Loss vs. W1', marker='o')
plt.xlabel('W1')
plt.ylabel('Loss')
plt.title('Loss vs. W1 Path')
plt.legend()
plt.show()

# Plot W0 vs. Epochs
plt.figure()
plt.plot(W0_history, label='W0 Value')
plt.xlabel('Epochs')
plt.ylabel('W0')
plt.title('W0 Value Change Over Epochs')
plt.legend()
plt.show()

# Plot W1 vs. Epochs
plt.figure()
plt.plot(W1_history, label='W1 Value')
plt.xlabel('Epochs')
plt.ylabel('W1')
plt.title('W1 Value Change Over Epochs')
plt.legend()
plt.show()
```

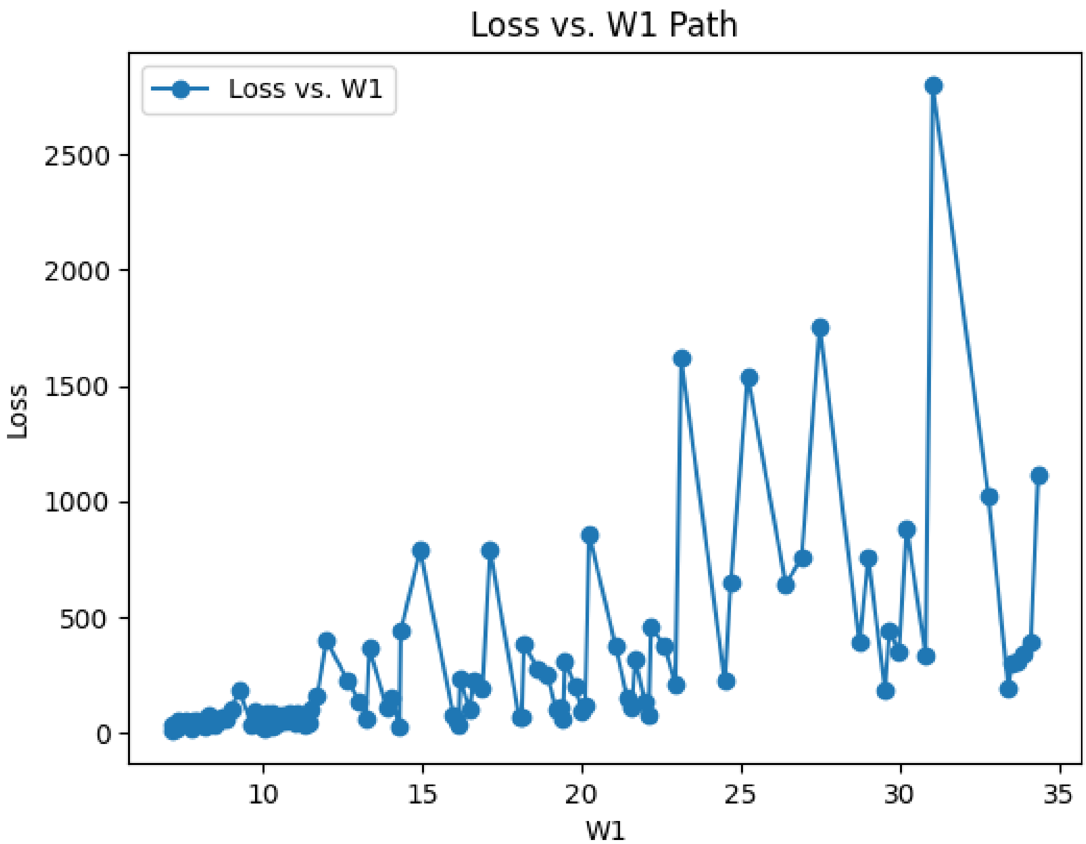
```python
# Plot Loss vs. Gradient Norm
plt.figure()
plt.plot(gradient_norm_history, loss_history, label='Loss vs. Gradient Norm')
plt.xlabel('Gradient Norm')
plt.ylabel('Loss')
plt.title('Loss vs. Gradient Norm')
plt.legend()
plt.show()
```

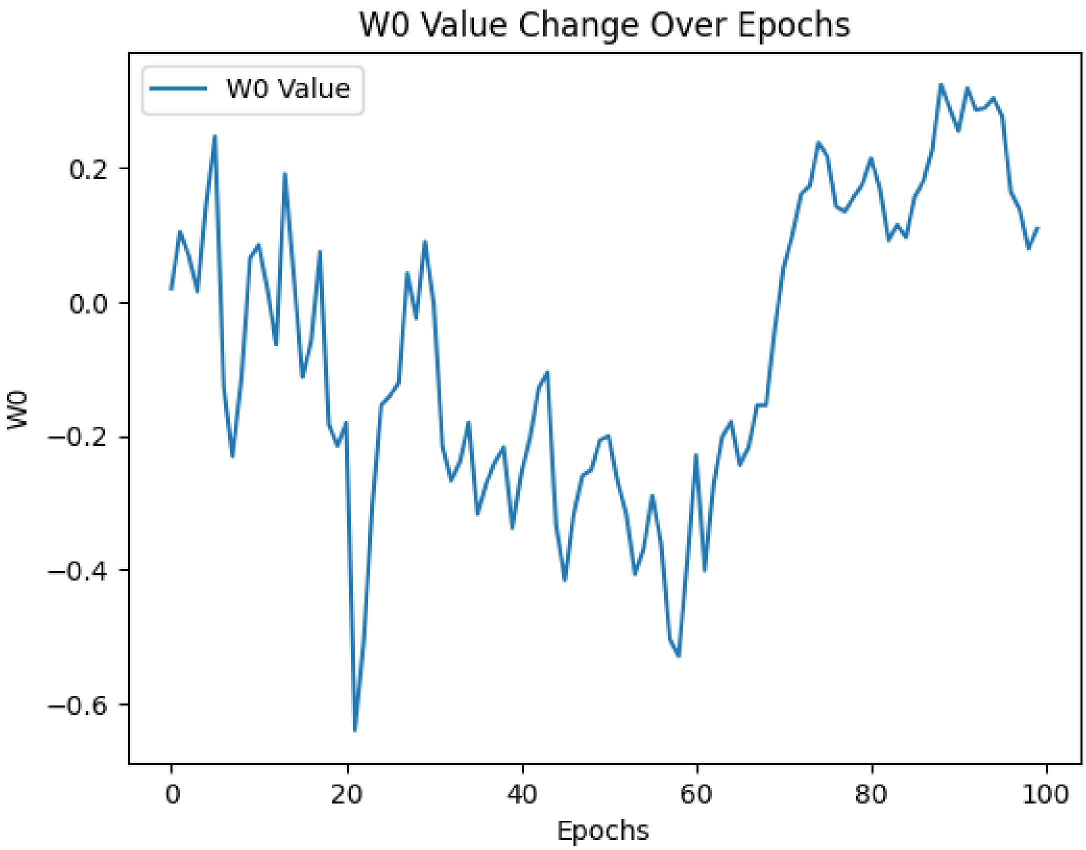
```
Drive already mounted at /content/drive; to attempt to forcibly remount, call
