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1 Axioms of Probability

Given a sample space S ,

(1) For any event $E \subseteq S$, $0 \leq \mathbb{P}(E) \leq 1$.

(2) $\mathbb{P}(S) = 1$.

(3) For mutually exclusive events E_1, E_2, \dots , $\mathbb{P}\left(\bigcup_{i=1}^{\infty} E_i\right) = \sum_{i=1}^{\infty} \mathbb{P}(E_i)$.

Define $\emptyset = \{\}$ as the empty set.

Claim. $\mathbb{P}(\emptyset) = 0$.

Proof. Consider the sequence of events $E_1 = S$, $E_2 = \emptyset$ for all $i \geq 2$. These events are mutually exclusive. By Axiom 3,

$$\begin{aligned}\mathbb{P}\left(\bigcup_{i=1}^{\infty} E_i\right) &= \sum_{i=1}^{\infty} \mathbb{P}(E_i). \\ \bigcup_{i=1}^{\infty} E_i &= S \cup \emptyset \cup \emptyset \cup \dots = S \\ \mathbb{P}(S) &= \sum_{i=1}^{\infty} \mathbb{P}(E_i) = \mathbb{P}(S) + \sum_{i=2}^{\infty} \mathbb{P}(\emptyset) \\ &\Rightarrow \sum_{i=2}^{\infty} \mathbb{P}(\emptyset) \Rightarrow \mathbb{P}(\emptyset) = 0\end{aligned}$$

□

Corollary 1.1

For any finite sequence of mutually exclusive events E_1, E_2, \dots, E_n ,

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

Proof. Extend to an infinite sequence of exclusive events by adding the empty set $E_i = \emptyset$ for all $i \geq n + 1$. Then $\bigcup_{i=1}^n E_i = \bigcup_{i=1}^{\infty} E_i$.

By Axiom 3,

$$\begin{aligned} \mathbb{P}\left(\bigcup_{i=1}^n E_i\right) &= \mathbb{P}\left(\bigcup_{i=1}^{\infty} E_i\right) \\ &= \sum_{i=1}^n \mathbb{P}(E_i) + \sum_{i=n+1}^{\infty} \mathbb{P}(\emptyset) \\ &= \sum_{i=1}^n \mathbb{P}(E_i) \quad (\text{since } \mathbb{P}(\emptyset) = 0) \end{aligned}$$

□

Proposition 1.1

Given a probability space (S, \mathbb{P}) , where S is the *sample space* and \mathbb{P} is the *probability function*, we have

$$\mathbb{P}(E^c) = 1 - \mathbb{P}(E).$$

Proof. Note that

- $E \cap E^c = \emptyset$
- $E \cup E^c = S$

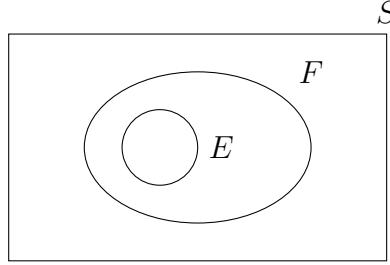
By Corollary, $1 = \mathbb{P}(S) = \mathbb{P}(E \cup E^c) = \mathbb{P}(E) + \mathbb{P}(E^c)$.

□

Proposition 1.2

Given a probability space (S, \mathbb{P}) , and nested sets $E \subseteq F \subseteq S$, then $\mathbb{P}(E) \leq \mathbb{P}(F)$.

Proof. Venn diagrams



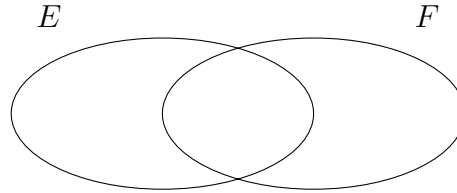
Note that $E \cap F = E$ and $E^c \cap F$ are exclusive events ($E \cap (E^c \cap F) = (E \cap E^c) \cap F = \emptyset \cap F = \emptyset$), and $(E \cap F) \cup (E^c \cap F) = (E \cup E^c) \cap F = S \cap F = F$.

By Corollary, $\mathbb{P}(F) = \mathbb{P}(E \cap F) + \mathbb{P}(E^c \cap F) = \mathbb{P}(E) + \mathbb{P}(E^c \cap F) \geq \mathbb{P}(E)$. \square

Example 1. Rolling a fair six-sided dice.

$$\Rightarrow \mathbb{P}(\text{rolling a 6}) \leq \mathbb{P}(\text{rolling an even number})$$

For arbitrary events, we observe:



Proposition 1.3

In a probability space (S, \mathbb{P}) , given any events $E, F \subseteq S$,

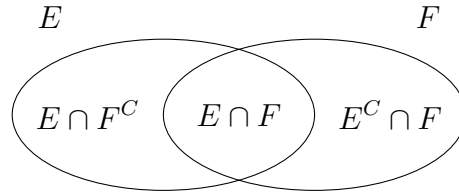
$$\mathbb{P}(E \cup F) = \mathbb{P}(E) + \mathbb{P}(F) - \mathbb{P}(E \cap F).$$

Corollary 1.2: Union bound

$$\mathbb{P}(E \cup F) \leq \mathbb{P}(E) + \mathbb{P}(F).$$

Proof. (Cor) $\mathbb{P}(E \cup F) = \mathbb{P}(E) + \mathbb{P}(F) - \mathbb{P}(E \cap F) \leq \mathbb{P}(E) + \mathbb{P}(F)$ □

Proof. (Prop)



We have unions of exclusive events

- $E \cup F = (E \cap F^c) \cup (E \cap F) \cup (E^c \cap F)$
- $E = (E \cap F^c) \cup (E \cap F), F = (E \cap F) \cup (E^c \cap F)$

By Corollary 1.1,

- $\mathbb{P}(E \cup F) = \mathbb{P}(E \cap F^c) + \mathbb{P}(E \cap F) + \mathbb{P}(E^c \cap F)$
- $\mathbb{P}(E) = \mathbb{P}(E \cap F^c) + \mathbb{P}(E \cap F)$
- $\mathbb{P}(F) = \mathbb{P}(E \cap F) + \mathbb{P}(E^c \cap F)$

$$\begin{aligned}
 \Rightarrow \mathbb{P}(E) + \mathbb{P}(F) &= \mathbb{P}(E \cap F^c) + \mathbb{P}(E \cap F) + \mathbb{P}(E \cap F) + \mathbb{P}(E^c \cap F) \\
 &= \mathbb{P}(E \cap F^c) + \mathbb{P}(E \cap F) + \mathbb{P}(E^c \cap F) + \mathbb{P}(E \cap F) \\
 &= \mathbb{P}(E \cup F) + \mathbb{P}(E \cap F)
 \end{aligned}$$

□

Example 2. Play a game against Real Madrid.

