

Lecture 2: Review of Probability Theory

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We will not formally define notions such as probability space or random variables; for a rigorous introduction, see any advanced probability theory textbook.

1 Random Variables

Informally, a random variable X is a quantity or object that is random. We assume that the random variable X takes value in a (sample) space Ω , which is the set of all possible outcomes. Most of the time we assume $\Omega \subseteq \mathbb{R}$, in which case the random variable X is said to be *real-valued*.

Discrete random variables. We say X is a *discrete* random variable if Ω is finite or countably infinite. A discrete random variable can be described by the probability mass function (PMF) $p : \Omega \rightarrow [0, 1]$, which is a non-negative function satisfying

$$\sum_{x \in \Omega} p(x) = 1.$$

An *event* $E \subseteq \Omega$ is a subset of outcomes. The probability of an event E is given by

$$\Pr(E) = \Pr(X \in E) = \sum_{x \in E} p(x).$$

Note that

$$\Pr(X = x) = \Pr(X \in \{x\}) = p(x).$$

Example 1. Toss a fair coin. The space is $\Omega = \{H, T\}$ or $\{0, 1\}$, where H or 1 means heads up, and T or 0 means tails up. The PMF is $p(H) = p(T) = 1/2$, which is a uniform distribution. The events are \emptyset , $\{H\}$, $\{T\}$, and $\{H, T\}$. The probability of each event is $\Pr(\emptyset) = 0$, $\Pr(\{H\}) = 1/2$, $\Pr(\{T\}) = 1/2$, and $\Pr(\{H, T\}) = 1$.

Example 2. Roll a fair die. The space is $\Omega = \{1, 2, 3, 4, 5, 6\}$. The PMF is $p(1) = p(2) = \dots = p(6) = 1/6$, which is a uniform distribution. There are $2^6 = 64$ events in total. For example, $\Pr(\emptyset) = 0$, $\Pr(\{1, 2, 3, 4, 5, 6\}) = 1$, and $\Pr(X \text{ is even}) = \Pr(X \in \{2, 4, 6\}) = 1/2$.

Example 3. Let X be the number of tosses of a fair coin until we see a head. The space is $\Omega = \mathbb{N}^+ = \{1, 2, \dots\}$. The PMF is $p(k) = 2^{-k}$ for each $k \in \mathbb{N}^+$. There are infinitely many events. For example, $\Pr(X \leq 3) = 7/8$.

Continuous random variables. Informally speaking, we say X is a *continuous* random variable if Ω is a “continuous” subset of \mathbb{R} (or \mathbb{R}^n), e.g., an interval or a union of disjoint intervals. In many cases, a continuous random variable can be described by the probability density function (PDF) $f : \Omega \rightarrow \mathbb{R}_{\geq 0}$, which is a non-negative integrable function satisfying

$$\int_{\Omega} f(x) dx = 1.$$

An *event* $E \subseteq \Omega$ is a “measurable” subset of outcomes, but not every subset. The probability of an event E is given by

$$\Pr(E) = \Pr(X \in E) = \int_E f(x) dx.$$

Example 4. The uniform distribution on $[0, 1]$ has PDF $f(x) = 1, \forall x \in [0, 1]$. The uniform distribution on $[0, 1] \cup [3, 4]$ has PDF $f(x) = 1/2, \forall x \in [0, 1] \cup [3, 4]$. The uniform distribution on $[0, 1/2]$ has PDF $f(x) = 2, \forall x \in [0, 1/2]$. Note that in all these examples, $\Pr(X = 0) = 0$.

Example 5. The *standard normal distribution* (also called *standard Gaussian distribution*) has PDF $f(x) = \frac{1}{\sqrt{2\pi}} e^{-x^2/2}, \forall x \in \mathbb{R}$.

2 Events

Definition 6 (Complement, Intersection, Union). Let $E, F \subseteq \Omega$ be events.

- E^c : Complement of E ; E does not happen.
- $E \cap F$: Intersection of E and F ; both E and F happen.
- $E \cup F$: Union of E and F ; either E or F happens.

Lemma 7. Let $E, F \subseteq \Omega$ be events.