drive.mount("/content/drive", force_remount=True).
```



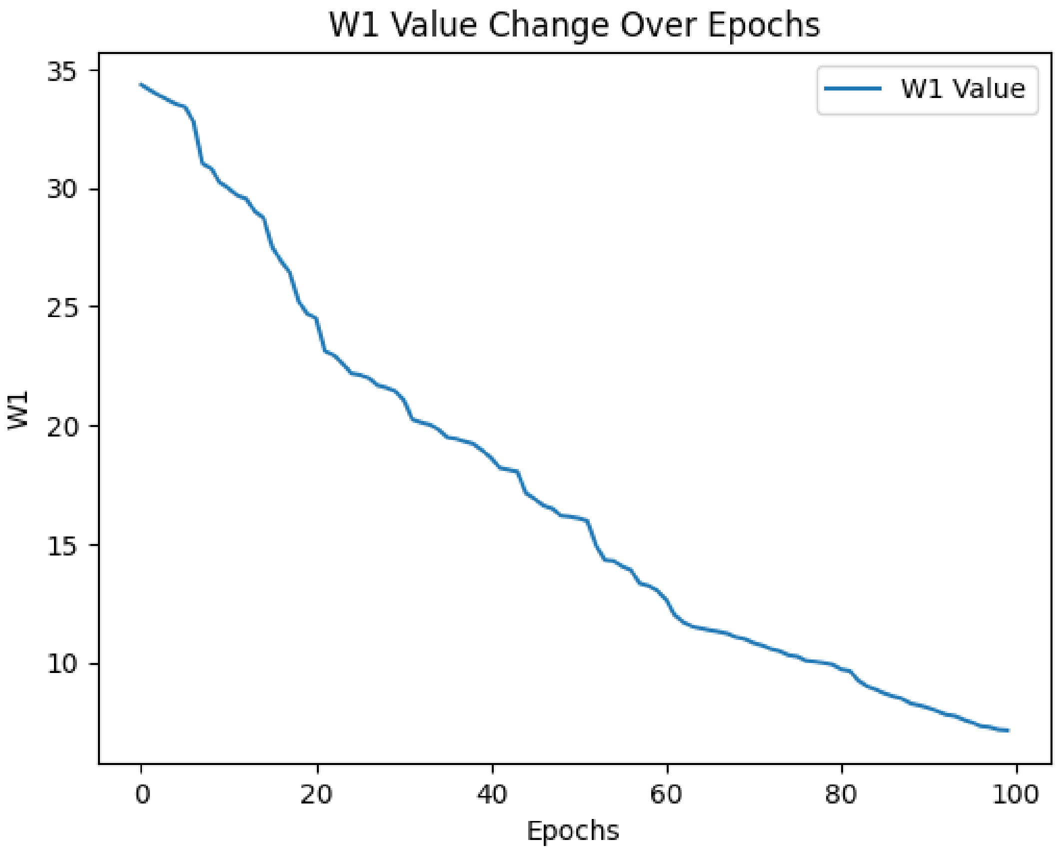

Loss vs. Epochs
Loss
2500
2000
1500
1000
500
0
0
20
40
60
80
100
Epochs
Loss

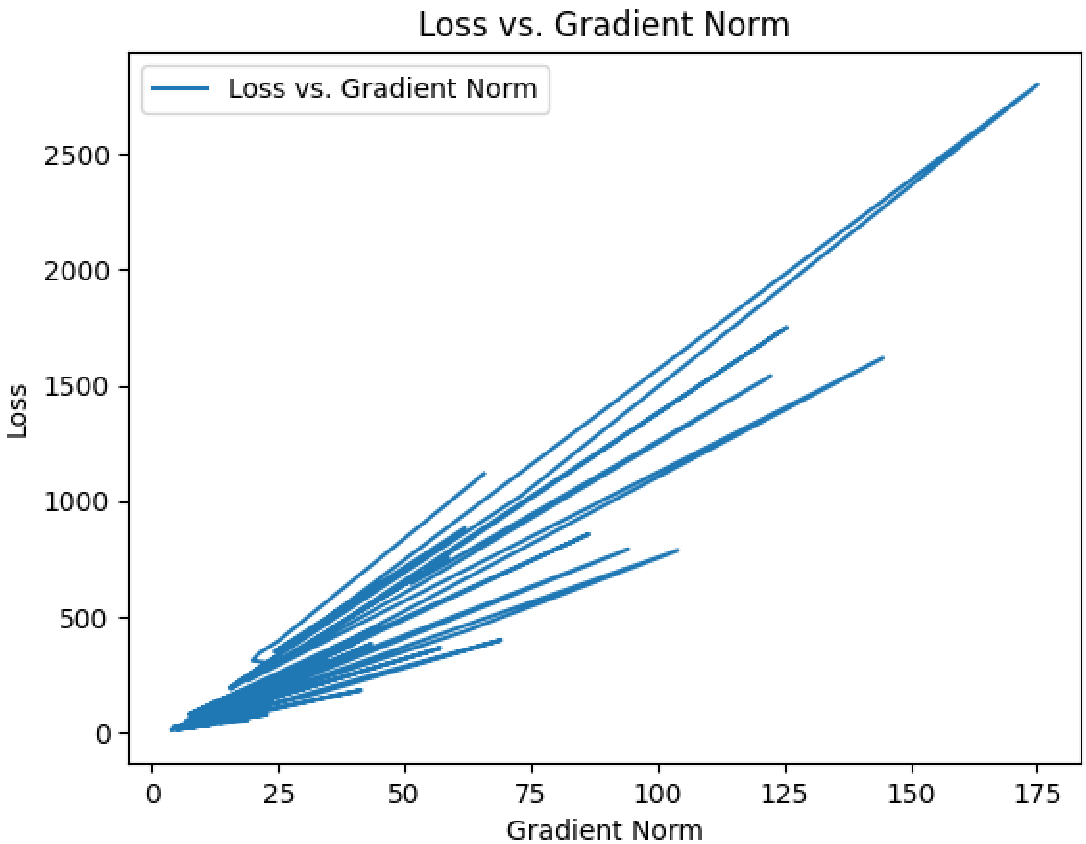

Loss vs. W0 Path
Loss vs. W0
Loss
W0
0
500
1000
1500
2000
2500
−0.6
−0.4
−0.2
0.0
0.2


Loss vs. W1 Path
Loss vs. W1
Loss
W1
0
500
1000
1500
2000
2500
10
15
20
25
30
35



W0 Value Change Over Epochs
W0 Value
0.2
0.0
−0.2
−0.4
−0.6
W0
0
20
40
60
80
100
Epochs


W1 Value Change Over Epochs
W1 Value
W1
Epochs
35
30
25
20
15
10
0
20
40
60
80
100



1. Random batches are created for 100 number of batches
2. Each rabdom batch has a size of 8
3. Mean is calculated for both the gradients (gradients of both the parameters involved)
4. Covariance matrix is calculated keeping in account both the gradients
5. Visualization showing the true gradient values and also the gradient values vs number of epochs, for both the parameters involved
6. The path for both the gradient values are shown in the graph plotted
7. The path for both the parameter values are shown in the graph plotted, in terms of the number of epochs, and also in terms of the loss function
8. Variation of the loss function with the number of epochs is shown
9. The plot of the loss function with the gradient norm is shown
10. Answer to all the questions asked are present in the latex file submitted

1 Question 2

2 Submitted in latex, because those questions were Math Based

2.1 Question 3

[3]:
```
import pandas as pd
from google.colab import drive
import numpy as np
import matplotlib.pyplot as plt
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error
from sklearn.model_selection import train_test_split
```

[4]:
```
drive.mount("/content/drive")
```