- $\mathbb{P}(\text{Mbappé scores}) = 0.5$
- $\mathbb{P}(\text{Vinicius scores}) = 0.4$

- $\mathbb{P}(\text{Mbappé and Vinicius both scores}) = 0.2$

Q. $\mathbb{P}(\text{Mbappé or Vinicius scores}) = ?$

Solution. Define events

- $E = \{\text{Mbappé scores}\}$
- $F = \{\text{Vinicius scores}\}$

$$\mathbb{P}(E) = 0.5, \mathbb{P}(F) = 0.4, \mathbb{P}(E \cap F) = 0.2$$

$$\stackrel{\text{Prop 3}}{\Rightarrow} \mathbb{P}(E \cup F) = \mathbb{P}(E) + \mathbb{P}(F) - \mathbb{P}(E \cap F) = 0.7$$

$$\stackrel{\text{Prop 1}}{\Rightarrow} \mathbb{P}(E^c \cap F^c) = \mathbb{P}((E \cup F)^c) = 1 - \mathbb{P}(E \cup F) = 0.3$$

Q. What can we say about $\mathbb{P}(E \cup F \cup G)$?

$$\begin{aligned} \mathbb{P}(E \cup F \cup G) &= \mathbb{P}((E \cup F) \cup G) \\ &= \mathbb{P}(E \cup F) + \mathbb{P}(G) - \mathbb{P}((E \cup F) \cap G) \\ &= \mathbb{P}(E) + \mathbb{P}(F) - \mathbb{P}(E \cap F) + \mathbb{P}(G) - \mathbb{P}((E \cup F) \cap G) \end{aligned}$$

where

$$\begin{aligned} \mathbb{P}((E \cup F) \cap G) &= \mathbb{P}((E \cap G) \cup (F \cap G)) \\ &= \mathbb{P}(E \cap G) + \mathbb{P}(F \cap G) - \mathbb{P}((E \cap G) \cap (F \cap G)) \\ &= \mathbb{P}(E \cap G) + \mathbb{P}(F \cap G) - \mathbb{P}(E \cap F \cap G) \end{aligned}$$

Therefore

$$\mathbb{P}(E \cup F \cup G) = \mathbb{P}(E) + \mathbb{P}(F) + \mathbb{P}(G) - \mathbb{P}(E \cap F) - \mathbb{P}(E \cap G) - \mathbb{P}(F \cap G) + \mathbb{P}(E \cap F \cap G).$$

Example 3. Roll a 60-sided dice. $\mathbb{P}(\text{roll in divisible by 2, 3, or 5})?$

Solution. Let $E = \{\text{div. by 2}\}$, $F = \{\text{div. by 3}\}$, $G = \{\text{div. by 5}\}$.

$$\mathbb{P}(E) = \frac{\# \text{even numbers in } 1, 2, \dots, 60}{60} = \frac{30}{60} = \frac{1}{2}.$$

$$\mathbb{P}(F) = \frac{1}{3}, \quad \mathbb{P}(G) = \frac{1}{5}.$$

$$\begin{aligned} \mathbb{P}(E \cap F) &= \mathbb{P}(\text{div by 2 of div by 3}) \\ &= \mathbb{P}(\text{div by 6}) = \frac{1}{6} \end{aligned}$$

$$\mathbb{P}(E \cap G) = \mathbb{P}(\text{div by 10}) = \frac{1}{10}$$

$$\mathbb{P}(F \cap G) = \mathbb{P}(\text{div by 15}) = \frac{1}{15}$$

$$\mathbb{P}(E \cap F \cap G) = \mathbb{P}(\text{div by 30}) = \frac{1}{30}$$

$$\begin{aligned} &\mathbb{P}(E \cup F \cup G) \\ &= \mathbb{P}(E) + \mathbb{P}(F) + \mathbb{P}(G) - \mathbb{P}(E \cap F) - \mathbb{P}(E \cap G) - \mathbb{P}(F \cap G) + \mathbb{P}(E \cap F \cap G) \\ &= \frac{1}{2} + \frac{1}{3} + \frac{1}{5} - \frac{1}{6} - \frac{1}{10} - \frac{1}{15} + \frac{1}{30} = \frac{22}{30} \end{aligned}$$

Inclusion-Exclusion. What is $\mathbb{P}\left(\bigcup_{i=1}^n E_i\right)$?

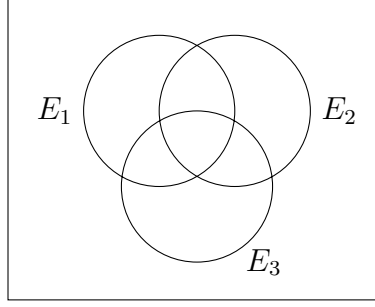
Use induction, we can get

$$\begin{aligned} \mathbb{P}\left(\bigcup_{i=1}^n E_i\right) &= \mathbb{P}\left(\left(\bigcup_{i=1}^{n-1} E_i\right) \cup E_n\right) \\ &= \sum_{i=1}^n \mathbb{P}(E_i) - \sum_{1 \leq i_1 < i_2 \leq n} \mathbb{P}(E_{i_1} \cap E_{i_2}) + \sum_{i_1 < i_2 < i_3} \mathbb{P}(E_{i_1} \cap E_{i_2} \cap E_{i_3}) - \dots \end{aligned}$$

Formally,

$$\mathbb{P}\left(\bigcup_{i=1}^n E_i\right) = \sum_{r=1}^n \sum_{1 \leq i_1 < i_2 < \dots < i_r \leq n} (-1)^{r+1} \mathbb{P}\left(\bigcap_{j=1}^r E_{i_j}\right).$$

Proof. (Inclusion-Exclusion Formula)



