Implementation & Interpretation of the Bayes' Theorem using Python

Basics of Bayes' Theorem

We can simply see Bayes' Theorem as the way to compute conditional probability.

A probability is a number in between 0 and 1 that represents the chance of an event happening.

Conjoint Probability: When A and B are two independent events, $p(A \cap B) = p(A) \times p(B)$

Important: the probability of a conjunction is $p(A \cap B) = p(A) \times p(B|A)$

To derive Bayes' Theorem, first we need to know that the conjunction is commutative,

which means $p(A \cap B) = p(B \cap A)$

Since the event A and B are interchangeable, we can also state that:

$p(A \cap B) = p(B) \times p(A|B) = p(A \cap B) = p(A) \times p(B|A)$

We then divide both side of $p(B) \times p(A|B) = p(A \cap B) = p(A) \times p(B|A)$ by $p(B)$

and we'll get the core equation of the Bayes' Theorem:

$$p(A|B) = \frac{p(A) \times p(B|A)}{p(B)}$$

Now this might seem a bit confusing because A and B are not defined yet, after we put this equation under the context of data analysis it becomes something like this:

$$p(H|D) = \frac{p(H) \times p(D|H)}{p(D)}$$

- $p(H)$ is the probability that our hypothesis is true before we take the data into consideration.
- $p(D)$ is the probability of the data under any hypothesis.
- $p(H|D)$ is the probability that the hypothesis is true after we have seen the data.
- $p(D|H)$ is the probability that the data is under our hypothesis.