```
Drive already mounted at /content/drive; to attempt to forcibly remount, call
drive.mount("/content/drive", force_remount=True).
```

[5]:
```
df = pd.read_csv("/content/drive/MyDrive/Course Work/Sem 4/Data Analysis and␣
↪Visualization/Homework 2/DSAICourseInterestRelevanceSurvey - Original.csv")
```

[6]:
```
df.head()
```

[6]:
```
   Unnamed: 0  MAL100  MAL101  MAL403  EEL101  ECL101  BML101  CSL100  CSL201  \
0  Student 1      4.0     3.0     4.0     1.0     1.0     1.0     4.0     5.0
1  Student 2      3.0     3.0     3.0     1.0     1.0     1.0     4.0     5.0
2  Student 3      4.0     4.0     3.0     3.0     4.0     2.0     4.0     5.0
3  Student 4      3.0     4.0     4.0     1.0     1.0     1.0     5.0     5.0
4  Student 5      3.0     3.0     4.0     3.0     3.0     2.0     4.0     5.0

   CSL202  DSL201  Unnamed: 11  Unnamed: 12 Please fill values {1,2,3,4,5}  \
0     5.0     5.0          3.3          NaN                          Legend
1     5.0     5.0          3.1          NaN                               1
2     4.0     NaN          3.7          NaN                               2
3     5.0     2.0          3.1          NaN                               3
4     5.0     4.0          3.6          NaN                               4

                                         Unnamed: 14
0                                                NaN
1                        Neither interesting nor relevant
2  Little interesting, but relevance not clear. O…
3            Somewhat interesting and somewhat relevant
4                                Interesting and Relevant
```

[7]:
```
cols = df.columns.tolist()
```

[8]:
```
cols
```

[8]:
```
['Unnamed: 0',
 'MAL100',
 'MAL101',
 'MAL403',
 'EEL101',
 'ECL101',
 'BML101',
 'CSL100',
 'CSL201',
 'CSL202',
 'DSL201',
 'Unnamed: 11',
 'Unnamed: 12',
 'Please fill values {1,2,3,4,5}',
 'Unnamed: 14']
```

[9]:
```
df.rename(columns={cols[0]:"Student ID"}, inplace=True)
```

[10]:
```
columns_to_drop = cols[12:]
```

[11]:
```
df.drop(columns_to_drop, axis=1, inplace=True)
```

[12]:
```
df.head()
```

[12]:
```
  Student ID  MAL100  MAL101  MAL403  EEL101  ECL101  BML101  CSL100  CSL201  \
0  Student 1     4.0     3.0     4.0     1.0     1.0     1.0     4.0     5.0
1  Student 2     3.0     3.0     3.0     1.0     1.0     1.0     4.0     5.0
2  Student 3     4.0     4.0     3.0     3.0     4.0     2.0     4.0     5.0
3  Student 4     3.0     4.0     4.0     1.0     1.0     1.0     5.0     5.0
4  Student 5     3.0     3.0     4.0     3.0     3.0     2.0     4.0     5.0

