

Learn

On the previous screen, we introduced these two equations without much explanation:

$$P(\text{Spam}|w_1, w_2, w_3, w_4) \propto P(\text{Spam}) \cdot P(w_1|\text{Spam}) \cdot P(w_2|\text{Spam}) \cdot P(w_3|\text{Spam}) \cdot P(w_4|\text{Spam})$$

$$P(\text{Spam}^C|w_1, w_2, w_3, w_4) \propto P(\text{Spam}^C) \cdot P(w_1|\text{Spam}^C) \cdot P(w_2|\text{Spam}^C) \cdot P(w_3|\text{Spam}^C) \cdot P(w_4|\text{Spam}^C)$$

To explain the mathematics behind these equations, let's start by looking at $P(\text{Spam}|w_1, w_2, w_3, w_4)$. Using the conditional probability formula, we can expand $P(\text{Spam}|w_1, w_2, w_3, w_4)$ like this (below, make sure you notice the \cap symbol in the numerator):

$$P(\text{Spam}|w_1, w_2, w_3, w_4) = \frac{P(\text{Spam} \cap (w_1, w_2, w_3, w_4))}{P(w_1, w_2, w_3, w_4)}$$

Recall that we learned in a previous screen that we can ignore the division, which means we can drop $P(w_1, w_2, w_3, w_4)$ to avoid redundant calculations (when we ignore the division, we also replace the equals sign with \propto , which means **directly proportional**):

$$P(\text{Spam}|w_1, w_2, w_3, w_4) \propto P(\text{Spam} \cap (w_1, w_2, w_3, w_4))$$

Note that (w_1, w_2, w_3, w_4) can be modeled as an intersection of four events:

$$w_1, w_2, w_3, w_4 = w_1 \cap w_2 \cap w_3 \cap w_4$$

For instance, we could think of a message like "thanks for your help" as the intersection of four words inside a single message: "thanks", "for", "your", and "help". In probability jargon, finding the value of $P(w_1 \cap w_2 \cap w_3 \cap w_4)$ means finding the probability that the four words w_1, w_2, w_3, w_4 occur together

Learn

With this in mind, our equation above transforms to:

$$P(\text{Spam} | w_1, w_2, w_3, w_4) \propto P(\text{Spam} \cap \underbrace{(w_1 \cap w_2 \cap w_3 \cap w_4)}_{(w_1, w_2, w_3, w_4)})$$

From set theory, we know that $A \cap (B \cap C) = A \cap B \cap C = C \cap B \cap A$, which means we can transform $P(\text{Spam} \cap (w_1 \cap w_2 \cap w_3 \cap w_4))$ in our equation above to make it suitable for further expansion:

$$\begin{aligned} P(\text{Spam} \cap (w_1 \cap w_2 \cap w_3 \cap w_4)) &= P(\text{Spam} \cap w_1 \cap w_2 \cap w_3 \cap w_4) \\ &= P(w_1 \cap w_2 \cap w_3 \cap w_4 \cap \text{Spam}) \end{aligned}$$

Now let's use the multiplication rule to expand $P(w_1 \cap w_2 \cap w_3 \cap w_4 \cap \text{Spam})$:

$$P(w_1 \cap w_2 \cap w_3 \cap w_4 \cap \text{Spam}) = P(w_1 | w_2 \cap w_3 \cap w_4 \cap \text{Spam}) \cdot P(w_2 \cap w_3 \cap w_4 \cap \text{Spam})$$

We can use the multiplication rule again to expand $P(w_2 \cap w_3 \cap w_4 \cap \text{Spam})$:

$$P(w_1 \cap w_2 \cap w_3 \cap w_4 \cap \text{Spam}) = P(w_1 | w_2 \cap w_3 \cap w_4 \cap \text{Spam}) \cdot \underbrace{P(w_2 | w_3 \cap w_4 \cap \text{Spam}) \cdot P(w_3 \cap w_4 \cap \text{Spam})}_{P(w_2 \cap w_3 \cap w_4 \cap \text{Spam})}$$

We can use the multiplication rule successively, until there's nothing more left to expand:

$$P(w_1 \cap w_2 \cap w_3 \cap w_4 \cap \text{Spam}) = P(w_1 | w_2 \cap w_3 \cap w_4 \cap \text{Spam}) \cdot P(w_2 \cap w_3 \cap w_4 \cap \text{Spam})$$

