

Conditional Probabilities and Bayes' Theorem

Conditional Probabilities

Let A and B be two events. If N is the total number of possible outcomes and N_A and N_B are the number of outcomes favourable to A and B, respectively, then the probabilities of A and B, denoted $P[A]$ and $P[B]$, respectively are:

$P[A] = N_A / N$ and $P[B] = N_B / N$. These are the *unconditional* probabilities of A and B occurring.

Then the probability of A occurring, *given that B has occurred*, is the conditional probability of A, denoted $P[A | B]$ and the probability of B occurring, *given that A has occurred* is the conditional probability of B, denoted $P[B | A]$.

Example: A dice is thrown: let A be the event that the outcome is a "2" and let B be the event that the outcome is an even number. Then $P[A]=1/6$ and $P[B]=1/2$ and $P[A|B]=1/3$.

If N_{AB} are the number of occurrences favourable to *both A and B*:

$$P[A | B] = \frac{N_{AB}}{N_B} = \frac{N_{AB}}{N} \frac{N}{N_B} = \frac{P[AB]}{P[B]}$$

$$\text{By identical argument: } P[B | A] = \frac{N_{AB}}{N_A} = \frac{P[AB]}{P[A]} \quad (1)$$

$$\Rightarrow P[A | B] = \frac{P[B | A]P[A]}{P[B]}$$

Given any two events A and B, we can write one of the events, say B as:

$$\begin{aligned} B &= (B \cap A) \cup (B \cap \bar{A}) \Rightarrow P[B] = P[AB] + P[\bar{A}B] \\ &\Rightarrow P[B] = P[B | A]P[A] + P[B | \bar{A}]P[\bar{A}] \end{aligned} \quad (2)$$

where: \bar{A} is the event "not-A".

Bayes' Theorem

Reverend Thomas Bayes – an 18th century Presbyterian minister – proved what is, arguably, the most important theorem in statistics (see “In Praise of Bayes”, *The Economist*, 28 September 2000).

Let T denote “theory” and D denote “data”. Then the probability of the theorem being true, *given that the data has been observed*, is:

$$P(T | D) = \frac{P(TD)}{P(D)} = \frac{P(D | T)P(T)}{P(D)} \quad (3)$$

where: $P(D) = P(D|T)P(T) + P(D|\bar{T})P(\bar{T})$, \bar{T} being the event that the theory is false.

Interpretation: $P(T)$ is the *prior* probability of the theory being true. Given the evidence of the data, this prior probability is updated to arrive at the *posterior* probability, $P(T|D)$. The quantity, $P(D|T)/P(D)$ is the *updating* factor.

Example: Suppose there is a test for cancer. Let B be the event that the person tested has cancer and let A be the event that the test is positive, i.e. says the person has cancer. Suppose $P[A|B] = 0.95$ and $P[\bar{A}|\bar{B}] = 0.95$. We are interested in $P[B|A]$, the probability that a person has cancer, given that the test is positive:

$$\begin{aligned} P[B|A] &= \frac{P[A|B]P[B]}{P[A]} = \frac{0.95 \times P[B]}{P[A|B]P[B] + P[\bar{A}|\bar{B}]P[\bar{B}]} \\ &= \frac{0.95 \times P[B]}{0.95 \times P[B] + (0.05)(1 - P[B])} \end{aligned}$$

If $P[B] = 0.005$, $P[B|A] = 0.087$!

Suppose we desire that $P[B|A] = 0.95$. What should $P[A|B] = P[\bar{A}|\bar{B}]$ be to achieve this? Solve for X in:

$$0.95 = \frac{X \times 0.005}{X \times 0.005 + (1 - X) \times 0.995} \Rightarrow X = 0.99974$$

Application to Asymmetric Information

The seller prices his cars, some at \$2500 and some at \$1000. He will always sell a good car for \$2500. He prices some of the bad cars at \$2500 and some at \$1000: the probability of a bad car being priced at \$2500 is μ and of it being priced at \$1000 is $1 - \mu$; half of his cars are bad cars.

The buyer will accept a car priced at \$2500 with probability q and reject such a car with probability $1 - q$; the buyer will always buy a car priced at \$1000. The buyer believes that any car priced at \$2500 is a bad car with probability β and a good car with probability $1 - \beta$.

What is the probability that a bad car is sold for \$2500?

For the buyer:

$$\beta = P(B|p = 2500) = \frac{P(p = 2500|B)P(B)}{P(p = 2500)} = \frac{0.5\mu}{0.5\mu + 0.5} \quad (4)$$

Note: $P(p = 2500) = P(p = 2500 | G)P(G) + P(p = 2500 | B)p(B) = 0.5 + 0.5\mu$

If the buyer rejects the car priced at \$2500, his payoff is zero; if he accepts the \$2500 car then his payoff is:

$(3200 - 2500 - 1700)\beta + (3200 - 2500 - 200)(1 - \beta) = -1000\beta + 500(1 - \beta)$. In equilibrium, his expected payoff from rejection or acceptance of a \$2500 car must be the same implying: $500(1 - \beta) - 1000\beta = 0 \Rightarrow \beta = \frac{1}{3}$.

Using this value of β to solve for μ : $\frac{1}{3} = \frac{0.5\mu}{0.5 + 0.5\mu} \Rightarrow \mu = \frac{1}{2}$

For the seller: If he offers a car for \$1000, his payoff is \$1000. If he offers a car for \$2500, his payoff is: $2500q + 0(1 - q)$. In equilibrium, the two payoffs are the

same: $1000 = 2500q \Rightarrow q = \frac{2}{5}$

What is the probability that a bad car is sold for \$2500?

$$\begin{aligned}
 P(\text{sold at } \$2500 | B) &= P(\text{offered at } \$2500 \cap \text{accepted at } \$2500 | B) \\
 &= \frac{P(\text{offered at } \$2500 \cap \text{accepted at } \$2500 \cap B)}{P(B)} \\
 &= \frac{P(\text{offered at } \$2500 \cap B)P(\text{accepted at } \$2500)}{P(B)} \quad (5) \\
 &= \frac{(1/2)\mu q}{(1/2)} = \frac{1}{2} \times \frac{2}{5} = 0.2
 \end{aligned}$$

So seller can shift 20% of his stock of bad cars at the higher price of \$2500.