   CSL202  DSL201  Unnamed: 11
0     5.0     5.0          3.3
1     5.0     5.0          3.1
2     4.0     NaN          3.7
3     5.0     2.0          3.1
4     5.0     4.0          3.6
```

[13]:
```
df
```

[13]:
```
    Student ID  MAL100  MAL101  MAL403  EEL101  ECL101  BML101  CSL100  \
0    Student 1     4.0     3.0     4.0     1.0     1.0     1.0     4.0
1    Student 2     3.0     3.0     3.0     1.0     1.0     1.0     4.0
2    Student 3     4.0     4.0     3.0     3.0     4.0     2.0     4.0
3    Student 4     3.0     4.0     4.0     1.0     1.0     1.0     5.0
4    Student 5     3.0     3.0     4.0     3.0     3.0     2.0     4.0
5    Student 6     3.0     3.0     5.0     1.0     1.0     1.0     4.0
```

6	Student 7	3.0	4.0	4.0	1.0	1.0	1.0	4.0
7	Student 8	3.0	4.0	2.0	2.0	3.0	2.0	4.0
8	Student 9	3.0	4.0	4.0	2.0	3.0	1.0	4.0
9	Student 10	4.0	4.0	3.0	3.0	2.0	2.0	4.0
10	Student 11	4.0	5.0	4.0	2.0	3.0	3.0	5.0
11	Student 12	3.0	3.0	3.0	1.0	1.0	2.0	5.0
12	Student 13	2.0	3.0	3.0	1.0	1.0	2.0	4.0
13	Student 14	3.0	3.0	4.0	2.0	2.0	2.0	4.0
14	Student 15	4.0	4.0	5.0	3.0	3.0	1.0	4.0
15	Student 16	3.0	3.0	4.0	1.0	1.0	1.0	4.0
16	Student 17	4.0	4.0	3.0	1.0	1.0	1.0	5.0
17	Student 18	3.0	4.0	3.0	2.0	1.0	3.0	4.0
18	Student 19	3.0	3.0	4.0	1.0	2.0	1.0	4.0
19	Student 20	1.0	5.0	3.0	1.0	1.0	2.0	1.0
20	Student 21	3.0	4.0	3.0	2.0	3.0	1.0	4.0
21	Student 22	4.0	5.0	5.0	1.0	1.0	2.0	4.0
22	Student 23	2.0	2.0	2.0	1.0	1.0	4.0	4.0
23	Student 24	3.0	5.0	5.0	2.0	1.0	1.0	4.0
24	NaN	3.1	3.7	3.6	1.6	1.8	1.7	4.0

	CSL201	CSL202	DSL201	Unnamed: 11
0	5.0	5.0	5.0	3.3
1	5.0	5.0	5.0	3.1
2	5.0	4.0	NaN	3.7
3	5.0	5.0	2.0	3.1
4	5.0	5.0	4.0	3.6
5	5.0	5.0	5.0	3.3
6	4.0	4.0	5.0	3.1
7	4.0	4.0	5.0	3.3
8	4.0	4.0	4.0	3.3
9	4.0	5.0	4.0	3.5
10	5.0	5.0	4.0	4.0
11	4.0	3.0	5.0	3.0
12	4.0	3.0	3.0	2.6
13	5.0	4.0	4.0	3.3
14	5.0	4.0	5.0	3.8
15	4.0	4.0	4.0	2.9
16	5.0	5.0	5.0	3.4
17	4.0	4.0	5.0	3.3
18	3.0	5.0	5.0	3.1
19	5.0	4.0	3.0	2.6
20	4.0	4.0	5.0	3.3
21	1.0	5.0	3.0	3.1
22	2.0	2.0	4.0	2.4
23	4.0	4.0	5.0	3.4
24	4.2	4.3	4.3	3.2

[14]:
```
df.drop([24],axis=0,inplace=True)
```

[15]:
```
df
```

[15]:
```
   Student ID  MAL100  MAL101  MAL403  EEL101  ECL101  BML101  CSL100  \
0   Student 1     4.0     3.0     4.0     1.0     1.0     1.0     4.0
1   Student 2     3.0     3.0     3.0     1.0     1.0     1.0     4.0
2   Student 3     4.0     4.0     3.0     3.0     4.0     2.0     4.0
3   Student 4     3.0     4.0     4.0     1.0     1.0     1.0     5.0
4   Student 5     3.0     3.0     4.0     3.0     3.0     2.0     4.0
5   Student 6     3.0     3.0     5.0     1.0     1.0     1.0     4.0
6   Student 7     3.0     4.0     4.0     1.0     1.0     1.0     4.0
7   Student 8     3.0     4.0     2.0     2.0     3.0     2.0     4.0
8   Student 9     3.0     4.0     4.0     2.0     3.0     1.0     4.0
9  Student 10     4.0     4.0     3.0     3.0     2.0     2.0     4.0
10 Student 11     4.0     5.0     4.0     2.0     3.0     3.0     5.0
11 Student 12     3.0     3.0     3.0     1.0     1.0     2.0     5.0
12 Student 13     2.0     3.0     3.0     1.0     1.0     2.0     4.0
13 Student 14     3.0     3.0     4.0     2.0     2.0     2.0     4.0
14 Student 15     4.0     4.0     5.0     3.0     3.0     1.0     4.0
15 Student 16     3.0     3.0     4.0     1.0     1.0     1.0     4.0
16 Student 17     4.0     4.0     3.0     1.0     1.0     1.0     5.0
17 Student 18     3.0     4.0     3.0     2.0     1.0     3.0     4.0
18 Student 19     3.0     3.0     4.0     1.0     2.0     1.0     4.0
19 Student 20     1.0     5.0     3.0     1.0     1.0     2.0     1.0
20 Student 21     3.0     4.0     3.0     2.0     3.0     1.0     4.0
21 Student 22     4.0     5.0     5.0     1.0     1.0     2.0     4.0
22 Student 23     2.0     2.0     2.0     1.0     1.0     4.0     4.0
23 Student 24     3.0     5.0     5.0     2.0     1.0     1.0     4.0

   CSL201  CSL202  DSL201  Unnamed: 11
0     5.0     5.0     5.0          3.3
1     5.0     5.0     5.0          3.1
2     5.0     4.0     NaN          3.7
3     5.0     5.0     2.0          3.1
4     5.0     5.0     4.0          3.6
5     5.0     5.0     5.0          3.3
6     4.0     4.0     5.0          3.1
7     4.0     4.0     5.0          3.3
8     4.0     4.0     4.0          3.3
9     4.0     5.0     4.0          3.5
10    5.0     5.0     4.0          4.0
11    4.0     3.0     5.0          3.0
12    4.0     3.0     3.0          2.6
13    5.0     4.0     4.0          3.3
14    5.0     4.0     5.0          3.8
15    4.0     4.0     4.0          2.9
```