We can write all the events as mutually exclusive unions

$$E_I = \left(\bigcap_{i \in I} E_i \right) \cap \left(\bigcap_{i \notin I} E_i^C \right) \text{ for } I \subseteq [n].$$

$$E_I = \{\text{outcomes where } E_i \text{ happens} \iff i \in I\}$$

For example, $\bigcup_{i=1}^n E_i = \bigcup_{I: I \neq \emptyset} E_I.$

$$\Rightarrow \mathbb{P} \left(\bigcup_{i=1}^n E_i \right) = \sum_{I \neq \emptyset} \mathbb{P}(E_I) \quad (*)$$

Given every $J \subseteq [n]$, $\mathbb{P} \left(\bigcap_{j \in J} E_j \right)$

$$\bigcap_{j \in J} E_j = \bigcup_{I: J \subseteq I} E_I$$

RHS:

$$\begin{aligned} & \sum_{r=1}^n \sum_{\substack{J \subseteq [n] \\ |J|=r}} (-1)^{r+1} \mathbb{P} \left(\bigcap_{j \in J} E_j \right) \\ &= \sum_{r=1}^n \sum_{\substack{J \subseteq [n] \\ |J|=r}} (-1)^{r+1} \mathbb{P} \left(\bigcup_{I: J \subseteq I} E_I \right) \\ &= \sum_{r=1}^n (-1)^{r+1} \sum_{J \subseteq [n], |J|=r} \sum_{I: J \subseteq I} \mathbb{P}(E_I) \quad (\text{mutually exclusive}) \\ &= \sum_{\substack{I \subseteq [n] \\ I \neq \emptyset}} \left(\sum_{r=1}^n \sum_{\substack{J \subseteq [n] \\ |J|=r}} (-1)^{r+1} \right) \mathbb{P}(E_I) \end{aligned}$$

Recall that no. of choices of J , $J \subseteq I$, $|J| = r$ is $\binom{|I|}{r}$.

$$\begin{aligned}
\Rightarrow \sum_{r=1}^n \sum_{\substack{J \subseteq [n] \\ |J|=r}} (-1)^{r+1} &= \sum_{r=1}^n \binom{|I|}{r} (-1)^{r+1} \\
&= \sum_{r=1}^{|I|} \binom{|I|}{r} (-1)^{r+1} \\
&= \sum_{r=0}^{|I|} \binom{|I|}{r} (-1)^{r+1} - \binom{|I|}{0} (-1)^{0+1} \\
&= - \sum_{r=0}^{|I|} \binom{|I|}{r} (-1)^r - (-1) \\
&= -(-1 + 1)^{|I|} + 1 = 1 \quad (\text{Binom Thm.})
\end{aligned}$$

$$\begin{aligned}
\therefore \sum_{r=1}^n (-1)^{r+1} \sum_{\substack{J \subseteq [n] \\ |J|=r}} \sum_{I: J \subseteq I} \mathbb{P}(E_I) \\
&= \sum_{\substack{I \subseteq [n] \\ I \neq \emptyset}} 1 \cdot \mathbb{P}(E_I) \\
&= \mathbb{P}\left(\bigcup_{i=1}^n E_i\right) \quad (*)
\end{aligned}$$

□

Warm-up. Randomly shuffle a deck of cards. Turn them over, one-by-one, until the first Ace.

Q. What is the probability that the next card is

- (a) Ace of spades?
- (b) Two of clubs?

Attempt to answer:

- (a) We remove A♠, shuffle remaining 51 cards, and place A♠ in a random position.
 \Rightarrow 51! ways to shuffle other cards

\Rightarrow 52 positions available for A_{\spadesuit}

For the event to occur, we must place the A_{\spadesuit} directly after the first ace.

$$\Rightarrow \mathbb{P}(a) = \frac{1}{52}$$

(b) Similarly, $\mathbb{P}(b) = \frac{1}{52}$.

Example 4. (Inclusion-Exclusion) There are a party with n people. They put their hats in a rack. When leaving, everybody takes a random hat from the rack.

Q. What is the probability that nobody gets their own hat?

Solution. $S = \{\text{bijection from hats to people}\}$, $|S| = n!$.

$E = \{\text{nobody gets their own hat}\}$.

Simpler events: $E_i = \{\text{ith person gets their own hat}\}$

$$E = \bigcap_{i=1}^n E_i^C = \left(\bigcup_{i=1}^n E_i \right)^C$$

$$\Rightarrow \mathbb{P}(E) = 1 - \mathbb{P}\left(\bigcup_{i=1}^n E_i\right)$$

$$\mathbb{P}(E_i) = \frac{1}{n}, \mathbb{P}(E_i \cap E_j) = \frac{(n-2)!}{n!},$$

$$\mathbb{P}(E_{i_1} \cap E_{i_2} \cap \dots \cap E_{i_r}) = \frac{(n-r)!}{n!}$$

Plug into Inclusion-Exclusion:

$$\begin{aligned} \mathbb{P}\left(\bigcup_{i=1}^n E_i\right) &= \sum_{r=1}^n (-1)^{r+1} \sum_{1 \leq i_1 < i_2 < \dots < i_r \leq n} \mathbb{P}(E_{i_1} \cap \dots \cap E_{i_r}) \\ &= \sum_{r=1}^n (-1)^{r+1} \sum_{1 \leq i_1 < i_2 < \dots < i_r \leq n} \frac{(n-r)!}{n!} \\ &= \sum_{r=1}^n (-1)^{r+1} \binom{n}{r} \frac{(n-r)!}{n!} \\ &= \sum_{r=1}^n \frac{(-1)^{r+1}}{r!} \end{aligned}$$

$$\mathbb{P}(E) = 1 - \mathbb{P}\left(\bigcup_{i=1}^n E_i\right) = 1 - \sum_{r=1}^n \frac{(-1)^{r+1}}{r!} = \sum_{r=0}^n \frac{(-1)^r}{r!}$$

$$\text{As } n \rightarrow \infty, \mathbb{P}(E) \rightarrow \sum_{r=0}^{\infty} \frac{(-1)^r}{r!} = e^{-1}.$$

2 Bonferroni Inequalities

Inclusion-Exclusion:

$$\mathbb{P}\left(\bigcup_{i=1}^n E_i\right) = \sum_i \mathbb{P}(E_i) - \sum_{i_1 < i_2} \mathbb{P}(E_{i_1} \cap E_{i_2}) + \sum_{i_1 < i_2 < i_3} \mathbb{P}(E_{i_1} \cap E_{i_2} \cap E_{i_3}) - \dots$$

Proposition 2.1

If t is odd, then

$$\mathbb{P}\left(\bigcup_{i=1}^n E_i\right) \leq \sum_{r=1}^t (-1)^{r+1} \sum_{1 \leq i_1 < i_2 < \dots < i_r \leq n} \mathbb{P}(E_{i_1} \cap \dots \cap E_{i_r})$$

If t is even, then

$$\mathbb{P}\left(\bigcup_{i=1}^n E_i\right) \geq \sum_{r=1}^t (-1)^{r+1} \sum_{1 \leq i_1 < i_2 < \dots < i_r \leq n} \mathbb{P}(E_{i_1} \cap \dots \cap E_{i_r})$$

In particular, the case $t = 1$ is called the *union bound*:

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

Proof. Proof by induction on t .