- $\Pr(E^c) = 1 - \Pr(E)$;
- $\Pr(E \cup F) = \Pr(E) + \Pr(F) - \Pr(E \cap F)$.
- $\Pr(E \cup F \cup G) = \Pr(E) + \Pr(F) + \Pr(G) - \Pr(E \cap F) - \Pr(F \cap G) - \Pr(G \cap E) + \Pr(E \cap F \cap G)$.

Definition 8 (Mutually Exclusive Events). We say the events E_1, \dots, E_n are *mutually exclusive* if $E_i \cap E_j = \emptyset$ for all $i \neq j$. That is, if any E_i happens then none of $E_j, j \neq i$ happen.

Lemma 9. If the events E_1, \dots, E_n are mutually exclusive, then

$$\Pr\left(\bigcup_{i=1}^n E_i\right) = \sum_{i=1}^n \Pr(E_i).$$

Lemma 10 (Union Bound). For any events E_1, \dots, E_n , we have

$$\Pr\left(\bigcup_{i=1}^n E_i\right) \leq \sum_{i=1}^n \Pr(E_i).$$

3 Conditioning

Definition 11 (Conditional Probability). Let $E, F \subseteq \Omega$ be events and suppose $\Pr(F) > 0$. The probability of E conditioned on F is defined as

$$\Pr(E \mid F) = \Pr(X \in E \mid X \in F) = \frac{\Pr(E \cap F)}{\Pr(F)}.$$

Example 12. Toss two fair coins. Given that at least one toss is a head, what is the probability that both tosses are heads? **A:** $1/3$.

Example 13. Roll a fair die. Given that the outcome is at least 4, what is the probability that the outcome is even? **A:** $2/3$.

Definition 14 (Independent Events). Two events $E, F \subseteq \Omega$ are said to be *independent* if

$$\Pr(E \cap F) = \Pr(E) \Pr(F).$$

Observe that E and F are independent iff either $\Pr(F) = 0$ or $\Pr(E | F) = \Pr(E)$. Namely, whether F happens or not has no effect on the chance of E happening.

Lemma 15. E and F are independent $\Leftrightarrow E^c$ and F are independent $\Leftrightarrow E$ and F^c are independent $\Leftrightarrow E^c$ and F^c are independent.

Example 16. Let X be the number of tosses of a fair coin until we see a head. Let E be the event that $X \leq 2$, and F be the event that X is even. Then we have:

$$\begin{aligned}\Pr(E) &= \Pr(X \in \{1, 2\}) = \frac{3}{4}; \\ \Pr(F) &= \Pr(X \in \{2, 4, 6, \dots\}) = \sum_{k=1}^{\infty} \frac{1}{2^{2k}} = \frac{1}{3}; \\ \Pr(E \cap F) &= \Pr(X = 2) = \frac{1}{4}.\end{aligned}$$

Since $\Pr(E \cap F) = \Pr(E) \Pr(F)$, we conclude that E and F are independent.

Theorem 17 (Law of Total Probability). *Let $E, F \subseteq \Omega$ be events and suppose $\Pr(F) \in (0, 1)$. Then we have*

$$\Pr(E) = \Pr(F) \Pr(E | F) + \Pr(F^c) \Pr(E | F^c).$$

Theorem 18 (Bayes' theorem). *Let $E, F \subseteq \Omega$ be events and suppose $\Pr(E) > 0$, $\Pr(F) \in (0, 1)$. Then we have*

$$\Pr(F | E) = \frac{\Pr(F) \Pr(E | F)}{\Pr(E)} = \frac{\Pr(F) \Pr(E | F)}{\Pr(F) \Pr(E | F) + \Pr(F^c) \Pr(E | F^c)}.$$

Example 19. Suppose we know $\Pr(\text{sunny}) = 0.7$, $\Pr(\text{rainy}) = 0.3$, $\Pr(\text{delayed} | \text{sunny}) = 0.1$, and $\Pr(\text{delayed} | \text{rainy}) = 0.3$. Then $\Pr(\text{delayed}) = 0.7 \times 0.1 + 0.3 \times 0.3 = 0.16$, and $\Pr(\text{rainy} | \text{delayed}) = \frac{0.3 \times 0.3}{0.16} = 0.5625$.