```
16     5.0     5.0     5.0           3.4
17     4.0     4.0     5.0           3.3
18     3.0     5.0     5.0           3.1
19     5.0     4.0     3.0           2.6
20     4.0     4.0     5.0           3.3
21     1.0     5.0     3.0           3.1
22     2.0     2.0     4.0           2.4
23     4.0     4.0     5.0           3.4
```

[16]:
```python
cols = df.columns.tolist()
n = len(cols)
column_to_drop = cols[n-1]
df.drop([column_to_drop],axis=1,inplace=True)
```

[17]:
```python
df
```

[17]:
```
    Student ID  MAL100  MAL101  MAL403  EEL101  ECL101  BML101  CSL100  \
0    Student 1     4.0     3.0     4.0     1.0     1.0     1.0     4.0
1    Student 2     3.0     3.0     3.0     1.0     1.0     1.0     4.0
2    Student 3     4.0     4.0     3.0     3.0     4.0     2.0     4.0
3    Student 4     3.0     4.0     4.0     1.0     1.0     1.0     5.0
4    Student 5     3.0     3.0     4.0     3.0     3.0     2.0     4.0
5    Student 6     3.0     3.0     5.0     1.0     1.0     1.0     4.0
6    Student 7     3.0     4.0     4.0     1.0     1.0     1.0     4.0
7    Student 8     3.0     4.0     2.0     2.0     3.0     2.0     4.0
8    Student 9     3.0     4.0     4.0     2.0     3.0     1.0     4.0
9   Student 10     4.0     4.0     3.0     3.0     2.0     2.0     4.0
10  Student 11     4.0     5.0     4.0     2.0     3.0     3.0     5.0
11  Student 12     3.0     3.0     3.0     1.0     1.0     2.0     5.0
12  Student 13     2.0     3.0     3.0     1.0     1.0     2.0     4.0
13  Student 14     3.0     3.0     4.0     2.0     2.0     2.0     4.0
14  Student 15     4.0     4.0     5.0     3.0     3.0     1.0     4.0
15  Student 16     3.0     3.0     4.0     1.0     1.0     1.0     4.0
16  Student 17     4.0     4.0     3.0     1.0     1.0     1.0     5.0
17  Student 18     3.0     4.0     3.0     2.0     1.0     3.0     4.0
18  Student 19     3.0     3.0     4.0     1.0     2.0     1.0     4.0
19  Student 20     1.0     5.0     3.0     1.0     1.0     2.0     1.0
20  Student 21     3.0     4.0     3.0     2.0     3.0     1.0     4.0
21  Student 22     4.0     5.0     5.0     1.0     1.0     2.0     4.0
22  Student 23     2.0     2.0     2.0     1.0     1.0     4.0     4.0
23  Student 24     3.0     5.0     5.0     2.0     1.0     1.0     4.0

    CSL201  CSL202  DSL201
0      5.0     5.0     5.0
1      5.0     5.0     5.0
2      5.0     4.0     NaN
3      5.0     5.0     2.0
```

```
4     5.0   5.0   4.0
5     5.0   5.0   5.0
6     4.0   4.0   5.0
7     4.0   4.0   5.0
8     4.0   4.0   4.0
9     4.0   5.0   4.0
10    5.0   5.0   4.0
11    4.0   3.0   5.0
12    4.0   3.0   3.0
13    5.0   4.0   4.0
14    5.0   4.0   5.0
15    4.0   4.0   4.0
16    5.0   5.0   5.0
17    4.0   4.0   5.0
18    3.0   5.0   5.0
19    5.0   4.0   3.0
20    4.0   4.0   5.0
21    1.0   5.0   3.0
22    2.0   2.0   4.0
23    4.0   4.0   5.0
```

[18]:
```python
df.drop(["Student ID"],axis=1,inplace=True)
```

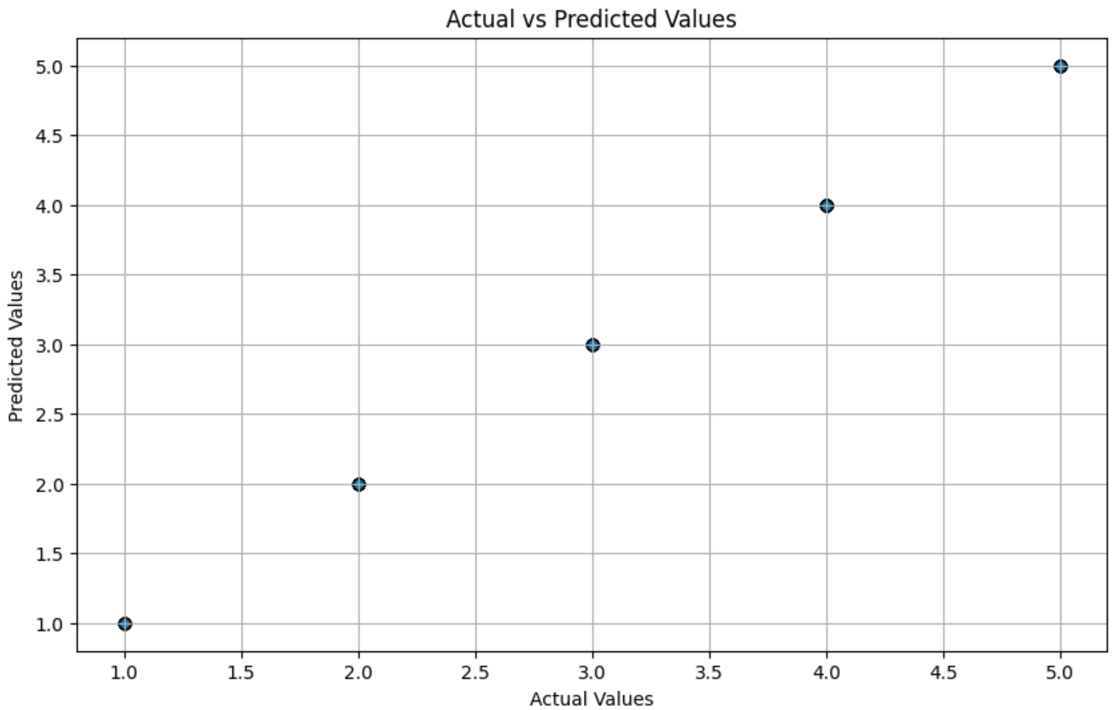
[19]:
```python
def introduce_missing_data(df, missing_percentage):
    df_missing = df.copy()
    num_missing = int(df.size * missing_percentage)
    missing_indices = np.random.choice(df.size, num_missing, replace=False)
    df_missing.values.ravel()[missing_indices] = np.nan
    return df_missing
```

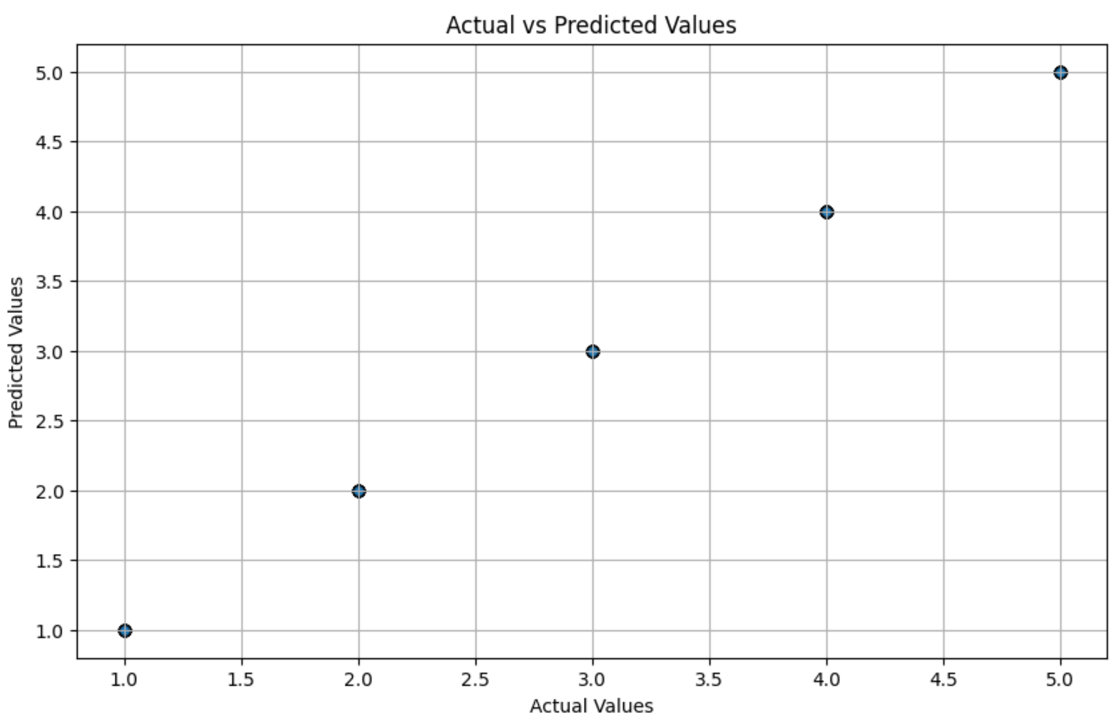
[20]:
```python
def predict_missing_values(df):
    df_filled = df.copy()
    mse_scores = []

