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Machine Learning

Module 5
Compressing Data via Dimensionality Reduction

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Introduction

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- Dimensionality reduction: techniques for reducing features in high-dimensional datasets
- Simplify data, speed up computation time, lower memory usage, and gain insight into data structure
- Topics covered:
  - Unsupervised dimensionality reduction via PCA
  - Supervised data compression via LDA
  - Non-linear dimensionality reduction and visualization via t-SNE

What is Dimensionality Reduction?

- Dimensionality reduction: reduce number of features in dataset while retaining relevant information
- Useful in many machine learning tasks to avoid overfitting or poor generalization
- High-dimensional data can be challenging to work with

Unsupervised Dimensionality Reduction via Principal Component Analysis (PCA)

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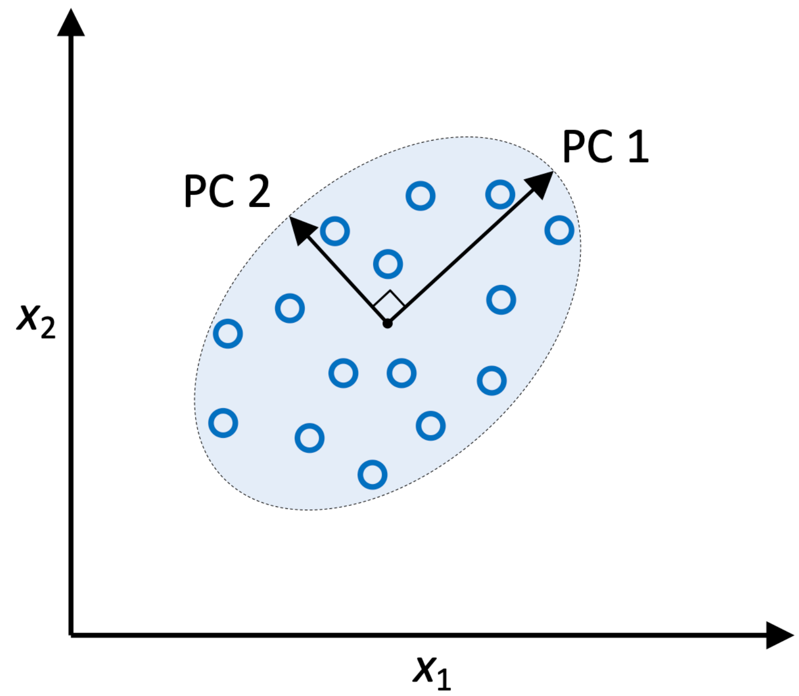
- Unsupervised dimensionality reduction via PCA
- Popular technique for reducing the dimensionality of high-dimensional data
- Finds the most important features or variables in the data
- Transforms the data into a new set of coordinates that capture the most significant variations in the data

PCA in a nutshell

- Identify patterns between data based on the correlations between features
- Find the directions of maximum variance in high-dimensional data
- Project the data onto a new subspace with equal or fewer dimentions than the original data
- Orthogona axes (principle component) of the new subspace can be interpreted as the direction of the maximum variance (s.t.: they are orthogonal)

