Machine Learning for Neuroscience

Slides and notebooks: `https://github.com/PBarnaghi/ML4NS`
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Lecture 4. Bayesian models
In lecture 4, we cover some of the basic concepts of Bayesian models.

Bayes' theorem, named after the statistician Thomas Bayes, describes the probability of an event, based on prior knowledge of conditions that might be related to an event. For example, if the risk of developing a neurological disorder is known to increase with age, Bayes' theorem allows the risk to an individual of a known age to be assessed conditioned on their age. In this lecture, we introduce Bayes' rule as four key components: the posterior or $p(A|B)$, the likelihood or $p(B|A)$, the prior or $p(A)$, and the marginalisation or $p(B)$.

Figure 4.1 illustrates Bayes' rule, which combines the definition of conditional probability with the product and sum rules.

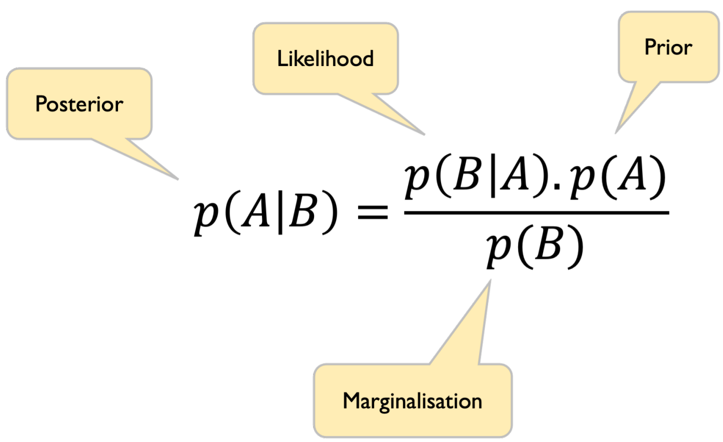

Figure 4.1. Bayes' Rule

We then discuss the use of Bayes' rule in classification (the probability of a label given some features). This is done using Naïve Bayes classifiers. Naive Bayes classifiers are known as such as they make two assumptions: that each feature is independent of every other feature, and that all features equally contribute towards the outcome. These assumptions in reality are not often the case. However, this generalisation allows Naïve Bayes to create "Naïve" but sometimes efficient prediction and classification models. We further expand on the objectives of the different types of Naïve Bayes classifiers, citing examples for each. While the Naïve classifiers could be helpful in different applications, the derived probability score are not reliable (i.e. the probability score in Naïve Bayes are good for the classification purpose but not for interpreting the actual probabilities of belonging to each class). Finally, we review the different metrics by which we might evaluate the performance of such models.

Figure 4.2 illustrates a confusion matrix for a classification model. From this matrix, we can derive the number of true positives, true negatives, false positives, and false negatives. From these numbers we can further derive our measures of accuracy, recall, precision, and the F1-score.

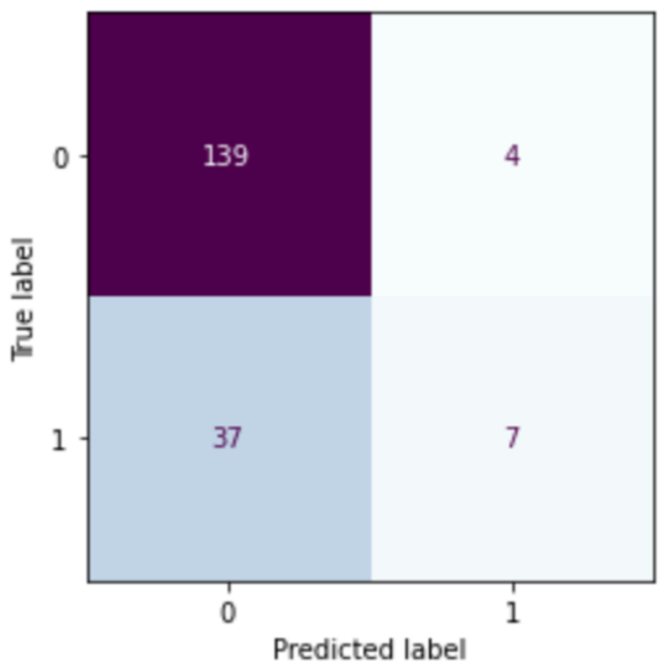

Figure 4.2. A Confusion Matrix for a Classification Model

The tutorial and assessment are combined with the previous lecture's tutorial and assessment and aim to further develop your skills in model building and evaluation (in the context of using Bayesian models). This tutorial and assessment will ask you to use sci-kit learn to develop your models. To further expand your understanding of how Naïve Bayes classifiers work, you could also try developing your own Bayesian model from scratch (see: [FN-0-1]).

End Notes

[0-1] https://medium.com/@rangavamsi5/naïve-bayes-algorithm-implementation-from-scratch-in-python-7b2cc39268b9