    for col in df.columns:
        if df[col].isnull().any():
            # Separate data into training and missing sets
            known_data = df_filled[df_filled[col].notnull()]
            unknown_data = df_filled[df_filled[col].isnull()]

            # Features and targets
            X_known = known_data.drop(columns=[col])
            y_known = known_data[col]

            X_unknown = unknown_data.drop(columns=[col])

            # Train a Linear Regression model
```

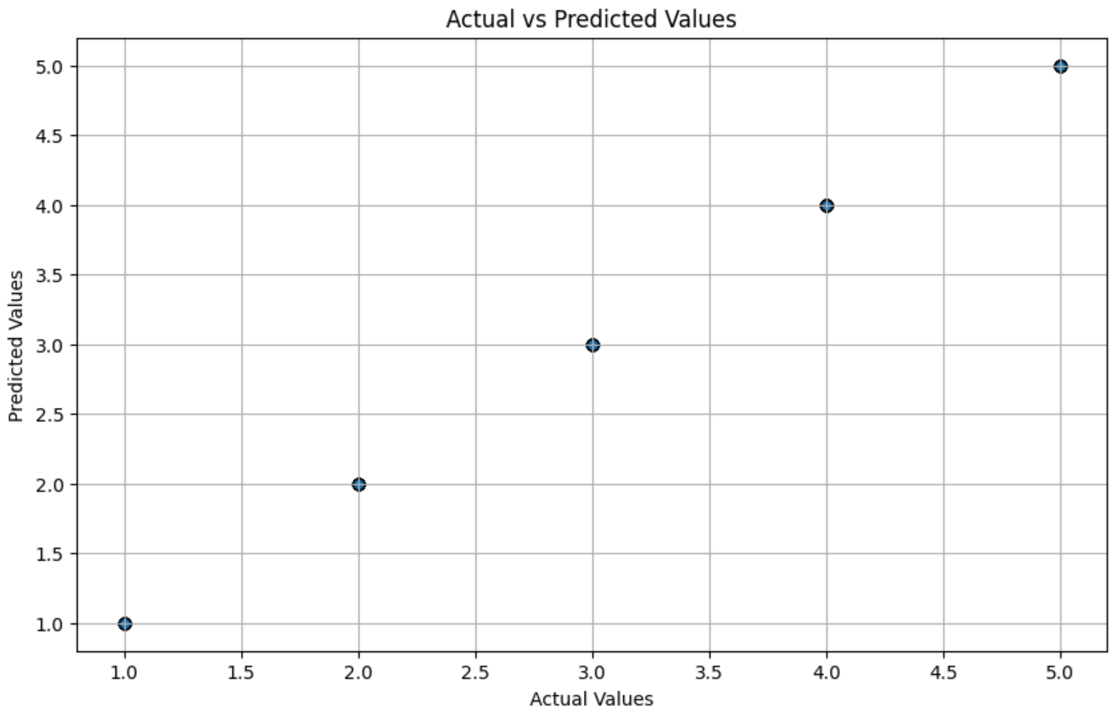
```
            model = LinearRegression()
            model.fit(X_known, y_known)

