

Individual Task 3 – Module 3

Bayes' Theorem in Real Life: Applying Bayes' Theorem in Medical Testing

INTRODUCTION :

Probability plays a very important role in real-life decision-making, especially in situations involving uncertainty. One of the most powerful concepts in probability theory is Bayes' Theorem. Bayes' Theorem provides a mathematical way to update the probability of an event based on new evidence. It helps us revise our beliefs when additional information becomes available. This concept is widely used in various fields such as medicine, finance, artificial intelligence, weather forecasting, and email spam filtering.

In this report, I will apply Bayes' Theorem to a real-world medical testing scenario. Medical tests are commonly used to detect diseases, but no test is perfectly accurate. Sometimes a test may give a false positive result (indicating disease when the person is healthy) or a false negative result (indicating no disease when the person is actually sick). Bayes' Theorem helps us calculate the actual probability that a person has a disease after receiving a positive test result. By analyzing this scenario step by step, this report demonstrates how mathematical probability directly affects healthcare decisions and patient understanding.

Understanding Bayes' Theorem

Bayes' Theorem is mathematically expressed as:

$$P(A | B) = [P(B | A) \times P(A)] / P(B)$$

In simple words, this formula calculates the probability of event A occurring given that event B has occurred. In medical testing terms, A represents the event that a person has a disease, and B represents the event that the test result is positive.

In this formula, $P(A)$ is called the prior probability, which represents the initial probability of having the disease before testing. $P(B | A)$ is the likelihood, meaning the probability that the test is positive if the person truly has the disease. $P(B)$ is the total probability of getting

positive test result. Finally, $P(A | B)$ is the posterior probability, which tells us the probability that the person actually has the disease after receiving a positive test result.

This theorem shows that the accuracy of a medical test depends not only on the test's reliability but also on how common the disease is in the population. This concept is often misunderstood in real life, where people assume that a positive test always means a very high chance of being sick.

Bayes' Theorem

The diagram illustrates Bayes' Theorem with the equation $P(A | B) = \frac{P(B | A) \cdot P(A)}{P(B)}$. The components are labeled as follows:

- Probability of B when A has already occurred** (yellow box) points to $P(B | A)$.
- Probability of A** (green box) points to $P(A)$.
- Probability of A when B has already occurred** (blue box) points to $P(A | B)$.
- Probability of B** (pink box) points to $P(B)$.

The equation is written in red and black text, with a horizontal line separating the numerator from the denominator.



Real-World Scenario Setup

Let us consider a disease that affects 1% of the population. This means that out of 10,000 people, about 100 people have the disease. Therefore, the prior probability $P(\text{Disease}) = 0.01$.

Now suppose there is a medical test for this disease with the following characteristics. The test correctly identifies 99% of people who have the disease. This is called sensitivity.

Therefore, $P(\text{Positive} | \text{Disease}) = 0.99$. The test also correctly identifies 95% of healthy people as disease-free. This is called specificity. This means that 5% of healthy people will incorrectly test positive. Therefore, $P(\text{Positive} | \text{No Disease}) = 0.05$.

At first glance, this test seems very accurate because 99% sensitivity and 95% specificity are high values. However, we must apply Bayes' Theorem to calculate the real probability that a person actually has the disease after receiving a positive result.

Step-by-Step Calculation Using Bayes' Theorem

To make the calculation easier, let us imagine testing 10,000 people.

Out of 10,000 people, 1% have the disease, which means 100 people are actually sick. Since the test correctly identifies 99% of sick individuals, 99 out of 100 sick people will test positive. One person will test negative incorrectly.

Now consider the 9,900 healthy people. Since the test has a 5% false positive rate, 5% of 9,900 healthy individuals will test positive. That equals 495 people.

Therefore, the total number of positive test results is 99 (true positives) + 495 (false positives) = 594 positive results.

Now we calculate the probability that a person who tested positive actually has the disease. Out of 594 positive results, only 99 are true cases. Therefore:

Probability = $99 / 594 \approx 0.1667$ or 16.67%

This means that even though the test is highly accurate, a person who tests positive only has about a 16.67% chance of actually having the disease. This result surprises many people because they assume a positive result means near certainty.

Interpretation of Results

The result shows that disease prevalence plays a crucial role in interpreting medical test outcomes. Even with a highly accurate test, if the disease is rare, false positives can outnumber true positives. This is why doctors often recommend additional confirmatory tests after an initial positive result.

This example highlights the importance of conditional probability in real-life decision-making. Without using Bayes' Theorem, a person might misunderstand the seriousness of their result. Medical professionals rely on Bayesian reasoning to provide better advice, reduce unnecessary panic, and design screening programs effectively.

The theorem also explains why mass screening for very rare diseases can sometimes lead to confusion. If the disease prevalence were higher, the probability of actually having the

disease after a positive test would increase significantly. Therefore, context matters greatly when interpreting probabilities.

Broader Applications of Bayes' Theorem

Although this report focuses on medical testing, Bayes' Theorem is widely used in many other real-world situations. In email spam filtering, the probability that an email is spam is calculated based on certain keywords and patterns. In weather forecasting, predictions are updated as new atmospheric data becomes available. In artificial intelligence, machine learning algorithms use Bayesian methods to improve predictions over time.

Bayesian reasoning is also used in legal decision-making, financial risk assessment, and fraud detection. In all these fields, the central idea remains the same: update prior beliefs using new evidence. This logical approach allows for more accurate predictions and better decisions under uncertainty.

CONCLUSION :

Bayes' Theorem is a powerful mathematical tool that helps us understand how probabilities change when new evidence is introduced. In the medical testing scenario discussed in this report, we discovered that even a highly accurate test does not guarantee a high probability of disease after a positive result. The actual probability depends heavily on how common the disease is in the population.

By applying Bayes' Theorem step by step, we calculated that a person who tests positive in a low-prevalence scenario has only about a 16.67% chance of actually having the disease. This example demonstrates how mathematical reasoning can prevent misunderstandings and improve decision-making.

In conclusion, Bayes' Theorem is not just a theoretical formula learned in mathematics class; it has real and practical applications in healthcare, technology, finance, and many other fields. Understanding this concept encourages critical thinking and informed interpretation of statistical information. In a world filled with data and uncertainty, Bayesian reasoning provides a logical framework for making smarter and more accurate decisions.