Learn

We can use the multiplication rule successively, until there's nothing more left to expand:

$$\begin{aligned}
 P(w_1 \cap w_2 \cap w_3 \cap w_4 \cap Spam) &= P(w_1 | w_2 \cap w_3 \cap w_4 \cap Spam) \cdot P(w_2 \cap w_3 \cap w_4 \cap Spam) \\
 &= P(w_1 | w_2 \cap w_3 \cap w_4 \cap Spam) \cdot P(w_2 | w_3 \cap w_4 \cap Spam) P(w_3 \cap w_4 \cap Spam) \\
 &= P(w_1 | w_2 \cap w_3 \cap w_4 \cap Spam) \cdot P(w_2 | w_3 \cap w_4 \cap Spam) P(w_3 | w_4 \cap Spam) \cdot P(w_4 \cap Spam) \\
 &= P(w_1 | w_2 \cap w_3 \cap w_4 \cap Spam) \cdot P(w_2 | w_3 \cap w_4 \cap Spam) P(w_3 | w_4 \cap Spam) \cdot P(w_4 | Spam) \cdot P(Spam)
 \end{aligned}$$

In theory, the last equation you see above is what we'd have to use if we wanted to calculate $P(Spam | w_1, w_2, w_3, w_4)$. However, the equation is pretty long for just four words. Also, imagine how would the equation look for a 50-word message — just think of how many calculations we'd have to perform!!

To make the calculations tractable for messages of all kinds of lengths, we can assume **conditional independence** between w_1, w_2, w_3 , and w_4 . This implies that:

$$\begin{aligned}
 P(w_1 | w_2 \cap w_3 \cap w_4 \cap Spam) &= P(w_1 | Spam) \\
 P(w_2 | w_3 \cap w_4 \cap Spam) &= P(w_2 | Spam) \\
 P(w_3 | w_4 \cap Spam) &= P(w_3 | Spam) \\
 P(w_4 | Spam) &= P(w_4 | Spam)
 \end{aligned}$$

Under the assumption of independence, our lengthy equation above reduces to:

$$P(w_1 \cap w_2 \cap w_3 \cap w_4 \cap Spam) = P(w_1 | Spam) \cdot P(w_2 | Spam) \cdot P(w_3 | Spam) \cdot P(w_4 | Spam) \cdot P(Spam)$$

$$P(\text{Spam}|w_1, w_2, w_3, w_4) \propto P(\text{Spam}) \cdot P(w_1|\text{Spam}) \cdot P(w_2|\text{Spam}) \cdot P(w_3|\text{Spam}) \cdot P(w_4|\text{Spam})$$

$$P(\text{Spam}^C|w_1, w_2, w_3, w_4) \propto P(\text{Spam}^C) \cdot P(w_1|\text{Spam}^C) \cdot P(w_2|\text{Spam}^C) \cdot P(w_3|\text{Spam}^C) \cdot P(w_4|\text{Spam}^C)$$

[← Dashboard](#)

The Naive Bayes Algorithm

Learn

To make the calculations tractable for messages of all kinds of lengths, we can assume **conditional independence** between w_1, w_2, w_3 , and w_4 . This implies that:

$$P(w_1|w_2 \cap w_3 \cap w_4 \cap \text{Spam}) = P(w_1|\text{Spam})$$

$$P(w_2|w_3 \cap w_4 \cap \text{Spam}) = P(w_2|\text{Spam})$$

$$P(w_3|w_4 \cap \text{Spam}) = P(w_3|\text{Spam})$$

$$P(w_4|\text{Spam}) = P(w_4|\text{Spam})$$

Under the assumption of independence, our lengthy equation above reduces to:

$$P(w_1 \cap w_2 \cap w_3 \cap w_4 \cap \text{Spam}) = P(w_1|\text{Spam}) \cdot P(w_2|\text{Spam}) \cdot P(w_3|\text{Spam}) \cdot P(w_4|\text{Spam}) \cdot P(\text{Spam})$$

The assumption of conditional independence is unrealistic in practice because words are often in a relationship of dependence. For instance, if you see the word "WINNER" in a message, the probability of seeing the word "money" is very likely to increase, so "WINNER" and "money" are most likely dependent. The assumption of conditional independence between words is thus *naive* since it rarely holds in practice, and this is why the algorithm is called **Naive Bayes** (also called **simple Bayes** or **independence Bayes**).

Despite this simplifying assumption, the algorithm works quite well in many real-word situations, and we'll see that ourselves in the guided project.

That being said, on the previous screen we assumed conditional independence when we introduced these two equations

$$P(\text{Spam}|w_1, w_2, w_3, w_4) \propto P(\text{Spam}) \cdot P(w_1|\text{Spam}) \cdot P(w_2|\text{Spam}) \cdot P(w_3|\text{Spam}) \cdot P(w_4|\text{Spam})$$

$$P(\text{Spam}^C|w_1, w_2, w_3, w_4) \propto P(\text{Spam}^C) \cdot P(w_1|\text{Spam}^C) \cdot P(w_2|\text{Spam}^C) \cdot P(w_3|\text{Spam}^C) \cdot P(w_4|\text{Spam}^C)$$