ARVIND SAI DOODA **A20553046**

CS584 Machine Learning - Reading Assignment 4

Reference Paper name :

LE: Belik and Niyogi, Laplacian eigenmaps for dimensionality reduction and data representation, Neural computation, 2003

SUMMARY :

- High-dimensional data often lies on or near a low-dimensional manifold. Need methods for dimensionality reduction that preserve local geometry.
- Use graph Laplacian and connections to Laplace-Beltrami operators to find embeddings that optimally preserve local neighborhood information.
- The Algorithm Construct nearest neighbor graph, choose weights based on heat kernel, compute eigenvectors of graph Laplacian for embedding.
- Demonstrated on synthetic and real datasets. Locality preserving, clustering interpretation, handles outliers and noise.

Pros:

- Simple and efficient algorithm based on sparse eigenvector computation.
- Geometric interpretation relating to manifold structure.
- Locality preserving properties useful for clustering and pattern recognition.
- Handles outliers and noise well due to local approximations.
- Extends spectral clustering ideas to dimensionality reduction.

Cons:

- Choice of parameters like k, t not well understood.
- Does not provide fully isometric embedding like Isomap.
- Convergence guarantees need more theoretical analysis.
- Effectiveness depends on underlying manifold assumption.
- Unsuited if global distances need to be preserved