Self Organizing Map (SOM)

The project impliments Self-Organizing Map (SOM) algorithm to cluster random 2D data points and evaluate the performance under different configurations.

Data Generation:

Generates a dataset of 100 random 2D data points using NumPy.Normalizes the generated data to the range [0, 1].

SOM Configuration:

Sets up a SOM grid with a size of 5x5. Defines three different configurations with varying learning rates, neighborhood sizes (sigma), and numbers of training iterations.

SOM Training and Evaluation:

Iterates over each configuration and trains a SOM using the MiniSom library. Calculates the quantization error, which measures the average distance between data points and their corresponding winning neurons in the SOM. Stores the results, including configuration details and quantization error, in a results table.

```
1 pip install minisom
1
    import numpy as np
    from minisom import MiniSom
3
    import matplotlib.pyplot as plt
    np.random.seed(42)
 6
    data = np.random.rand(100, 2)
8
    data = (data - data.min(axis=0)) / (data.max(axis=0) - data.min(axis=0))
9
10
    som_size = (5, 5)
    input size = 2
11
12
    learning_rate = 0.5
13
    sigma = 1.0
14
    som = MiniSom(som_size[0], som_size[1], input_size, sigma=sigma, learning_rate=learning_rate)
15
16
17
    som.train_random(data, 1000)
18
19
    mapped_data = som.win_map(data)
20
    plt.figure(figsize=(8, 8))
21
22
23
    for i in range(som_size[0]):
24
        for j in range(som_size[1]):
25
            cluster\_points = np.array(mapped\_data[(i, j)]) # Convert the list to a NumPy array
            if cluster_points.shape[0] > 0: # Check if there are any points in the cluster
26
27
                plt.scatter(cluster\_points[:, 0], cluster\_points[:, 1], label=f'Cluster \{i\}-\{j\}')
28
29
    plt.scatter(som.get_weights()[:, :, 0].flatten(), som.get_weights()[:, :, 1].flatten(), marker='x', color='k', label='SOM cer
30
    plt.title('Self-Organizing Map Clustering')
31
32
    plt.legend()
33
    plt.show()
34
```

Self-Organizing Map Clustering

```
1.0
                                     ×
                                              Cluster 0-0
                                              Cluster 0-1
                                              Cluster 0-2
                                              Cluster 0-3
0.8
                                              Cluster 0-4
                                              Cluster 1-0
                                              Cluster 1-1
                                              Cluster 1-2
                                              Cluster 1-3
0.6
                                              Cluster 1-4
                                              Cluster 2-0
                                              Cluster 2-1
                                              Cluster 2-2
                                              Cluster 2-3
0.4
                                              Cluster 2-4
                                              Cluster 3-0
                                              Cluster 3-1
                                             Cluster 3-2
```

Configuration

LR=0.5, Sigma=1.0, Iter=1000 0.0569 LR=0.3, Sigma=0.8, Iter=1500 0.0654 LR=0.7, Sigma=1.5, Iter=800 0.0673

Quantization Error

```
1 import numpy as np
  2 from minisom import MiniSom
  3 from scipy.spatial.distance import euclidean
  5 np.random.seed(42)
  6 data = np.random.rand(100, 2)
  8 data = (data - data.min(axis=0)) / (data.max(axis=0) - data.min(axis=0))
  9
10 \text{ som\_size} = (5, 5)
11
12 configurations = [
                  {'learning_rate': 0.5, 'sigma': 1.0, 'num_iterations': 1000},
13
                  {'learning_rate': 0.3, 'sigma': 0.8, 'num_iterations': 1500},
{'learning_rate': 0.7, 'sigma': 1.5, 'num_iterations': 800},
14
15
16 l
17
18 results_table = []
19
20 for config in configurations:
21
22
                  som = MiniSom(som_size[0], som_size[1], data.shape[1], sigma=config['sigma'], learning_rate=config['learning_rate'])
23
24
                  \verb|som.train_random(data, config['num_iterations'])| \\
25
26
27
28
                  quantization_error = 0
29
                  for i in range(data.shape[0]):
30
                             x = data[i]
31
                            winner = som_winner(x)
32
                             quantization_error += euclidean(x, som.get_weights()[winner])
33
34
                  quantization_error /= data.shape[0]
35
36
37
                  results_table.append({'config': config, 'quantization_error': quantization_error})
38
39
40 print("{:<25} {:<15}".format("Configuration", "Quantization Error"))
41 print("="*45)
42 for result in results_table:
                  config\_str = f"LR=\{result['config']['learning\_rate']\}, \\ Sigma=\{result['config']['sigma']\}, \\ Iter=\{result['config']['num\_ite']\}, \\ Sigma=\{result['config']['sigma']\}, \\ Sigma=\{result['config']], \\ Sigm
43
44
                  print("{:<25} {:<15.4f}".format(config_str, result['quantization_error']))</pre>
45
```

▼ Summary

The output summarises the quantization error for each combination of learning rate, sigma, and number of iterations, allowing for a comparison of different configurations. Lower the quantization error, the better the SOM model is.

The quantization error serves as a metric to assess how well the SOM is able to represent the input data for each configuration. The project provides insights into the impact of different parameters on the clustering performance of the SOM algorithm.

Configuration		Quantization Error
		Iter=1000 0.0569
	,	Iter=1500 0.0654 Iter=800 0.0673