Linear Models for Classification

Discriminate Functions – Probabilistic Generative Models – Probabilistic Discriminative Models – Laplace Approximation – Bayesian Logistic Regression

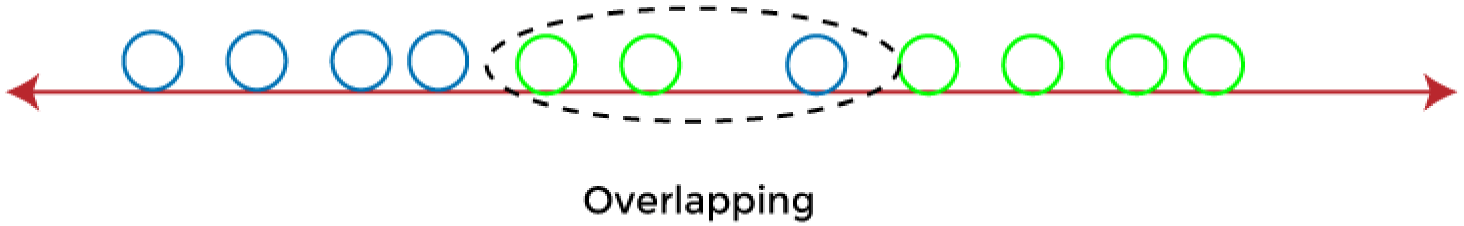
Linear Discriminant Analysis (LDA) in Machine Learning

- ***Linear Discriminant Analysis (LDA) is one of the commonly used dimensionality reduction techniques in machine learning to solve more than two-class classification problems.***
- ***It is also known as Normal Discriminant Analysis (NDA) or Discriminant Function Analysis (DFA).***

What is Linear Discriminant Analysis (LDA)?

- ***Linear Discriminant analysis is one of the most popular dimensionality reduction techniques used for supervised classification problems in machine learning***.
- It is also considered a pre-processing step for modeling differences in ML and applications of pattern classification.

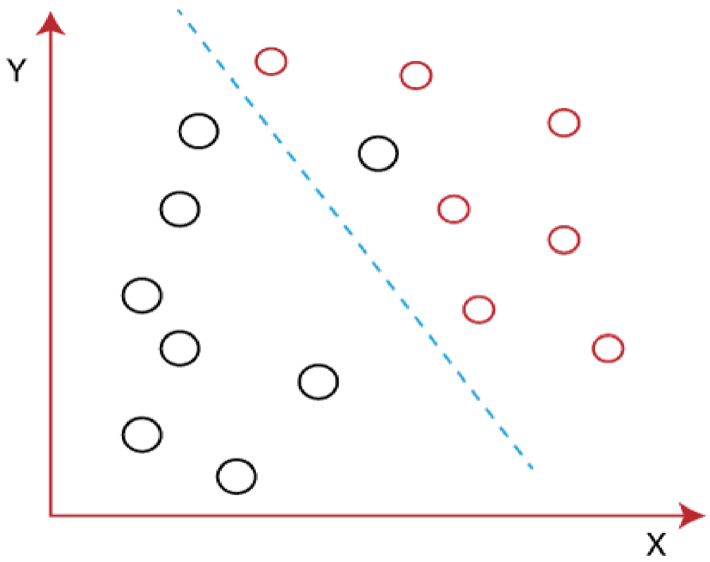
- Whenever there is a requirement to separate two or more classes having multiple features efficiently, the Linear Discriminant Analysis model is considered the most common technique to solve such classification problems.
- For e.g., if we have two classes with multiple features and need to separate them efficiently. When we classify them using a single feature, then it may show overlapping.



To overcome the overlapping issue in the classification process, we must increase the number of features regularly.