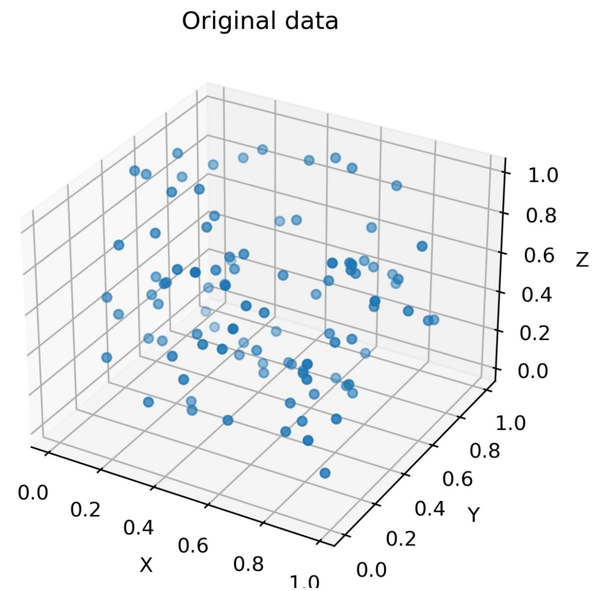


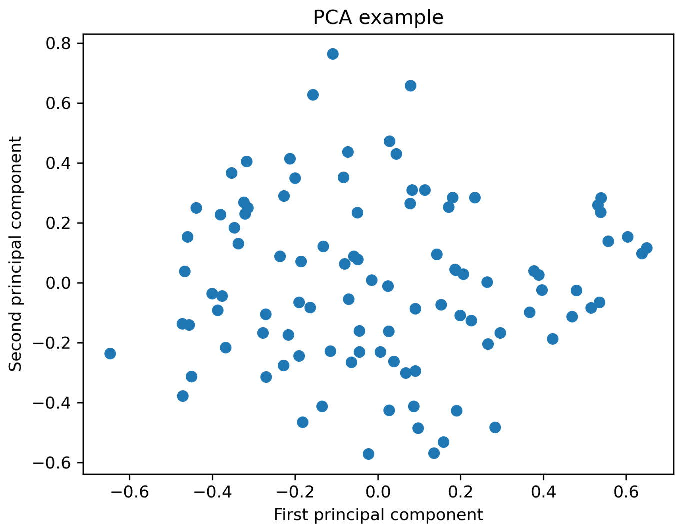
PCA Algorithm

- PCA algorithm:
  1. Center the data around its mean
  2. Compute the covariance matrix of the centered data
  3. Calculate the eigenvectors and eigenvalues of the covariance matrix
  4. Sort the eigenvectors in descending order of their corresponding eigenvalues
  5. Select the top k eigenvectors as the new basis for the data
  6. Transform the data into the new basis

PCA Example

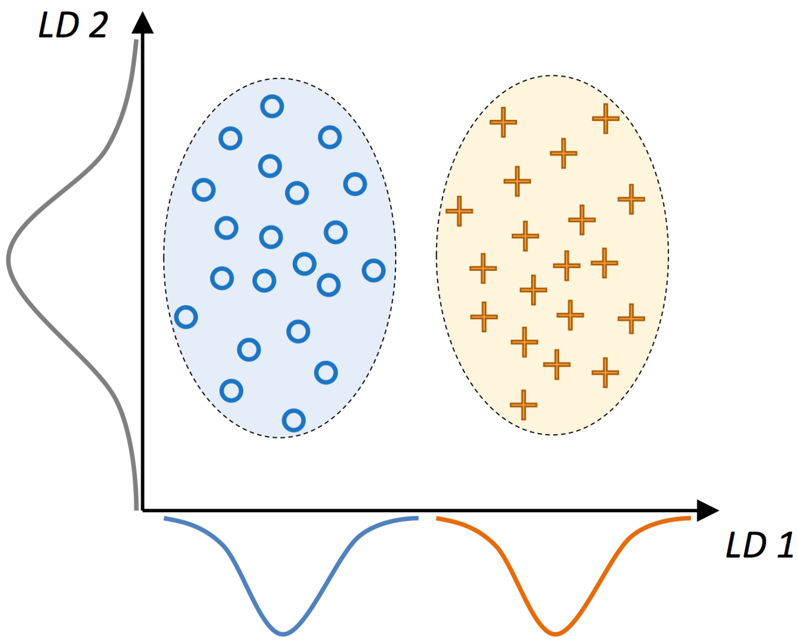
- PCA example: reducing the dimensionality of a dataset from 3 to 2
- Plot the data in the new two-dimensional space, with x-axis as the first principal component and y-axis as the second principal component
- Visualization of high-dimensional data in a more meaningful way
- Use Jupyter notebook to apply PCA to the Iris dataset, reduce the dimensionality from 4 to 2, and create a scatter plot of the reduced data to visualize the relationships between the different species of Iris flowers.





Supervised Data Compression via Linear Discriminant Analysis (LDA)

- Supervised data compression via LDA
- Used in classification problems to find a projection of the data that maximizes the separability between different classes
- LDA is often used in combination with other classification algorithms to improve their performance

