Locally Linear Embedding (LLE)

Introduction:

Locally Linear Embedding (LLE) is a nonlinear dimensionality reduction technique that aims to preserve the local relationships within the data. Unlike linear methods such as Principal Component Analysis (PCA), LLE works well for capturing the intrinsic geometry of high-dimensional data when it lies on a low-dimensional manifold. LLE is particularly effective at unfolding twisted or curved structures.

Intuition:

The core intuition behind LLE is that local relationships between neighboring data points are preserved in the lower-dimensional representation. It assumes that points on the manifold can be reconstructed as linear combinations of their neighbors. By focusing on preserving these local linear relationships, LLE can capture complex structures that may be missed by linear methods.

Algorithm:

1. Neighborhood Identification:

• For each data point, identify its k-nearest neighbors in the high-dimensional space.

2. Local Linear Reconstruction:

• Express each data point as a linear combination of its neighbors. Find the weights that minimize the reconstruction error.

3. Weight Matrix:

• Create a weight matrix that represents the linear coefficients for the reconstruction of each point.

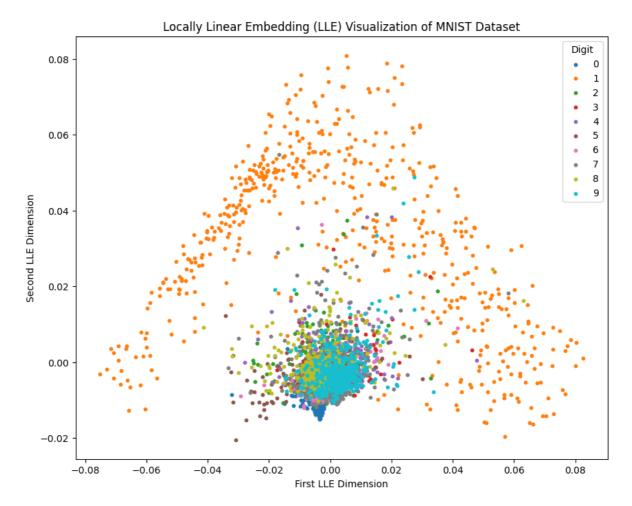
4. Global Coordinates:

 Derive the low-dimensional representation by finding global coordinates that minimize the differences between local linear relationships in the high-dimensional and lowdimensional spaces.

Implementation in Python (Mnist Data):

```
import numpy as np
   import matplotlib.pyplot as plt
   from sklearn.datasets import fetch_openml
    from sklearn.manifold import LocallyLinearEmbedding
5
6 # Load MNIST dataset
7
   mnist = fetch_openml('mnist_784')
   X = mnist.data.astype('float64')
9
   y = mnist.target.astype('int')
10 | # Sample only a subset of the data for faster processing (optional)
11
    sample\_size = 5000
12
    idx = np.random.choice(len(X), sample_size, replace=False)
   X_sample = X.iloc[idx] # Use iloc for integer-based indexing
13
    y_sample = y.iloc[idx]
14
    # Apply Locally Linear Embedding to the data
15
16
    n_neighbors = 30
```

```
17
    n_{components} = 2
18
    11e = LocallyLinearEmbedding(n_neighbors=n_neighbors,
    n_components=n_components, method='standard', random_state=42)
    X_lle = lle.fit_transform(X_sample)
19
20
21
    # Plot the results
    plt.figure(figsize=(10, 8))
22
    for digit in range(10):
23
        plt.scatter(X_lle[y_sample == digit, 0], X_lle[y_sample == digit, 1],
24
    label=str(digit), s=10)
    plt.title('Locally Linear Embedding (LLE) Visualization of MNIST Dataset')
25
26
    plt.xlabel('First LLE Dimension')
    plt.ylabel('Second LLE Dimension')
27
28
    plt.legend(title='Digit', loc='upper right')
29
    plt.show()
```



In this example:

- We load the mnist dataset using fetch_openml('mnist_784').
- LLE is applied to reduce the dimensionality of the mnist dataset to 2D.
- The resulting LLE representation is visualized, and points are colored based on the mnist digits.

This code uses scikit-learn's implementation of LLE, making it straightforward to apply to various datasets. Adjust the parameters such as n_neighbors based on the characteristics of your data.