ASSIGNMENT 6 :- Naive Bayes

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Naïve Bayes :-

The Naïve Bayes Classifier is a technique that leverages Bayes' Theorem to make predictions, especially useful when there are many features (inputs) in a dataset. Although it’s a relatively simple method, it can sometimes outperform more complex classification algorithms.

Let’s break it down with an example:

Imagine we have a set of objects that are either GREEN or RED, and we want to classify a new object based on these existing ones. The key point is that there are twice as many GREEN objects as RED objects. This means that intuitively, the new object is more likely to be GREEN simply because there are more GREEN objects. This belief about the data is called prior probability — essentially, it's the probability we assign to each class (GREEN or RED) based on how many examples of each we have.

In this case, since there are 60 objects in total, with 40 GREEN and 20 RED, the prior probabilities for each class are:

Probability of GREEN: 40/60 = 0.67

Probability of RED: 20/60 = 0.33

The Role of Likelihood

Now, to classify a new object (let’s say it's a WHITE circle), we need to consider how likely it is for this object to be in each class based on its neighbors. We assume that the more GREEN (or RED) objects in the surrounding area, the more likely the new object is to belong to that class. So, we draw a circle around the new object and count how many GREEN and RED objects fall within that circle.

For example, let’s say that within the circle, we have 1 GREEN object and 3 RED objects. This means the likelihood of the new object being GREEN is smaller than the likelihood of it being RED, because there are more RED objects nearby.

Combining Prior and Likelihood

Even though we initially thought the object would be more likely GREEN (because there are more GREEN objects in total), the likelihood of it being RED (due to its neighbors) outweighs that. To combine both our prior belief (probability) and the likelihood (neighbor count), we use Bayes’ Rule. The result is the posterior probability, which tells us which class (GREEN or RED) the new object is most likely to belong to.

In this case, the posterior probability will indicate that the new object is more likely to be RED.

Technical Details

In more formal terms, the Naïve Bayes classifier tries to compute the posterior probability for each class given a set of predictor variables. Let’s say we have several features (variables), represented as X = {x₁, x₂, ..., xᵈ}. We want to calculate the probability that a new case belongs to class Cⱼ, where C = {c₁, c₂, ..., cᵈ}.

Bayes’ rule tells us that:

The magic of Naïve Bayes comes from the assumption that the features are independent from each other. This simplifies the calculation since we can treat each feature independently when calculating the likelihood. Instead of trying to compute the joint probability of all features at once, we can break it down into separate calculations for each feature.

The final prediction is made by choosing the class with the highest posterior probability. Even though assuming independence between features might not always hold true in real-world data, this assumption often doesn’t dramatically affect the results. It simplifies the process without compromising the accuracy, especially for classification near the decision boundary.

Conclusion

To sum up, the Naïve Bayes Classifier is a powerful yet simple algorithm that uses Bayes’ Theorem to make predictions. It works particularly well when you have many features and makes the problem easier by assuming the features are independent. Despite this simplification, it can still perform well, often better than more complex methods in many cases.