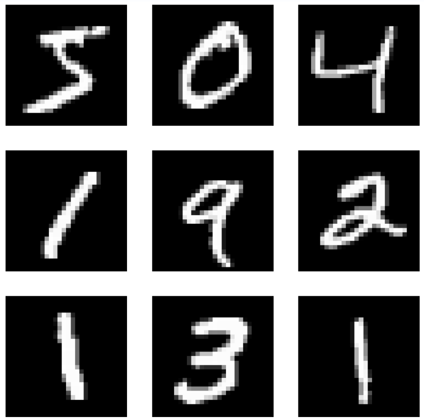


LDA Algorithm

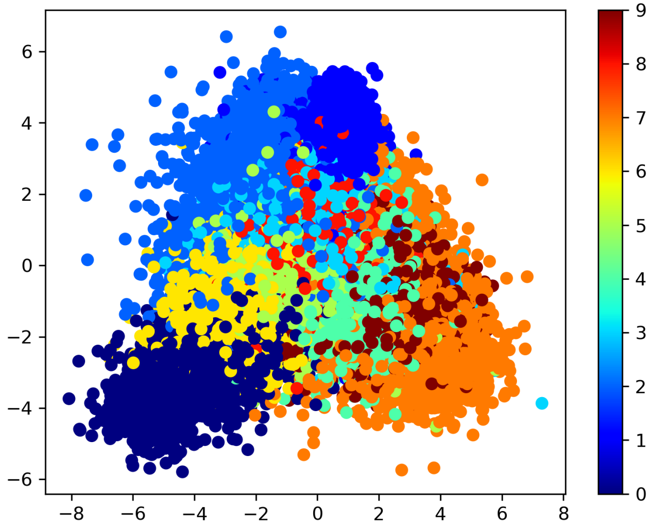
1. Compute the mean vectors of each class
2. Compute the scatter matrix within classes and the scatter matrix between classes
3. Calculate the eigenvectors and eigenvalues of the inverse of the within-class scatter matrix multiplied by the between-class scatter matrix
4. Sort the eigenvectors in descending order of their corresponding eigenvalues
5. Select the top k eigenvectors as the new basis for the data
6. Transform the data into the new basis

LDA Example

- LDA example: Classification of handwritten digits using the MNIST dataset
- High-dimensional dataset with 784 features
- After applying LDA, project the data into a lower-dimensional space where the classes are more easily separable
- Train a logistic regression classifier on the reduced-dimensional data for better classification performance



Few samples of MNIST dataset



Project the high-dimensional MNIST data (784 features) into a 2-dimensional space

Non-Linear Dimensionality Reduction and Visualization

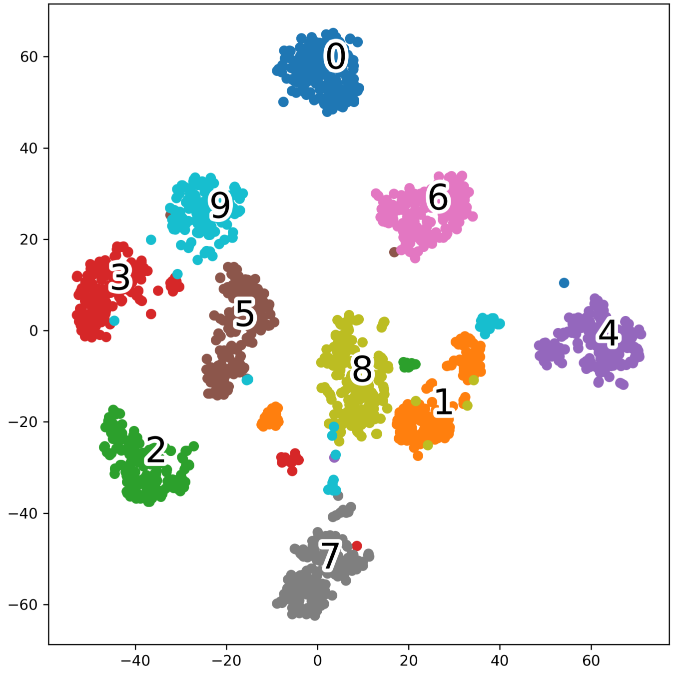
- Linear dimensionality reduction is not always sufficient for capturing the full structure of high-dimensional data
- Non-linear dimensionality reduction techniques can be used to find a non-linear transformation that preserves the relevant information
- Visualization of high-dimensional data in a lower-dimensional space can aid in understanding the underlying structure of the data

t-SNE

- t-SNE: popular non-linear dimensionality reduction technique
- Maps high-dimensional data to a two-dimensional space while preserving pairwise distances between data points
- Often used for visualizing high-dimensional data in a lower-dimensional space where clusters and patterns can be more easily observed

t-SNE Example

- t-SNE example: high-dimensional dataset of images of handwritten digits
- After applying t-SNE, project the data into a two-dimensional space where the different digit classes form distinct clusters
- Visualization of high-dimensional data in a more meaningful way to gain insights into the structure of the data and the relationships between different classes



Conclusion

- Covered three important topics: unsupervised dimensionality reduction via PCA, supervised data compression via LDA, and non-linear dimensionality reduction and visualization via t-SNE
- Dimensionality reduction is a key tool in machine learning for reducing computation time, lowering memory footprint, and visualizing high-dimensional data
- Hope this lecture has provided a good understanding of these techniques and their applications