**Bayesian vs. Frequentist Inference**

**Are you Bayesian or Frequentist?**



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Regarding the probability school of thought, there are two main approaches: the Bayesian and the frequentist approaches. Both of these approaches have their own strengths and weaknesses, and they are often used in different circumstances to help determine the probability of events.

So, what are their differences? Is one better than the other? This is a wrong question to ask; Bayesian thinking is based on the idea that probabilities represent a degree of belief in an event occurring. This approach is often used when there is uncertainty about the likelihood of an event occurring or when new information becomes available that can affect the probability of an event occurring.

On the other hand, the frequentist approach is based on the idea that the probability of an event occurring is equal to the long-run frequency with which that event occurs. This approach is often used when the probability of an event is determined by collecting data and observing how often the event occurs in a large number of trials.

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**An Intuitive Example**

To understand the differences better, let’s go through a simple example. Imagine a box with a bunch of marbles in it, and you want to know what color marbles are in the box. In the Bayesian approach, you might start by guessing that there are mostly red marbles in the box because you have seen many red marbles in similar containers. As you reach into the box and pull out marbles, you can update your guess based on the colors you see. So, if you pull out a bunch of blue marbles, you might start to think that there are primarily blue marbles in the box, and you can adjust your guess accordingly.

In the frequentist approach, you would not make a guess about the colors of the marbles in the box. Instead, you would just reach in and start pulling out marbles, counting the number of red, blue, and other colored marbles you see. After you have pulled out a large number of marbles, you can calculate the probability of seeing a particular color by dividing the number of marbles of that color by the total number of marbles you pulled out. This probability is not a guess but rather a property of the random process that determines the colors of the marbles in the box.

**The Pros and Cons**

One advantage of the Bayesian approach is that it allows us to incorporate prior information and beliefs into our analysis and update them as new evidence becomes available. This can be particularly useful in situations where data is scarce or difficult to collect.

In contrast, the frequentist approach only considers the data at hand and does not consider any prior information or beliefs. This can make the frequentist approach more objective, but it can also make it less flexible and less able to adapt to new information.

Another advantage of the Bayesian approach is that it provides a natural framework for quantifying uncertainty. Because Bayesian probabilities are a measure of personal belief, they can be interpreted directly as statements about the degree of uncertainty associated with a particular hypothesis or proposition. In contrast, the frequentist approach does not provide a natural way to quantify uncertainty and requires additional tools and assumptions to make statements about it.

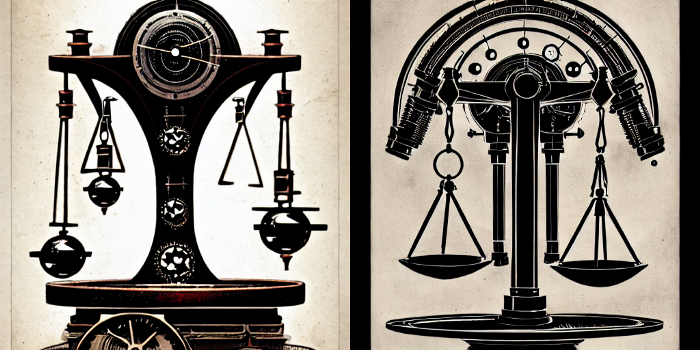


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A disadvantage of the Bayesian approach is that it can be computationally intensive, especially for complex problems with many variables. Applying Bayesian methods to large or real-time data sets can make it difficult. In contrast, the frequentist approach is typically more computationally efficient, which makes it well-suited to applications where speed is a concern.

Overall, both the Bayesian and frequentist approaches have their strengths and weaknesses, and the choice of which method to use depends on the problem at hand and the goals of the analysis.

**Quantifying Uncertainty**

But why the Bayesian approach provides a framework for quantifying uncertainty? Let’s go through an example. Imagine that you are trying to estimate the probability that it will rain tomorrow. In the Bayesian approach, you start by assigning a prior probability to this event, based on your experience, the weather report you got with a google search, and other relevant information. For example, you might believe there is a 60% chance of rain tomorrow because you have seen it rain on similar days.



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Now, suppose that you observe that the sky is cloudy today. You can use this new information to update your belief about the probability of rain tomorrow. In the Bayesian approach, you would use Bayes’ theorem, which tells us how to revise our probabilities in light of new evidence. Applying Bayes’ theorem to this situation, you might find that the probability of rain tomorrow is now 80% because the cloudy sky today is more consistent with showers tomorrow than with no rain.

In this example, the probability of rain tomorrow is a measure of your degree of uncertainty about this event. Because Bayesian probabilities are a measure of personal belief, they can be interpreted directly as statements about uncertainty: you believe that there is an 80% probability of rain tomorrow, which means that you are quite uncertain about whether it will rain or not. In general, the higher the probability of an event, the less uncertainty there is about that event, and vice versa. If you were confident that it will rain tomorrow, you might assign a probability of 1.0 to this event. In contrast, if you were utterly unsure whether it will rain, you might assign a probability of 0.5. Ultimately, the degree of uncertainty associated with an event is up to you to decide based on your own beliefs and the evidence you have.

In contrast, the frequentist approach does not provide a natural way to quantify uncertainty in this way because frequentist probabilities are not a measure of personal belief. Instead, they are a property of the underlying random process that generates the data.

**Conclusion**

Bayesian and frequentist thinking are two different approaches to statistical inference. Bayesian thinking is based on the idea of subjective probability, where the probability of an event is based on an individual’s beliefs or knowledge about the event. In contrast, frequentist probability is objective and is based solely on the frequency of an event occurring in a large number of trials.

One key advantage of Bayesian thinking is that it allows for the incorporation of prior knowledge or beliefs into the analysis, which can help to make more accurate predictions or inferences. However, it can be more computationally complex than frequentist methods and is subject to individual bias.

Frequentist thinking is more straightforward and easier to implement than Bayesian methods, particularly for large datasets. However, it does not allow for the incorporation of prior knowledge or beliefs and does not provide a natural framework to discuss uncertainty.

**About the Author**

My name is [Dimitris Poulopoulos](https://www.dimpo.me/?utm_source=medium&utm_medium=article&utm_campaign=bayesian-frequentist), and I’m a machine learning engineer working for [Arrikto](https://www.arrikto.com/). I have designed and implemented AI and software solutions for major clients such as the European Commission, Eurostat, IMF, the European Central Bank, OECD, and IKEA.

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