**Linear Discriminant Analysis (LDA) in Machine Learning: *Example, Concept and Applications***

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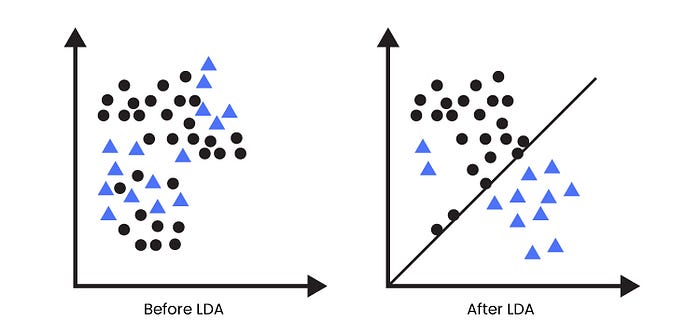
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“***Linear Discriminant Analysis (LDA) is a dimensionality reduction and classification technique commonly used in machine learning and pattern recognition. In the context of classification it aims to find a linear combination of features that best separates different classes or categories of data. It seeks to reduce the dimensionality of the feature space while preserving as much of the class-separability information as possible.”***



[source](https://www.analyticssteps.com/blogs/introduction-linear-discriminant-analysis-supervised-learning)

let’s walk through a simple example to understand how Linear Discriminant Analysis (LDA) works:

**Example: Iris Flower Classification**



[source](https://www.embedded-robotics.com/iris-dataset-classification/)

Suppose we have a dataset of iris flowers with four features: sepal length, sepal width, petal length, and petal width. We want to classify these flowers into three species: Setosa, Versicolor, and Virginica.

***Steps:***

1. **Data Preparation:** Let’s say we have 150 iris samples with four features each, and the samples are evenly distributed among the three species.
2. **Compute Class Statistics:**Calculate the mean and covariance matrix for each feature in each class. This gives us three mean vectors and three covariance matrices (one for each class).
3. **Compute Between-Class and Within-Class Scatter Matrices:**Calculate the between-class scatter matrix by computing the differences between the mean vectors of each class and the overall mean, and then summing these outer products. Calculate the within-class scatter matrix by summing the covariance matrices of each class, weighted by the number of samples in each class.
4. **Compute Eigenvectors and Eigenvalues:**Solve the generalized eigenvalue problem using the between-class scatter matrix and the within-class scatter matrix. This gives us a set of eigenvectors and their corresponding eigenvalues.
5. **Select Discriminant Directions:**Sort the eigenvectors by their eigenvalues in descending order. Let’s say we want to reduce the dimensionality to 2, so we select the top two eigenvectors.
6. **Transform Data:**Project the original iris data onto the two selected eigenvectors. This gives us a new two-dimensional representation of the data.
7. **Classification:**In the reduced-dimensional space, we can use a classifier (e.g., k-nearest neighbors) to classify the iris flowers into one of the three species based on their positions in the reduced space.

LDA aims to find the projection (linear combination of features) that maximizes the separation between the classes while minimizing the variance within each class. This way, the classes become more distinguishable in the lower-dimensional space.

In our iris flower example, LDA would find the best linear combination of sepal length, sepal width, petal length, and petal width that maximizes the separability between the Setosa, Versicolor, and Virginica species. The reduced-dimensional space could potentially help in better classifying new iris samples.

LDA is a versatile technique used primarily for classification and dimensionality reduction tasks.**Let’s discuss some common applications of Linear Discriminant Analysis:**

1. **Face Recognition:** LDA is frequently employed in face recognition systems. By reducing the dimensionality of face images while preserving the essential information for distinguishing between individuals, LDA helps improve the efficiency and accuracy of recognition algorithms.
2. **Medical Diagnosis:**In medical fields, LDA can aid in diagnosing diseases or conditions based on patient data. For instance, it can be used to classify patients as healthy or suffering from a particular disease based on a set of medical features.
3. **Biometrics:** Beyond face recognition, LDA can also be applied to other biometric identification systems, such as fingerprint recognition and iris recognition. It helps in extracting relevant features for distinguishing between individuals.
4. **Quality Control and Manufacturing**: LDA can assist in identifying defects in products by classifying items as defective or non-defective based on various measurements or attributes. This is particularly useful in industries like manufacturing and production.
5. **Document Classification**: LDA can be used for categorizing documents into different classes or topics. For instance, it might be used to classify emails into spam and non-spam categories or news articles into different sections.
6. **Marketing and Customer Segmentation**: By classifying customers into different segments based on their purchasing behavior, demographic information, and preferences, LDA helps businesses tailor their marketing strategies to specific customer groups.
7. **Remote Sensing and Image Analysis**: LDA can be used for classifying land cover types in satellite images or aerial photographs. It helps differentiate between different types of terrain, vegetation, or land use.
8. **Pattern Recognition:**LDA is a fundamental tool in pattern recognition tasks, where the goal is to recognize recurring patterns or structures in data. This can be applied in various domains, including finance, biology, and signal processing.

Overall, LDA finds applications in fields where classification and dimensionality reduction are crucial for data analysis, decision-making, and problem-solving.

**Pros:**

1. **Dimensionality Reduction with Class Separation:**LDA aims to maximize the separation between classes while reducing the dimensionality of the data. It’s particularly effective when there’s a clear distinction between classes, and it can help improve the efficiency and performance of classification algorithms.
2. **Utilizes Class Information:** LDA takes advantage of class labels during its computation, which can lead to better separation of classes compared to unsupervised techniques like Principal Component Analysis (PCA).
3. **Works Well for Small Sample Sizes**: LDA can handle situations where the number of samples is small compared to the number of features. This makes it suitable for cases where collecting a large amount of training data is challenging.
4. **Interpretable Results:** The reduced-dimensional representation obtained through LDA can often be more interpretable than the original feature space. This can aid in understanding the important factors driving the classification.
5. **Data Visualization**: The reduced-dimensional space generated by LDA can be visualized, making it easier to observe the separation between classes and the distribution of data points.
6. **Robust to Outliers**: LDA is less sensitive to outliers compared to other methods like k-nearest neighbors. This is due to its reliance on class means and variances rather than individual data points.

**Cons:**

1. **Sensitive to Class Distribution**: LDA assumes that the classes have approximately equal covariance matrices and follow a Gaussian distribution. If these assumptions are not met, the performance of LDA can degrade. In cases where the assumptions don’t hold, techniques like Quadratic Discriminant Analysis (QDA) or non-parametric methods might be more appropriate.
2. **Prone to Overfitting**: When the number of features is much larger than the number of samples, LDA can be prone to overfitting. Regularization techniques or dimensionality reduction methods may be needed to address this issue.
3. **Doesn’t Handle Nonlinear Relationships:** LDA assumes linear relationships between features and classes. If the relationships are nonlinear, LDA might not capture the underlying patterns accurately.
4. **Requires Well-Defined Classes:**LDA is a supervised technique and relies on class labels for training. If class labels are ambiguous or if the classes are not well-defined, LDA might not perform optimally.
5. **Doesn’t Incorporate Feature Interaction:** LDA considers each feature independently and doesn’t account for interactions between features. In some cases, interactions might be important for accurate classification.
6. **May Not Capture Complex Patterns:**LDA’s linear nature might not capture complex decision boundaries that nonlinear techniques like support vector machines or neural networks can handle.

LDA is a great tool for classification and dimensionality reduction, especially in scenarios where class separability is clear and sample sizes are limited. However, its effectiveness depends on meeting its underlying assumptions, and it might not be the best choice when dealing with highly nonlinear or complex datasets.

**Conclusion:**

In conclusion, Linear Discriminant Analysis stands as a versatile and potent technique in the fields of machine learning, pattern recognition, and data analysis. Its ability to balance dimensionality reduction with class separation makes it a valuable tool for tackling a range of classification challenges. However, its linear nature restricts its ability to capture intricate nonlinear relationships present in some datasets. These limitations call for careful consideration and assessment of the dataset’s characteristics before employing LDA.

As the field of machine learning continues to evolve, Linear Discriminant Analysis remains a foundational technique that continues to contribute to advancements across various domains.

*Hey there, Amazing Readers! I hope this article jazzed up your knowledge about LDA, its applications, and the steps involved behind the scenes. Thanks for taking the time to read this.*

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