



Why

Since one and only one outcome occurs, given a distribution on outcomes, we define the probability of a set of outcomes as the sum of their probabilities.

Definition

Suppose p is a distribution on a *finite* set of outcomes Ω . Given an event $E \subset \Omega$, we define the *event probability* of E under p as the sum of the probabilities of the outcomes in E .

Notation

It is common to define a function $P : \mathcal{P}(\Omega) \rightarrow \mathbf{R}$ by

$$P(A) = \sum_{a \in A} p(a) \quad \text{for all } A \subset \Omega$$

We call this function P the *event probability function* (or the *probability measure*) associated with p . Since it depends on the sample space Ω and the distribution p , we occasionally denote this dependence by $P_{\Omega,p}$ or P_p .

Example: a single six-sided die

We model rolling a single die with the set of outcomes $\Omega = \{1, \dots, 6\}$ as usual. We $p : \Omega \rightarrow \mathbf{R}$ by $p(\omega) = 1/6$ for $\omega = 1, \dots, 6$. In other words, p is the constant function at value $1/6$ on Ω . Now, we model the event that the number of pips showing is an even number by the set E defined by $E = \{2, 4, 6\}$. Given all this modeling, the probability of the event E is

$$\sum_{\omega \in E} p(\omega) = p(2) + p(4) + p(6) = 1/2.$$

Properties of event probabilities

As a result of the conditions on p , \mathbf{P} satisfies

1. $\mathbf{P}(A) \geq 0$ for all $A \subset \Omega$;

2. $\mathbf{P}(\Omega) = 1$ (and $\mathbf{P}(\emptyset) = 0$);
3. $\mathbf{P}(A) + \mathbf{P}(B)$ for all $A, B \subset \Omega$ and $A \cap B = \emptyset$. This statement follows from the more general identity

$$\mathbf{P}(A \cup B) = \mathbf{P}(A) + \mathbf{P}(B) - \mathbf{P}(A \cap B)$$

for $A, B \subset \Omega$, by using $\mathbf{P}(\emptyset) = 0$ of (2) above.

These three conditions are sometimes called the *axioms of probability for finite sets*. Do all such \mathbf{P} satisfying (1)-(3) have a corresponding underlying probability distribution?

In other words, suppose $f : \mathcal{P}(\Omega) \rightarrow \mathbf{R}$ satisfies (1)-(3). Define $q : \Omega \rightarrow \mathbf{R}$ by $q(\omega) = f(\{\omega\})$. If f satisfies the axioms, then q is a probability distribution. For this reason we call any function satisfying (i)-(iii) an *event probability function* (or a *(finite) probability measure*).

Other basic consequences

Probability by cases

Let \mathbf{P} be a probability event function. Suppose A_1, \dots, A_n partition Ω . Then for any $B \subset \Omega$,

$$\mathbf{P}(B) = \sum_{i=1}^n \mathbf{P}(A_i \cap B).$$

Some authors call this the *law of total probability*.

Monotonicity

If $A \subseteq B$, then $\mathbf{P}(A) \leq \mathbf{P}(B)$. This is easy to see by splitting B into $A \cap B$ and $B - A$, and applying (1) and (3).

Subadditivity

For $A, B \subset \Omega$, $\mathbf{P}(A \cup B) \leq \mathbf{P}(A) + \mathbf{P}(B)$. This is easy to see from the more general identity in (3) above. This is sometimes referred to as a *union bound*, in reference to *bounding* the quantity $\mathbf{P}(A \cup B)$.