$\bigcup_{i=1}^n E_i \rightarrow$ want to write as a union of mutually exclusive events

$$\bigcup_{i=1}^n E_i = E_1 \cup (E_2 \cap E_1^C) \cup (E_3 \cap E_1^C \cap E_2^C) \cup \dots \cup (E_n \cap E_1^C \cap E_2^C \cap \dots \cap E_{n-1}^C)$$

$$\Rightarrow \mathbb{P}\left(\bigcup_{i=1}^n E_i\right) = \mathbb{P}\left(\bigcup_{i=1}^n \left(E_i \cap \left(\bigcap_{j < i} E_j^C\right)\right)\right)$$

$$\Rightarrow \mathbb{P}\left(\bigcup_{i=1}^n E_i\right) = \sum_{i=1}^n \mathbb{P}\left(E_i \cap \left(\bigcap_{j < i} E_j^C\right)\right) \quad (*)$$

Base case. ($t = 1$) For each i , $E_i \cap \left(\bigcap_{j < i} E_j^C \right) \subseteq E_i$.

$$\stackrel{\text{Prop 2}}{\Rightarrow} \mathbb{P} \left(E_i \cap \left(\bigcap_{j < i} E_j^C \right) \right) \leq \mathbb{P}(E_i) \text{ by } (*).$$

Induction step.

$$\begin{aligned} E_i &= \left(E_i \cap \left(\bigcap_{j < i} E_j^C \right) \right) \cup \left(E_i \cap \left(\bigcap_{j < i} E_j^C \right)^C \right) \\ &= \left(E_i \cap \left(\bigcap_{j < i} E_j^C \right) \right) \cup \left(E_i \cap \left(\bigcup_{j < i} E_j \right) \right) \\ &\Rightarrow \mathbb{P} \left(E_i \cap \left(\bigcap_{j < i} E_j^C \right) \right) = \mathbb{P}(E_i) - \mathbb{P} \left(E_i \cap \left(\bigcup_{j < i} E_j \right) \right) \\ &\Rightarrow \mathbb{P} \left(E_i \cap \left(\bigcap_{j < i} E_j^C \right) \right) = \mathbb{P}(E_i) - \underbrace{\mathbb{P} \left(\bigcup_{j < i} (E_i \cap E_j) \right)}_{(\dagger)} \end{aligned}$$

Apply the $(t - 1)$ -Bonferroni Inequality to (\dagger) .

For example: ($t = 2$) By the case of $t = 1$,

$$\mathbb{P} \left(\bigcup_{j < i} (E_i \cap E_j) \right) \leq \sum_{j < i} \mathbb{P}(E_i \cap E_j)$$

plug $(*) \rightarrow (\dagger)$

$$\begin{aligned} &\Rightarrow \mathbb{P} \left(E_i \cap \left(\bigcup_{j < i} E_j \right) \right) \geq \mathbb{P}(E_i) - \sum_{j < i} \mathbb{P}(E_i \cap E_j) \\ &\stackrel{(*)}{\Rightarrow} \mathbb{P} \left(\bigcup_{i=1}^n E_i \right) \geq \sum_i \left(\mathbb{P}(E_i) - \sum_{j < i} \mathbb{P}(E_i \cap E_j) \right) = \sum_i \mathbb{P}(E_i) - \sum_{j < i} \mathbb{P}(E_i \cap E_j) \end{aligned}$$

□

3 Continuity of Probability

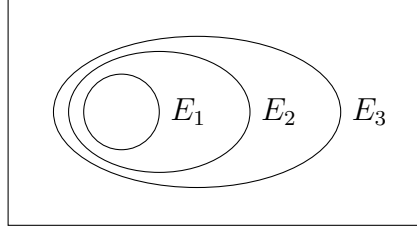
Definition 1. Let E_1, E_2, E_3, \dots be a sequence of sets. We say the sequence is *increasing* if $E_1 \subseteq E_2 \subseteq E_3 \subseteq \dots$ and define $\lim_{n \rightarrow \infty} E_n = \bigcup_{n=1}^{\infty} E_n$.

The sequence is *decreasing* if $E_1 \supseteq E_2 \supseteq E_3 \supseteq \dots$ and define $\lim_{n \rightarrow \infty} E_n = \bigcap_{n=1}^{\infty} E_n$.

Proposition 3.1

If E_1, E_2, E_3, \dots is increasing or decreasing, then $\mathbb{P}\left(\lim_{n \rightarrow \infty} E_n\right) = \lim_{n \rightarrow \infty} \mathbb{P}(E_n)$.

Proof. Suppose $E_1 \subseteq E_2 \subseteq E_3 \subseteq \dots$. Then $\lim_{n \rightarrow \infty} E_n = \bigcup_{n=1}^{\infty} E_n$.



Let $F_n = E_n \setminus \left(\bigcup_{i=1}^{n-1} E_i\right)$. Then F_1, F_2, \dots are mutually exclusive.

$$\Rightarrow \bigcup_{i=1}^n F_i = E_n = \bigcup_{i=1}^n E_i$$

$$\begin{aligned} \mathbb{P}\left(\lim_{n \rightarrow \infty} E_n\right) &= \mathbb{P}\left(\bigcup_{i=1}^{\infty} E_i\right) \\ &= \mathbb{P}\left(\bigcup_{i=1}^{\infty} F_i\right) && \text{(Axiom 3)} \\ &= \lim_{n \rightarrow \infty} \sum_{i=1}^n \mathbb{P}(F_i) && \text{(def. of infinite sum)} \\ &= \lim_{n \rightarrow \infty} \mathbb{P}\left(\bigcup_{i=1}^n F_i\right) && \text{(Axiom 3)} \\ &= \lim_{n \rightarrow \infty} \mathbb{P}(E_n) \end{aligned}$$

If $E_1 \supseteq E_2 \supseteq E_3 \supseteq \dots$ is decreasing, then $E_1^C \subseteq E_2^C \subseteq E_3^C \subseteq \dots$ is increasing and $\left(\lim_{n \rightarrow \infty} E_n\right)^C = \lim_{n \rightarrow \infty} E_n^C$.

$$\begin{aligned}
\Rightarrow \mathbb{P}\left(\lim_{n \rightarrow \infty} E_n\right) &= 1 - \mathbb{P}\left(\left(\lim_{n \rightarrow \infty} E_n\right)^C\right) \\
&= 1 - \mathbb{P}\left(\lim_{n \rightarrow \infty} E_n^C\right) \\
&= 1 - \lim_{n \rightarrow \infty} \mathbb{P}(E_n^C) \\
&= 1 - \lim_{n \rightarrow \infty} (1 - \mathbb{P}(E_n)) && \text{(Prop. 1)} \\
&= \lim_{n \rightarrow \infty} \mathbb{P}(E_n)
\end{aligned}$$

□

Given any sequence of sets E_1, E_2, E_3, \dots , we define

$$\limsup_{n \rightarrow \infty} E_n := \bigcap_{n=1}^{\infty} \left(\bigcup_{i=n}^{\infty} E_i \right) = \lim_{n \rightarrow \infty} \underbrace{\left(\bigcup_{i=n}^{\infty} E_i \right)}_{\text{decreasing sequence}}.$$

Remark. $\limsup_{n \rightarrow \infty} E_n := \bigcap_{n=1}^{\infty} \left(\bigcup_{i=n}^{\infty} E_i \right)$ is the event that infinitely many of events of the events E_n occur.

Theorem 3.1: 1st Borel-Cantelli Lemma

If E_1, E_2, E_3, \dots is a sequence of events and $\sum_{n=1}^{\infty} \mathbb{P}(E_n) < \infty$, then $\mathbb{P}\left(\limsup_{n \rightarrow \infty} E_n\right) = 0$.

Proof.

$$\begin{aligned}
&\mathbb{P}\left(\limsup_{n \rightarrow \infty} E_n\right) \\
&= \mathbb{P}\left(\lim_{n \rightarrow \infty} \left(\bigcup_{i=n}^{\infty} E_i \right)\right) && \text{(continuity)}
\end{aligned}$$

$$\begin{aligned}
&= \lim_{n \rightarrow \infty} \mathbb{P} \left(\left(\bigcup_{i=n}^{\infty} E_n \right) \right) \\
&\leq \lim_{n \rightarrow \infty} \sum_{i=n}^{\infty} \mathbb{P}(E_i) \rightarrow 0 \text{ since } \sum_{n=1}^{\infty} \mathbb{P}(E_n) < \infty
\end{aligned}$$

□

Application. (1st Borel-Cantelli Lemma)

(1) Promotion in a restaurant: the n th customer rolls n dice. If all rolls are even, then they get free food for life!

Let $E_n = \{n\text{th customer gets free food for life}\}$. $S = \{1, 2, \dots, 6\}^n$, $E_n = \{2, 4, 6\}^n$.

$$\mathbb{P}(E_n) = \frac{|\{2, 4, 6\}^n|}{|\{1, 2, \dots, 6\}^n|} = \frac{3^n}{6^n} = 2^{-n}.$$

Since $\sum_{n=1}^{\infty} \mathbb{P}(E_n) = \sum_{n=1}^{\infty} 2^{-n} = 1 < \infty$, the 1st Borel Cantelli Lemma states $\mathbb{P}(\limsup_{n \rightarrow \infty} E_n) = 0$.

\Rightarrow almost surely, only have to give finitely many customers free food!

(2) Roll a die infinitely many times. We are interested in the no. of even numbers.

Let $e_n = \frac{\#\{\text{even rolls in first } n \text{ rolls}\}}{n}$.

Fix $\varepsilon > 0$. Let $E_n = \left\{ e_n \geq \frac{1}{2} + \varepsilon \right\}$.

$S = \{1, 2, 3, 4, 5, 6\}^n$. Count E_n :

(a) Choose how many even rolls r : $\left(\frac{1}{2} + \varepsilon\right)n \leq r \leq n$ (Apply the sum rule over choice of r).

(b) Choose which rolls are even: $\binom{n}{r}$ choices.

(c) Each roll has 3 choice $\{2, 4, 6\}$ if even, $\{1, 3, 5\}$ if odd. Product rule $\Rightarrow 3^n$ choice.

Putting it all together:

$$|E_n| = \sum_{r=\lceil (\frac{1}{2} + \varepsilon)n \rceil}^n \binom{n}{r} 3^n$$

$$\mathbb{P}(E_n) = \frac{|E_n|}{|S_n|} = \frac{\sum_{r=\lceil (\frac{1}{2}+\varepsilon)n \rceil}^n \binom{n}{r} 3^r}{6^n} = \frac{\sum_{r=\lceil (\frac{1}{2}+\varepsilon)n \rceil}^n \binom{n}{r}}{2^n}$$

Approximation. If $\frac{1}{2} \leq \alpha \leq 1$,

$$\sum_{r=\lceil \alpha n \rceil}^n \binom{n}{r} \leq 2^{n\mathcal{H}(\alpha)}$$

where \mathcal{H} is the binary entropy function, defined as $\mathcal{H}(\alpha) = -\alpha \log_2 \alpha - (1 - \alpha) \log_2 (1 - \alpha)$.
 $0 \leq \mathcal{H}(\alpha) \leq 1$ with $\mathcal{H}(\alpha) = 1$ iff $\alpha = \frac{1}{2}$.

$$\mathbb{P}(E_n) = \frac{\sum_{r=\lceil (\frac{1}{2}+\varepsilon)n \rceil}^n \binom{n}{r}}{2^n} \leq \frac{2^{n\mathcal{H}(\frac{1}{2}+\varepsilon)}}{2^n} = 2^{-\delta n}$$

where $\mathcal{H}\left(\frac{1}{2} + \varepsilon\right) = (1 - \delta)n$ for some $\delta = \delta(\varepsilon) > 0$.

$$\Rightarrow \mathbb{P}(E_n) \leq 2^{-\delta n}$$

$$\Rightarrow \sum_{n=1}^{\infty} \mathbb{P}(E_n) < \infty$$

1st Borel Cantelli $\Rightarrow \mathbb{P}(\limsup_{n \rightarrow \infty} E_n) = 0$.

\Rightarrow almost surely, there exists N such that for all $n \geq N$, E_n doesn't happen $e_n < \frac{1}{2} + \varepsilon$.

By symmetry, same is true for ratio of odd numbers. \Rightarrow exists N' such that for all $n \geq N'$,
 $e_n > \frac{1}{2} - \varepsilon$.

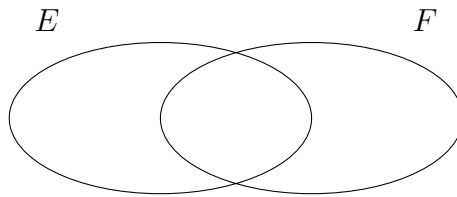
\Rightarrow exists N'' such that for all $n \geq N''$, $\frac{1}{2} - \varepsilon < e_n < \frac{1}{2} + \varepsilon$.

Since $\varepsilon > 0$ is arbitrary, $\lim_{n \rightarrow \infty} e_n = \frac{1}{2}$.

4 Conditional Probabilities

Example 5. Know that a die roll is prime. What is the probability that it is even?

$$1 : 0 \quad 2 : \frac{1}{3} \quad 3 : \frac{1}{3} \quad 4 : 0 \quad 5 : \frac{1}{3} \quad 6 : 0 \quad \mathbb{P}(\text{even}) = \frac{1}{3}.$$



Interested in probability of E .

→ told that event F occurs

→ for E to happen, $E \cap F$ must happen

Outcomes outside F now have zero probability \Rightarrow to make total probability 1, we divide by $\mathbb{P}(F)$.

Definition 2. The *conditional probability* of E given F is

$$\mathbb{P}(E|F) = \frac{\mathbb{P}(E \cap F)}{\mathbb{P}(F)}.$$

Observation.

- $E \cap F \subseteq F \Rightarrow 0 \leq \mathbb{P}(E \cap F) \leq \mathbb{P}(F) \Rightarrow 0 \leq \mathbb{P}(E|F) \leq 1$.
- If E, F are disjoint, then $\mathbb{P}(E|F) = 0$.
- $\mathbb{P}(E \cap F) = \mathbb{P}(E|F)\mathbb{P}(F)$.

Example 6. (See Example 4.) There are a party with n people and n hats. What is the probability that nobody gets their own hat?

Solution. Before: calculated inclusion-exclusion

$$\mathbb{P}(0 \text{ people get own hats}) = \sum_{k=0}^n \frac{(-1)^k}{k!} \rightarrow e^{-1}$$

$$\mathbb{P}(n \text{ people get own hats}) = \frac{1}{n!}$$

Fix a set R of r people. Let $E_R = \{\text{people in } R \text{ get own hats and people not in } R \text{ don't}\}$.

$$\begin{aligned} \mathbb{P}(\text{exactly } r \text{ people get own hats}) &= \mathbb{P}\left(\bigcup_{R:|R|=r} E_R\right) \\ &= \sum_{R:|R|=r} \mathbb{P}(E_R) \\ &= \binom{n}{r} \mathbb{P}(E_{\{1, \dots, r\}}) \end{aligned}$$

$$E_R = \underbrace{\{r+1, r+2, \dots, n \text{ don't get own hats}\}}_E \cap \underbrace{\{1, 2, \dots, r \text{ do get own hats}\}}_F$$

Use $\mathbb{P}(E \cap F) = \mathbb{P}(E|F)\mathbb{P}(F)$.

$$\begin{aligned} \mathbb{P}(E|F) &= \mathbb{P}(\{\text{nobody gets own hat in a party of } n-r \text{ people}\}) \\ &= \sum_{k=1}^{n-r} \frac{(-1)^k}{k!} \rightarrow e^{-1} \text{ if } n-r \rightarrow \infty \end{aligned}$$

Let $F_i = \{i\text{th person gets own hat}\}$. $F = F_1 \cap F_2 \cap \dots \cap F_r$.

$$\begin{aligned} \mathbb{P}(F) &= \mathbb{P}((F_1 \cap F_2 \cap \dots \cap F_{r-1}) \cap F_r) \\ &= \mathbb{P}(F_r | F_1 \cap F_2 \cap \dots \cap F_{r-1}) \mathbb{P}((F_1 \cap F_2 \cap \dots \cap F_{r-2}) \cap F_{r-1}) \\ &= \dots = \mathbb{P}(F_r | F_1 \cap F_2 \cap \dots \cap F_{r-1}) \mathbb{P}(F_{r-1} | F_1 \cap F_2 \cap \dots \cap F_{r-2}) \dots \mathbb{P}(F_1) \end{aligned}$$

$$\begin{aligned} \text{Observe that } \mathbb{P}(F_1) &= \frac{1}{n}, \mathbb{P}(F_2|F_1) = \frac{1}{n-1}, \dots, \mathbb{P}(F_i|F_1 \cap F_2 \cap \dots \cap F_{i-1}) = \frac{1}{n-i+1} \\ \Rightarrow \mathbb{P}(F) &= \frac{1}{n} \cdot \frac{1}{n-1} \cdot \dots \cdot \frac{1}{n-r+1} = \frac{(n-r)!}{n!}. \end{aligned}$$

$$\mathbb{P}(\text{exactly } r \text{ people get own hats}) = \binom{n}{r} \mathbb{P}(E_{\{1, \dots, r\}}) \approx \binom{n}{r} \frac{1}{e} \cdot \frac{(n-r)!}{n!} = \frac{1}{r!e}$$

Suppose we can partition the sample space

$$S = F_1 \cup F_2 \cup \dots \cup F_n$$

Then for any event $E \subseteq S$,

$$\begin{aligned} E &= E \cap S = E \cap \left(\bigcup_{i=1}^n F_i \right) = \bigcup_{i=1}^n (E \cap F_i) \\ \Rightarrow \mathbb{P}(E) &\stackrel{\text{Axiom 3}}{=} \sum_{i=1}^n \mathbb{P}(E \cap F_i) \\ \Rightarrow \mathbb{P}(E) &= \sum_{i=1}^n \mathbb{P}(E|F_i) \mathbb{P}(F_i) \end{aligned}$$

This is the *Law of Total Probability*.

Example 7. Go on holiday to Australia. Want to go to the beach. Maybe go swimming depending on the weather.

- if sunny: go swimming with probability 70%
- if not sunny: go swimming with probability 30%

Weather forecast: 80% chance of sunny. $\mathbb{P}(\text{swimming})$?

Solution.

$$\begin{aligned}\mathbb{P}(\text{swimming}) &= \mathbb{P}(\text{swimming}|\text{sunny})\mathbb{P}(\text{sunny}) + \mathbb{P}(\text{swimming}|\text{not sunny})\mathbb{P}(\text{not sunny}) \\ &= 0.7 \times 0.8 + 0.3 \times 0.2 = 0.62\end{aligned}$$

Warm-up. Game show (Monty Hall)

- Three doors: behind one door is a car, behind the other two are goats.
- You choose one, then the host open another door that he knows has a goat.
- Offer you the option to switch doors. Should you?

Example 8. (See Example 7.) $\mathbb{P}(\text{sunny}) = 0.8$

$$\mathbb{P}(\text{swim}|\text{sunny}) = 0.7, \quad \mathbb{P}(\text{swim}|\text{not sunny}) = 0.3$$

$$\mathbb{P}(\text{bite}|\text{swim}) = 0.5, \quad \mathbb{P}(\text{bite}|\text{not swim}) = 0.01$$

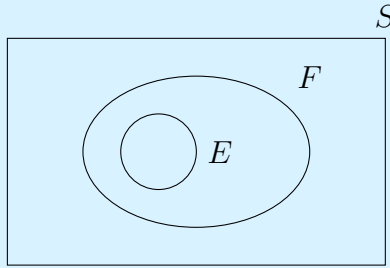
By law of total probability, $\mathbb{P}(\text{bite}) = 0.3138$.

Q. If I do get bitten by a shark, what is the probability it was sunny?

Solution.

$$\mathbb{P}(\text{sunny}|\text{bite}) = \frac{\mathbb{P}(\text{sunny} \cap \text{bite})}{\mathbb{P}(\text{bite})}$$

$$\mathbb{P}(\text{sunny} \cap \text{bite}) = \mathbb{P}(\text{bite} \cap \text{sunny}) = \mathbb{P}(\text{bite}|\text{sunny})\mathbb{P}(\text{sunny})$$



$$\begin{aligned}
 \mathbb{P}(\text{bite}|\text{sunny}) &= \mathbb{P}(\text{bite}|\text{swim, sunny})\mathbb{P}(\text{swim}|\text{sunny}) \\
 &\quad + \mathbb{P}(\text{bite}|\text{not swim, sunny})\mathbb{P}(\text{not swim}|\text{sunny}) \\
 &= \mathbb{P}(\text{bite}|\text{swim})\mathbb{P}(\text{swim}|\text{sunny}) + \mathbb{P}(\text{bite}|\text{not swim})\mathbb{P}(\text{not swim}|\text{sunny}) \\
 &= 0.5 \times 0.7 + 0.01 \times 0.3 = 0.353
 \end{aligned}$$

$$\begin{aligned}
 \mathbb{P}(\text{sunny}|\text{bite}) &= \frac{\mathbb{P}(\text{sunny} \cap \text{bite})}{\mathbb{P}(\text{bite})} \\
 &= \frac{0.353 \times 0.8}{0.3138} = \boxed{0.8999...}
 \end{aligned}$$

Theorem 4.1: Bayes' Rule

If we have a partition $S = F_1 \cup F_2 \cup \dots \cup F_n$ and an event $E \subseteq S$, then

$$\mathbb{P}(F_i|E) = \frac{\mathbb{P}(E|F_i)\mathbb{P}(F_i)}{\sum_{j=1}^n \mathbb{P}(E|F_j)\mathbb{P}(F_j)}.$$

Proof. By definition, $\mathbb{P}(F_i|E) = \frac{\mathbb{P}(F_i \cap E)}{\mathbb{P}(E)}$.

Law of total probability: $\mathbb{P}(E) = \sum_{j=1}^n \mathbb{P}(E|F_j)\mathbb{P}(F_j)$

$$\mathbb{P}(F_i \cap E) = \mathbb{P}(E \cap F_i) = \mathbb{P}(E|F_i)\mathbb{P}(F_i)$$

□

Example 9. 1% of the population has COVID. Rapid test for COVID has 95% accuracy, with 5% chance of “false positive” and 5% chance of “false negative”.

Q. A random person tests positive. What is the probability they have COVID?

Solution. Let S be the population. Let

$$F_1 = \{\text{people with COVID}\}, \quad \mathbb{P}(F_1) = 0.01$$

$$F_2 = \{\text{people without COVID}\}, \quad \mathbb{P}(F_2) = 0.99$$

$$E = \{\text{test positive}\}, \quad \mathbb{P}(E|F_1) = 0.95$$

$$\mathbb{P}(E|F_2) = 0.05$$

$$\begin{aligned} \mathbb{P}(F_1|E) &= \frac{\mathbb{P}(E|F_1)\mathbb{P}(F_1)}{\mathbb{P}(E|F_1)\mathbb{P}(F_1) + \mathbb{P}(E|F_2)\mathbb{P}(F_2)} && \text{(Bayes')} \\ &= \frac{0.95 \times 0.01}{0.95 \times 0.01 + 0.05 \times 0.99} \\ &= \boxed{0.1610} \end{aligned}$$

Example 10. DNA test:

- $\mathbb{P}(\text{positive}|\text{match}) = 1$
- $\mathbb{P}(\text{positive}|\text{not match}) = 0.0001$
- City of population 2500000
- Random person \rightarrow DNA matches sample from the crime scene

$\mathbb{P}(\text{guilty})?$

Solution. Let $S = \{\text{all people in the city}\}$, $F_1 = \{\text{guilty}\}$, $F_2 = \{\text{not guilty}\}$.

$$\mathbb{P}(F_1) = \frac{1}{2500000}, \quad \mathbb{P}(F_2) = \frac{2499999}{2500000}.$$

Let $E = \{\text{match on DNA test}\}$. $\mathbb{P}(E|F_1) = 1$, $\mathbb{P}(E|F_2) = 0.0001$.

$$\begin{aligned}\mathbb{P}(F_1|E) &= \frac{\mathbb{P}(E|F_1)\mathbb{P}(F_1)}{\mathbb{P}(E|F_1)\mathbb{P}(F_1) + \mathbb{P}(E|F_2)\mathbb{P}(F_2)} && \text{(Bayes')} \\ &= \frac{1 \times \frac{1}{2500000}}{1 \times \frac{1}{2500000} + \frac{1}{10000} \left(1 - \frac{1}{2500000}\right)} \\ &= \boxed{0.003984\dots}\end{aligned}$$

5 Independent Events

Definition 3. If $\mathbb{P}(E|F) = \mathbb{P}(E)$, then we say E and F are *independent*. Otherwise they are *dependent*.