            # Predict missing values
            predicted_values = model.predict(X_unknown)
            df_filled.loc[unknown_data.index, col] = predicted_values

            # Evaluate using MSE (if possible)
            X_train, X_test, y_train, y_test = train_test_split(X_known,␣
↪y_known, test_size=0.2, random_state=42)
            model.fit(X_train, y_train)
            y_pred = model.predict(X_test)
            mse = mean_squared_error(y_test, y_pred)
            mse_scores.append(mse)

    return df_filled, mse_scores
```

[21]:
```
def visualize_results(original, predicted):
    plt.figure(figsize=(10, 6))
    plt.scatter(original, predicted, alpha=0.6, edgecolors='k')
    plt.xlabel('Actual Values')
    plt.ylabel('Predicted Values')
    plt.title('Actual vs Predicted Values')
    plt.grid(True)
    plt.show()
```

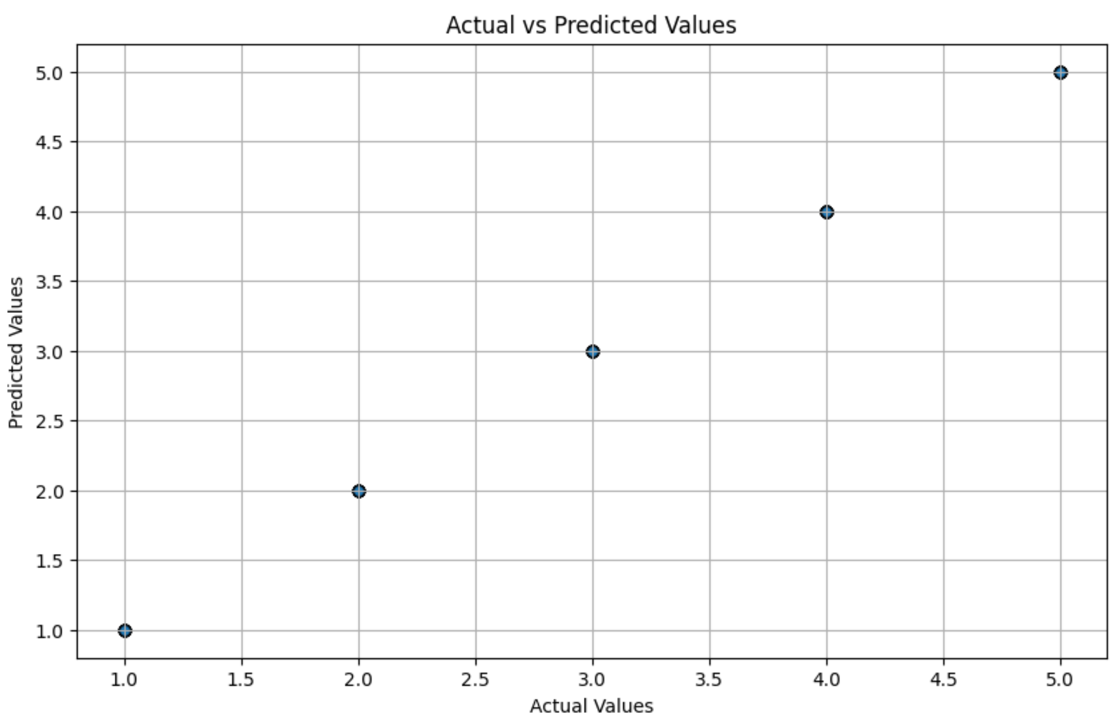
[22]:
```
missing_percentages = [0.2, 0.4, 0.6, 0.8]

for missing_percentage in missing_percentages:
    df_missing = introduce_missing_data(df, missing_percentage)
    df_filled, mse_scores = predict_missing_values(df_missing)
    visualize_results(df_missing, df_filled)
```


Actual vs Predicted Values
Predicted Values
Actual Values
1.0
1.5
2.0
2.5
3.0
3.5
4.0
4.5
5.0


Actual vs Predicted Values
Predicted Values
Actual Values
1.0
1.5
2.0
2.5
3.0
3.5
4.0
4.5
5.0



Actual vs Predicted Values
Predicted Values
Actual Values
1.0
1.5
2.0
2.5
3.0
3.5
4.0
4.5
5.0



Actual vs Predicted Values
Predicted Values
Actual Values
1.0
1.5
2.0
2.5
3.0
3.5
4.0
4.5
5.0