Experiment: Principal Component Analysis (PCA) vs Linear Discriminant Analysis (LDA) vs T-distributed Stochastic Neighbour Embedding (t-SNE) vs Multi-Dimensional Scaling (MDS) vs Singular Value Decomposition (SVD)

Title:

Implementing dimensionality reduction algorithms on a specific dataset and comparing its outcomes

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Aim:

Implement the dimensionality reduction techniques and compare their outcomes. (PCA, LDA, t-SNE, MDS, SVD, etc)

Objective:

Students will learn:

- The implementation of the Multi-Dimensional Scaling, principal component analysis and Linear Discriminant analysis and T-distributed stochastic neighbour embedding and Singular Value Decomposition on a dataset.
- Visualization and interpretation of results.

Explanation / Stepwise Procedure / Algorithm

Dimensionality Reduction Techniques

Principal Component Analysis (PCA)

PCA reduces high-dimensional data while keeping most of its information. It identifies key directions (principal components) where data varies the most and projects it onto them.

Steps:

1. Standardize the data.
2. Compute the covariance matrix.
3. Find eigenvectors and eigenvalues.
4. Select top k eigenvectors.
5. Project data onto these eigenvectors.

Uses:

- Reducing dimensions
- Finding patterns in data
- Improving machine learning performance

Linear Discriminant Analysis (LDA)

LDA is a supervised technique that finds the best way to separate different classes. It is useful when features are many, but samples are few.

Steps:

1. Standardize the data.
2. Compute within-class and between-class scatter matrices.
3. Find eigenvectors and eigenvalues.
4. Select top k eigenvectors.
5. Project data onto these eigenvectors.

Uses:

- Reducing dimensions
- Improving classification performance
- Identifying key features for classification

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t-Distributed Stochastic Neighbor Embedding (t-SNE)

t-SNE maps high-dimensional data to a lower-dimensional space while preserving local relationships. It is mainly used for visualization.

Steps:

1. Compute data similarity using a Gaussian kernel.
2. Convert it into a probability distribution.
3. Define a cost function for differences between high- and low-dimensional data.
4. Minimize the cost function.

Uses:

- Visualizing high-dimensional data
- Detecting clusters and patterns
- Preserving local structure in data

Singular Value Decomposition (SVD)

SVD breaks a matrix into three smaller matrices, capturing key patterns. It is widely used in image compression, recommendations, and noise reduction.

Steps:

1. Decompose matrix X into U, Σ, and VT:
    - U: Left singular vectors
    - Σ: Singular values (importance)
    - VT: Right singular vectors
2. Keep top k singular values and vectors.
3. Use these components to create a lower-dimensional representation.

Uses:

- Reducing dimensions
- Removing noise
- Feature extraction
- Applications in text mining & image processing

Multidimensional Scaling (MDS)

MDS represents high-dimensional data in lower dimensions while maintaining pairwise distances. It helps visualize similarities in data.

Steps:

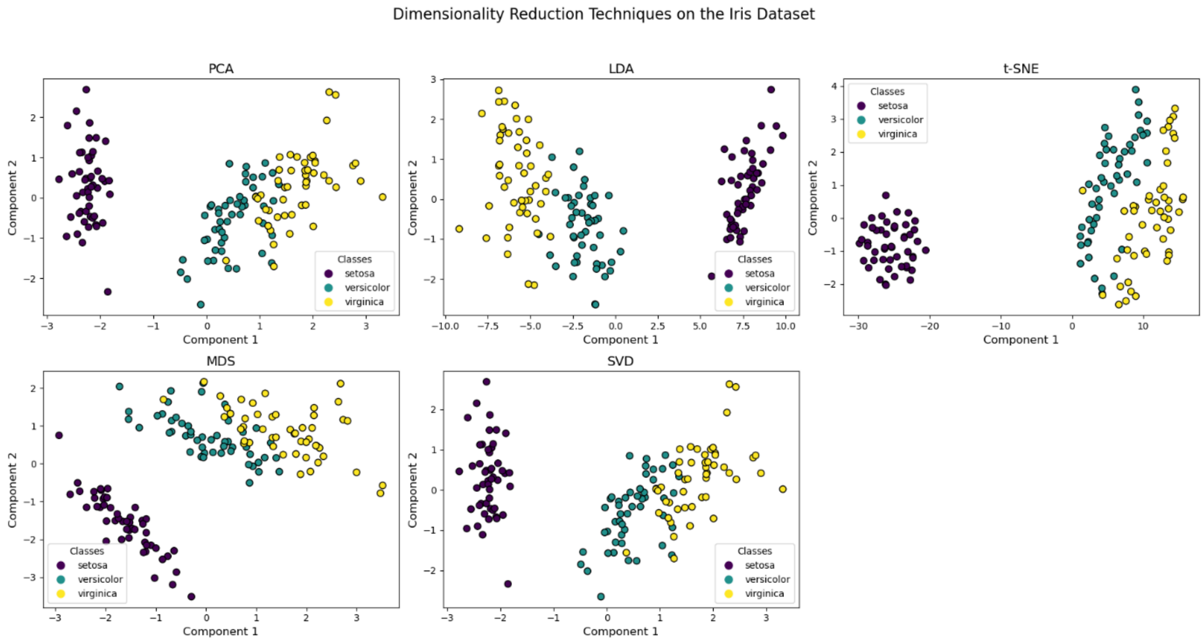
1. Compute the dissimilarity matrix.
2. Convert it for eigenvalue decomposition or define a cost function.
3. Perform decomposition or use an optimization algorithm.
4. Select top k dimensions.
5. Assign new coordinates to data points.

Uses:

- Visualizing data in 2D/3D
- Understanding relationships between points
- Preserving distances in dimensionality reduction
- Market research and psychology analysis

Figures/Diagrams

- MDS and LDA, PCA and t-SNE plots plotted for the dataset.
- Comparison between MDS, LDA,PCA and t-SNE.



Challenges Encountered

1. Different techniques work in different ways, making it hard to choose the best one.
2. Some methods, like t-SNE and MDS, take longer to process large datasets.
3. Understanding the reduced data can be tricky, as some details may be lost.

Conclusion

- Dimensionality reduction makes data easier to analyse and improves performance.
- Each method has its strengths, so the choice depends on the data and purpose.
- Comparing results helps in selecting the most suitable technique.