Example:

- Let's assume we have to classify two different classes having two sets of data points in a 2-dimensional plane as shown below image:

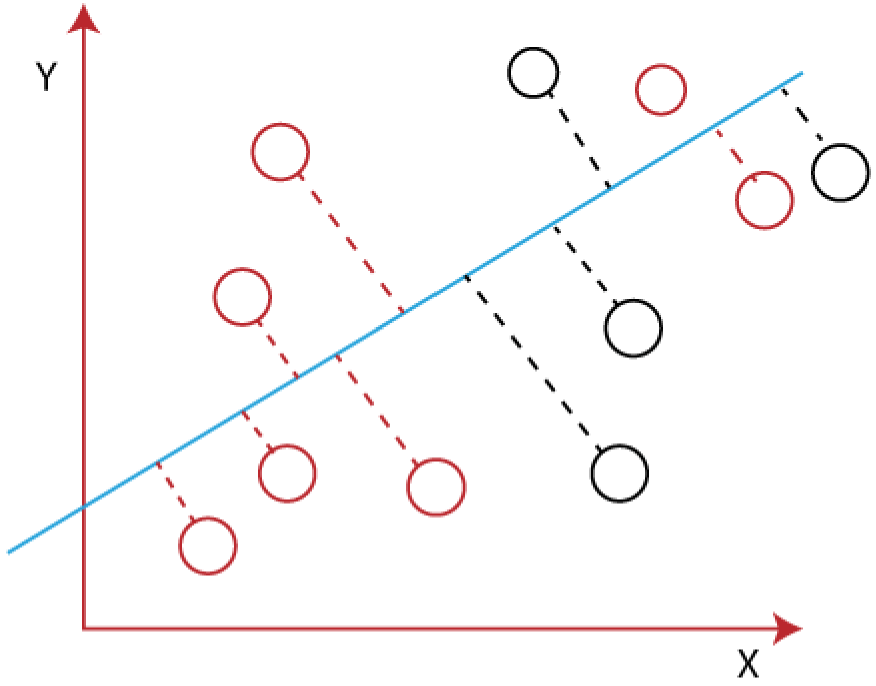


- However, it is impossible to draw a straight line in a 2-d plane that can separate these data points efficiently but using linear Discriminant analysis;
- we can dimensionally reduce the 2-D plane into the 1-D plane. Using this technique,
- we can also maximize the separability between multiple classes.

How Linear Discriminant Analysis (LDA) works?

- Linear Discriminant analysis is used as a dimensionality reduction technique in machine learning, using which we can easily transform a 2-D and 3-D graph into a 1-dimensional plane.
- Let's consider an example where we have two classes in a 2-D plane having an X-Y axis, and we need to classify them efficiently.
- As we have already seen in the above example that LDA enables us to draw a straight line that can completely separate the two classes of the data points.
- Here, LDA uses an X-Y axis to create a new axis by separating them using a straight line and projecting data onto a new axis.

- Hence, we can maximize the separation between these classes and reduce the 2-D plane into 1-D.



To create a new axis, Linear Discriminant Analysis uses the following criteria:

- It maximizes the distance between means of two classes.
- It minimizes the variance within the individual class.
- Using the above two conditions, LDA generates a new axis in such a way that it can maximize the distance between the means of the two classes and minimizes the variation within each class.
- In other words, we can say that the new axis will increase the separation between the data points of the two classes and plot them onto the new axis.

Why LDA?

- Logistic Regression is one of the most popular classification algorithms that perform well for binary classification but falls short in the case of multiple classification problems with well-separated classes.
- At the same time, LDA handles these quite efficiently.
- LDA can also be used in data pre-processing to reduce the number of features, just as PCA, which reduces the computing cost significantly.
- LDA is also used in face detection algorithms.
- In Fisherfaces, LDA is used to extract useful data from different faces. Coupled with eigenfaces, it produces effective results.

Drawbacks of Linear Discriminant Analysis (LDA)

- Although, LDA is specifically used to solve supervised classification problems for two or more classes which are not possible using logistic regression in machine learning.
- But LDA also fails in some cases where the Mean of the distributions is shared. In this case, LDA fails to create a new axis that makes both the classes linearly separable.
- To overcome such problems, we use **non-linear Discriminant analysis** in machine learning.

Real-world Applications of LDA

- **Face Recognition**
- **Medical**
- **Customer Identification**
- **For Predictions**
- **In Learning**