



## Result

**Proposition 1.** *Suppose  $P$  is a probability measure on a finite set of outcomes  $\Omega$ . For any two events  $A, B$  with  $P(A), P(B) > 0$ , we have*

$$P(A | B) = \frac{P(B | A)P(A)}{P(B)}.$$

*Proof.* By definition, we have

$$P(A | B) = \frac{P(A \cap B)}{P(B)}.$$

And also symmetrically,

$$P(B | A) = \frac{P(A \cap B)}{P(A)}.$$

From this second equation we have  $P(A \cap B) = P(B | A)P(A)$ , which we can substitute into the numerator of the first expression to obtain the result.  $\square$

This result is known by many names including *Bayes' rule*, *Bayes rule* (no possessive), *Bayes' formula*, and *Bayes' theorem*.

It is a *basic* consequence of the *definition* of conditional probability, but it is *useful* in the case that we are given problem data in terms of the probabilities on the right hand side of the above equation.

## Examples

### Diagnostic test

Suppose we want to model the situation in which a rare disease afflicts 0.5% of a population and we have a diagnostic test that is 99% accurate.

We consider the population  $\Omega$  of people. We agree to partition the population into  $D$  and  $H$  so that

$$D \cup H = \Omega \quad \text{and} \quad D \cap H = \emptyset$$

$D$  is the set of people with the disease, and  $H$  is the set of *healthy* people without the disease. Similarly, we agree to partition the population into  $R$  and  $N$  so that

$$R \cup N = \Omega \quad \text{and} \quad P \cap N = \emptyset$$

$R$  is the set of people who test positive, and  $N$  is the set of people who test negative.

We agree that 0.5% of the the population being afflicted means,  $P(D) = 0.005$ . We agree that having a 99% accurate test means *means*

$$P(D \mid R) = 0.99 \quad \text{and} \quad P(H \mid N) = 0.99$$

Now, what is the conditional probability of having the disease given that the test is positive? Using Bayes rule,

$$P(D \mid R) = \frac{P(R \mid D)P(D)}{P(R \mid D)P(D) + P(R \mid H)P(H)}$$

Using our supposed values,

$$P(D \mid R) = \frac{0.99 \cdot 0.005}{0.99 \cdot 0.005 + 0.01 \cdot 0.995} \approx 0.33$$

This may be viewed as suprising, since the test is perceived to be accurate.

The frequentist interpretation is clear: if have many outcomes, say a thousand individuals, we may expect that about five of these thousand have the disease. The test is likely to diagnose these correctly. However, of the other 995 people, about 1% of them—say 10 people—will be misdiagnosed. Thus we may expect to see about 15 positive test results, but only five of which correspond to individuals with the disease.

### Compound form

More is true.

**Proposition 2.** *Suppose  $P$  is a finite probability measure on a set of outcomes  $\Omega$ . For any three events  $A, B, C$  with  $P(A), P(B), P(C) > 0$ , we have*

$$P(A \mid B \cap C) = \frac{P(B \mid A \cap C)P(A \mid C)}{P(B \mid C)}.$$

*Proof.* Future editions will include, the strategy is the same as above.  $\square$



