Bayesian Statistics

Introduction

Many analysts still find **Bayesian Statistics** (also known as **Bayesian Probability**) to be unintelligible. Many of us have abandoned statistics because of the amazing power of machine learning. We are now only interested in learning about machine learning. Is this not true? We don't realize that there are other approaches to solving problems in the actual world except machine learning. Even if there is data involved in these problems, it does not always assist us in solving business problems. Without a doubt, having a solid understanding of statistics will help you tackle challenging analytical issues, regardless of the volume of data.

A British mathematician named Thomas Bayes developed what was known as the **"Bayes Theorem"** in the 1770s. The significance of "Bayesian Statistics" hasn't diminished even after decades. In fact, several of the greatest colleges in the world currently offer in-depth courses on this subject. This inspiration led me to write this introduction to Bayesian statistics. I've made an effort to provide examples to help simplify the ideas. Basic probability and statistics prior knowledge are preferred. If you want to learn everything there is to know about statistics and probability, you should take this course. You will have a practical understanding of Bayesian Statistics and its related ideas at the end of this article.

$P(D)$ serves as the proof. This is the probability of the data calculated by adding up (or integrating) all conceivable values of, weighted by how strongly we think those specific values of are true. This informs us the likelihood of experiencing a particular sequence of flips for all scenarios where we may have had different beliefs about the fairness of the coin (but weren't sure).

$P(\theta|D)$ is the parameter's posterior belief as determined by the evidence, or the number of heads. From this point on, we'll explore this concept's mathematical ramifications in more detail. Not to worry. It's not too difficult to get at its mathematics once you comprehend them.

We need two mathematical models beforehand in order to define our model effectively. One to depict the likelihood function $P(D|\theta)$, and the other to depict the previous belief distribution. The posterior belief $P(\theta|D)$ distribution is the product of these two.

Instincts tell us that since the prior and posterior are both theories about how equally coins are distributed, they should both have the same mathematical form. So have that in mind. We'll discuss it once again. As a result, the Bayes theorem is supported by a variety of functions. Since it's crucial to understand them, I've gone into great depth.

__**Conclusion**__

The purpose of this essay was to encourage you to consider the various statistical philos ophies that are available and how each of them cannot be used in every circumstance.

Overview

For students majoring in statistics or minoring in statistics, our proposed course is a popular elective. For 13 weeks, we meet twice a week for a total of 26 class meetings. 75 minutes are allotted for each class meeting, and some lectures double as computer labs. Probability and multivariable calculus are prerequisites for the course. We place particular emphasis on joint densities of conditionally independently and identically distributed random variables and transformation of random variables among the calculus and probability topics because these are essential abilities in expressing joint posterior distributions. At the start of the course, we give a thorough overview of these subjects. While it isn't necessary, a typical student in this course may have prior experience to statistics. We do not assume that students have prior R experience, given the likelihood that they do. We assign three **DataCamp1** courses within the first several weeks of the course: Introduction to R, Intermediate R, and Introduction to the **Tidyverse**, all of which are available through DataCamp for the classroom, to make sure students are prepared for statistical computing in the course. 5 Although we've had students with mod backgrounds choose to use tidyverse, we have chosen to primarily use base R instead of tidyverse in this course because we do not assume prior R experience.

We have two primary learning goals: students must be able to: (1) comprehend the basics of Bayesian statistics, such as the Bayes rule and the prior, posterior, and posterior predictive distributions; and (2) apply Bayesian inference techniques to real-world and scientific topics. Our selection of subjects and their substance is guided by these training objectives: