

Probability basics

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Defining probabilities

Definition 0.1 (Sample space). The **sample space** of a random experiment, denoted Ω , is the **set** of all of its possible outcomes.

Example 0.1 (Sample space of a die roll). Rolling a six-sided die once has sample space $\Omega = \{1, 2, 3, 4, 5, 6\}$.

Definition 0.2 (Event). An **event** is a subset of the **sample space** Ω : a set of outcomes.

Remark. When Ω is uncountable, such as an interval of real numbers, only the subsets in a designated **σ -algebra** $\mathcal{S}$ on Ω count as events; every set that arises in these notes is in $\mathcal{S}$. When Ω is finite or **countably infinite**, every subset of Ω can be an event, because the collection of all subsets of Ω is a σ -algebra (**all subsets form a σ -algebra**), as in **σ -algebras for die rolls**.

Example 0.2 (Rolling an even number). In Example 0.1, the event “the roll is even” is $A = \{2, 4, 6\}$.

Definition 0.3 (Occurrence of an event). An **event** A **occurs** when the outcome of the experiment is in A , and does not occur when the outcome is not in A .

Example 0.3 (Rolling a 4). In Example 0.2, if the die shows 4, the event “the roll is even”, $\{2, 4, 6\}$, occurs, because $4 \in \{2, 4, 6\}$, and the event “the roll is at most 2”, $\{1, 2\}$, does not occur.

Definition 0.4 (Complement of an event). The **complement** of an **event** A , denoted $\neg A$, is the event that A does not **occur**: the set of outcomes in the sample space Ω that are not in A .

$$\neg A \stackrel{\text{def}}{=} \Omega \setminus A$$

Remark. Other sources write A^c or $\bar{A}$.

Example 0.4 (Rolling an odd number). In Example 0.2, the complement of the event “the roll is even”, $A = \{2, 4, 6\}$, is the event “the roll is odd”, $\neg A = \{1, 3, 5\}$.

Definition 0.5 (Mutually exclusive events). Finitely or countably many sets $A_1, A_2, \dots$, such as **events**, are **mutually exclusive** (also called **disjoint**, **pairwise disjoint**, or **mutually disjoint**) when no two of them share an element:

$$A_i \cap A_j = \emptyset \quad \text{for all } i \neq j$$

Remark. The math notes define the same property for sets in general, as **pairwise disjoint**.

Example 0.5 (Low and high rolls). In Example 0.1, the events “the roll is at most 2”, $\{1, 2\}$, and “the roll is at least 5”, $\{5, 6\}$, are mutually exclusive: no roll is in both. The events “the roll is even”, $\{2, 4, 6\}$, and “the roll is at most 2”, $\{1, 2\}$, are not mutually exclusive: a roll of 2 is in both.

Definition 0.6 (Partition of an event). A **partition** of an **event** A is a finite or countably infinite collection of events $A_1, A_2, \dots$ that satisfies:

- The events $A_1, A_2, \dots$ are **mutually exclusive**.
- Their union is A : $\bigcup_i A_i = A$.

A partition of the **sample space** is the case $A = \Omega$.

Remark. Some sources also require each piece A_i to contain at least one outcome.

Example 0.6 (Partitioning the die roll). In Example 0.1, the events “the roll is even”, $\{2, 4, 6\}$, and “the roll is odd”, $\{1, 3, 5\}$, are mutually exclusive, and their union is Ω , so they partition the sample space. So do the six single-outcome events $\{1\}, \{2\}, \dots, \{6\}$.

The events $\{1, 2\}$ and $\{5, 6\}$ from Example 0.5 do not partition Ω : their union leaves out 3 and 4.

Definition 0.7 (Probability measure). A **probability measure** on a **sample space** Ω , often denoted $\Pr()$ or $P()$, is a **measure** on the **events** of Ω that gives the whole sample space probability 1:

$$\Pr(\Omega) = 1$$

Example 0.7 (Probability measure for a fair die). For the die roll in Example 0.1, define $\Pr(A) \stackrel{\text{def}}{=} |A|/6$, where $|A|$ is the number of outcomes in A . This function is $1/6$ times the counting measure $\mu(A) = |A|$ on the die rolls (**counting elements is a measure**), so it is a **measure** on the events of Ω , and it gives $\Pr(\Omega) = 6/6 = 1$. The event “the roll is even” from Example 0.2 has probability $\Pr(\{2, 4, 6\}) = 3/6 = 1/2$.

Corollary 0.1 (Probability measures are finitely additive). *Every **probability measure** is **finitely additive**: for any **mutually exclusive** events $A_1, \dots, A_n$,*

$$\Pr(A_1 \cup \dots \cup A_n) = \sum_{i=1}^n \Pr(A_i)$$

i Proof

Proof. A probability measure is a measure (Definition 0.7), so **measures are finitely additive** applies to it. $\square$

Theorem 0.1 (Continuity of probability). *If $A_1 \supseteq A_2 \supseteq \dots$ are events with $\bigcap_{i=1}^{\infty} A_i = \emptyset$, then:*

$$\lim_{n \rightarrow \infty} \Pr(A_n) = 0$$

i Proof

Proof. For each i , let $B_i \stackrel{\text{def}}{=} A_i \setminus A_{i+1}$, the outcomes in A_i but not in A_{i+1} . Each $B_i = A_i \cap (\Omega \setminus A_{i+1})$ is an event, by **closure properties of a σ -algebra**. The B_i are **pairwise disjoint**. For $i < j$, $B_j \subseteq A_j \subseteq A_{i+1}$, while B_i has no outcomes in A_{i+1} , so $B_i \cap B_j = \emptyset$. $A_n = \bigcup_{i=n}^{\infty} B_i$ for each n . For $i \geq n$, $B_i \subseteq A_i \subseteq A_n$, so the union is contained in A_n .

Conversely, let $\omega \in A_n$. Since $\bigcap_i A_i = \emptyset$, ω is not in every A_i ; since the A_i are nested, the indices i with $\omega \in A_i$ are $1, \dots, m$ for some $m \geq n$. Then $\omega \in A_m$ and $\omega \notin A_{m+1}$, so $\omega \in B_m$.

$\Pr(A_1)$ is finite. The events A_1 and $\Omega \setminus A_1$ are disjoint with union Ω , so Corollary 0.1 applies to them:

$$\begin{aligned} \Pr(A_1) &\leq \Pr(A_1) + \Pr(\Omega \setminus A_1) \quad (\Pr(\Omega \setminus A_1) \geq 0) \\ &= \Pr(\Omega) \quad (\text{finite additivity of } \Pr) \\ &= 1 \quad (\text{definition of a probability measure}) \end{aligned}$$

The limit. For each n :

$$\begin{aligned} \Pr(A_n) &= \Pr\left(\bigcup_{i=n}^{\infty} B_i\right) \quad (A_n = \bigcup_{i=n}^{\infty} B_i) \\ &= \sum_{i=n}^{\infty} \Pr(B_i) \quad (\text{countable additivity; the } B_i \text{ are pairwise disjoint}) \end{aligned}$$

With $n = 1$, this says the series $\sum_{i=1}^{\infty} \Pr(B_i)$ has the finite total $\Pr(A_1)$. So, for $n \geq 2$:

$$\begin{aligned} \Pr(A_n) &= \sum_{i=1}^{\infty} \Pr(B_i) - \sum_{i=1}^{n-1} \Pr(B_i) \quad (\text{split off the first } n-1 \text{ terms; the total is finite}) \\ &= \Pr(A_1) - \sum_{i=1}^{n-1} \Pr(B_i) \quad (\text{the case } n = 1) \end{aligned}$$

As $n \rightarrow \infty$, the partial sums $\sum_{i=1}^{n-1} \Pr(B_i)$ converge to the total $\Pr(A_1)$, so $\Pr(A_n) \rightarrow \Pr(A_1) - \Pr(A_1) = 0$. $\square$

Remark. Requiring countable additivity, not just finite additivity, enables results such as Theorem 0.1, and it is what makes sums over countably infinite [partitions](#) valid.

Theorem 0.2 (Kolmogorov axioms). *A function $\Pr$ that assigns a real number $\Pr(A)$ to each [event](#) A of a sample space Ω is a [probability measure](#) if and only if it satisfies:*

1. For any event A , $\Pr(A) \geq 0$.
2. The probability of the whole sample space is 1:

$$\Pr(\Omega) = 1$$

3. $\Pr$ is [countably additive](#): for any [mutually exclusive](#) events $A_1, A_2, \dots$,

$$\Pr\left(\bigcup_{i=1}^{\infty} A_i\right) = \sum_{i=1}^{\infty} \Pr(A_i)$$

Proof

Proof. Suppose $\Pr$ is a probability measure. It is a [measure](#), so its values lie in the [extended non-negative reals](#) $[0, \infty]$, which gives axiom 1, and it is countably additive, which is axiom 3. Axiom 2 is the condition $\Pr(\Omega) = 1$ in Definition [0.7](#).

Conversely, suppose $\Pr$ satisfies the three axioms. By axiom 1, $\Pr$ takes values in $[0, \infty]$, so axiom 3 says $\Pr$ is countably additive in the sense of the [definition of countable additivity](#). Then, by [countable additivity and the empty set](#), $\Pr(\emptyset)$ is 0 or ∞ ; $\Pr(\emptyset)$ is a real number, so $\Pr(\emptyset) = 0$. So $\Pr$ satisfies both conditions of the [definition of a measure](#) ($\Pr(\emptyset) = 0$ and countable additivity) and is a measure on the events of Ω . With axiom 2, $\Pr$ is a probability measure (Definition [0.7](#)). $\square$

Remark. Many sources define a probability measure by these three axioms instead; the theorem shows that the two definitions agree. The axioms are named for Kolmogorov, who introduced them in 1933 (see [Wikipedia: Probability axioms](#)). The axiom form does not list $\Pr(\emptyset) = 0$; the proof above derives it.

Theorem 0.3 (Probability of a subset's intersection). *If A and B are events and $A \subseteq B$, then $\Pr(A \cap B) = \Pr(A)$.*

Proof

Proof. Since $A \subseteq B$, every outcome in A is also in B , so $A \cap B = A$, and therefore $\Pr(A \cap B) = \Pr(A)$. $\square$

Theorem 0.4 (An event and its complement sum to 1). *For any event A and its [complement](#) $\neg A$:*

$$\Pr(A) + \Pr(\neg A) = 1$$

Proof

Proof. The events A and $\neg A$ are disjoint, and their union is Ω .

$$\begin{aligned} \Pr(A) + \Pr(\neg A) &= \Pr(A \cup \neg A) && \text{(additivity of probability for disjoint events)} \\ &= \Pr(\Omega) && (A \cup \neg A = \Omega) \\ &= 1 && \text{(probability of the sample space is 1)} \end{aligned}$$

$\square$

Corollary 0.2 (Complement rule). *For any event A :*

$$\Pr(\neg A) = 1 - \Pr(A)$$

i Proof

Proof. Subtract $\Pr(A)$ from both sides of Theorem 0.4. □

Corollary 0.3 (Complement rule in probability (π) notation). *If the probability of an event A is $\Pr(A) = \pi$, then the probability that A does not occur is:*

$$\Pr(\neg A) = 1 - \pi$$

i Proof

Proof.

$$\begin{aligned}\Pr(\neg A) &= 1 - \Pr(A) && \text{(complement rule)} \\ &= 1 - \pi && \text{(substitute } \Pr(A) = \pi \text{)}\end{aligned}$$

□

Example 0.8 (Probability of not rolling a six). For a fair die, the event “the roll is a six” has probability $\pi = 1/6$, so by Corollary 0.3 the probability of not rolling a six is $1 - 1/6 = 5/6$.

Conditional probability

Definition 0.8 (Conditional probability). For two events A and B with $\Pr(B) > 0$, the **conditional probability** of A given B , denoted $\Pr(A \mid B)$, is:

$$\Pr(A \mid B) \stackrel{\text{def}}{=} \frac{\Pr(A \cap B)}{\Pr(B)}$$

Example 0.9 (Rolling a six, given an even roll). For a fair die (Example 0.7), let $A = \{6\}$ and $B = \{2, 4, 6\}$. Then $A \cap B = \{6\}$, so:

$$\begin{aligned}
\Pr(A \mid B) &= \frac{\Pr(A \cap B)}{\Pr(B)} && \text{(definition of conditional probability)} \\
&= \frac{1/6}{3/6} && \text{(substitute the probabilities)} \\
&= \frac{1}{3} && \text{(simplify)}
\end{aligned}$$

Theorem 0.5 (Law of conditional probability). *For any two events A and B with $\Pr(B) > 0$:*

$$\Pr(A \cap B) = \Pr(A \mid B) \cdot \Pr(B)$$

i Proof

Proof. Rearranging Definition 0.8:

$$\begin{aligned}
\Pr(A \mid B) &= \frac{\Pr(A \cap B)}{\Pr(B)} && \text{(definition of conditional probability)} \\
\Pr(A \cap B) &= \Pr(A \mid B) \cdot \Pr(B) && \text{(multiply both sides by } \Pr(B))
\end{aligned}$$

□

Example 0.10 (Applying the law of conditional probability). Suppose 30% of adults exercise regularly ($\Pr(E) = 0.30$), and among adults who exercise regularly, 60% have low blood pressure ($\Pr(L \mid E) = 0.60$).

Then, by Theorem 0.5, the probability that a randomly selected adult both exercises regularly and has low blood pressure is:

$$\begin{aligned}
\Pr(L \cap E) &= \Pr(L \mid E) \cdot \Pr(E) && \text{(law of conditional probability)} \\
&= 0.60 \cdot 0.30 && \text{(substitute the given values)} \\
&= 0.18 && \text{(multiply)}
\end{aligned}$$

Theorem 0.6 (Law of total probability). *If $B_1, B_2, \dots$ is a **partition** of the sample space, with $\Pr(B_i) > 0$ for every i , then for any event A :*

$$\Pr(A) = \sum_i \Pr(A \mid B_i) \cdot \Pr(B_i)$$

i Proof

Proof. Since $B_1, B_2, \dots$ partition the sample space, the events $A \cap B_1, A \cap B_2, \dots$ are mutually exclusive and their union is A . By [countable additivity](#), and then by Theorem 0.5:

$$\begin{aligned}\Pr(A) &= \sum_i \Pr(A \cap B_i) && \text{(countable additivity for partition of } A\text{)} \\ &= \sum_i \Pr(A \mid B_i) \cdot \Pr(B_i) && \text{(law of conditional probability; } \Pr(B_i) > 0\text{)}\end{aligned}$$

□

Theorem 0.7 (Bayes' theorem). *For any two events A and B with $\Pr(A) > 0$ and $\Pr(B) > 0$:*

$$\Pr(A \mid B) = \frac{\Pr(B \mid A) \cdot \Pr(A)}{\Pr(B)}$$

i Proof

Proof. By Definition 0.8 and Theorem 0.5:

$$\begin{aligned}\Pr(A \mid B) &= \frac{\Pr(A \cap B)}{\Pr(B)} && \text{(definition of conditional probability)} \\ &= \frac{\Pr(B \cap A)}{\Pr(B)} && \text{(intersection is commutative: } A \cap B = B \cap A\text{)} \\ &= \frac{\Pr(B \mid A) \cdot \Pr(A)}{\Pr(B)} && \text{(law of conditional probability applied to } \Pr(B \cap A)\text{)}\end{aligned}$$

□

Example 0.11 (Positive predictive value of a medical test). Suppose a disease test has 99% sensitivity and 99% specificity, and the prevalence of the disease in the population is 7%.

Let D be the event “person has the disease” and $+$ be the event “test is positive”. Then:

- $\Pr(+ \mid D) = 0.99$ (sensitivity)
- $\Pr(\neg+ \mid \neg D) = 0.99$ (specificity), so the false positive rate is $\Pr(+ \mid \neg D) = 1 - 0.99 = 0.01$
- $\Pr(D) = 0.07$ (prevalence)

By Theorem 0.7, with the denominator expanded by the [law of total probability](#) over the partition $\{D, \neg D\}$:

$$\begin{aligned}
\Pr(D \mid +) &= \frac{\Pr(+ \mid D) \cdot \Pr(D)}{\Pr(+)} && \text{(Bayes' theorem)} \\
&= \frac{\Pr(+ \mid D) \cdot \Pr(D)}{\Pr(+ \mid D) \cdot \Pr(D) + \Pr(+ \mid \neg D) \cdot \Pr(\neg D)} && \text{(law of total probability)} \\
&= \frac{0.99 \cdot 0.07}{0.99 \cdot 0.07 + 0.01 \cdot 0.93} && \text{(substitute the given values)} \\
&= \frac{0.0693}{0.0693 + 0.0093} && \text{(multiply each term in the numerator and denominator)} \\
&= \frac{0.0693}{0.0786} && \text{(add the denominator's two terms)} \\
&\approx 0.88 && \text{(divide)}
\end{aligned}$$

Even with a highly accurate test (99% sensitive and 99% specific), only about 88% of people who test positive actually have the disease, because the disease prevalence is relatively low (7%).

Video lecture

Hutchinson's [Probability Refresher](#) (27 min) covers conditional distributions, the law of total probability, the chain rule of probability, and Bayes' rule (Hutchinson, n.d.). The login for the video site is posted [on Canvas](#).

References

Hutchinson, Brian. n.d. *DATA 471/571 (Machine Learning) and CSCI 481/581 (Deep Learning) Video Lectures*. Western Washington University. Accessed September 28, 2026. https://facultyweb.cs.wvu.edu/~hutchib2/video_lectures/data371/.