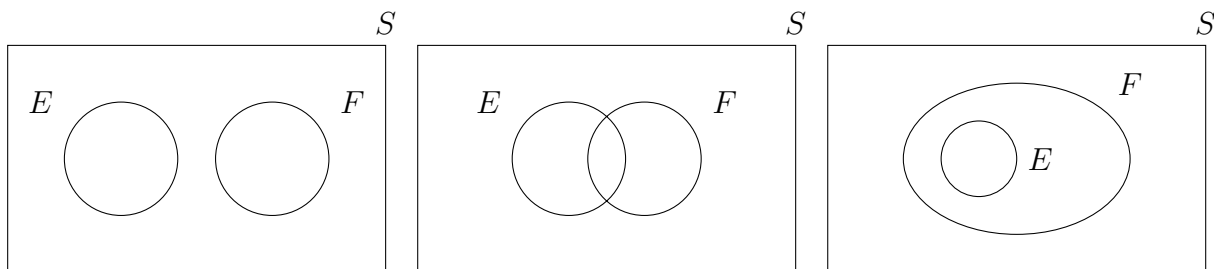
Equivalently, E and F are independent iff

$$\mathbb{P}(E \cap F) = \mathbb{P}(E)\mathbb{P}(F).$$

Corollary 5.1

Independence is symmetric in E, F .

Quiz. Which of the following pairs of events can be independent?



Example 11. $E_1 = \{\text{first roll is a 4}\}$, $E_2 = \{\text{second roll is a 3}\}$

$F_1 = \{\text{sum is 6}\}$, $F_2 = \{\text{sum is 7}\}$

Which pairs are independent?

Solution.

$$S = \{(1, 1), \dots, (1, 6), (2, 1), \dots, (2, 6), \dots, (6, 1), \dots, (6, 6)\}$$

$$E_1 = \{(4, 1), (4, 2), \dots, (4, 6)\}, \quad \mathbb{P}(E_1) = \frac{6}{36} = \frac{1}{6}.$$

$$E_2 = \{(1, 3), (2, 3), \dots, (6, 3)\}, \quad \mathbb{P}(E_2) = \frac{6}{36} = \frac{1}{6}.$$

$$E_1 \cap E_2 = \{(4, 3)\}, \quad \mathbb{P}(E_1 \cap E_2) = \frac{1}{36} = \mathbb{P}(E_1)\mathbb{P}(E_2).$$

$\Rightarrow E_1, E_2$ are independent.

$$F_1 = \{(1, 5), (2, 4), (3, 3), (4, 2), (5, 1)\}, \quad \mathbb{P}(F_1) = \frac{5}{36}.$$

$$E_1 \cap F_1 = \{(4, 2)\}, \quad \mathbb{P}(E_1 \cap F_1) = \frac{1}{36} \neq \frac{5}{36} \cdot \frac{1}{6} = \mathbb{P}(E_1)\mathbb{P}(F_1).$$

$\Rightarrow E_1, F_1$ are not independent.

F_1, F_2 not independent. They are disjoint.

$$F_2 = \{(1, 6), (2, 5), (3, 4), (4, 3), (5, 2), (6, 1)\}, \quad \mathbb{P}(F_2) = \frac{6}{36} = \frac{1}{6}.$$

$$E_i \cap F_2 = \{(4, 3)\}, \quad \mathbb{P}(E_i \cap F_2) = \frac{1}{36} = \frac{1}{6} \cdot \frac{1}{6} = \mathbb{P}(E_i)\mathbb{P}(F_2).$$

$\Rightarrow E_1, E_2$ are both independent of F_2 .

Claim. If E, F are independent, then E, F^C are independent.

Proof.

$$\begin{aligned} \mathbb{P}(E \cap F^C) &= \mathbb{P}(E) - \mathbb{P}(E \cap F) \\ &= \mathbb{P}(E) - \mathbb{P}(E)\mathbb{P}(F) && \text{(independence)} \\ &= \mathbb{P}(E)(1 - \mathbb{P}(F)) = \mathbb{P}(E)\mathbb{P}(F^C) \end{aligned}$$

□

However, if

E_1, F are independent, and

E_2, F are independent,

that doesn't mean

$E_1 \cup E_2, F$ are independent, or

$E_1 \cap E_2, F$ are independent.

Definition 4. We say E_1, E_2, E_3 are (mutually) independent if:

- $\mathbb{P}(E_1 \cap E_2 \cap E_3) = \mathbb{P}(E_1)\mathbb{P}(E_2)\mathbb{P}(E_3)$
- $\mathbb{P}(E_1 \cap E_2) = \mathbb{P}(E_1)\mathbb{P}(E_2)$
- $\mathbb{P}(E_1 \cap E_3) = \mathbb{P}(E_1)\mathbb{P}(E_3)$
- $\mathbb{P}(E_2 \cap E_3) = \mathbb{P}(E_2)\mathbb{P}(E_3)$

all hold.

There is a more general version:

Definition 5. Given a sequence of events E_1, E_2, E_3, \dots , we say they are (mutually) independent if for any finite set I of indices,

$$\mathbb{P}\left(\bigcap_{i \in I} E_i\right) = \prod_{i \in I} \mathbb{P}(E_i)$$

Example 12. Inclusion-Exclusion for independent events.

Let $E_1, E_2, E_3, \dots, E_n$ be independent.

$$\begin{aligned} \mathbb{P}\left(\bigcup_{i=1}^n E_i\right) &= \sum_{\substack{I \subseteq [n] \\ I \neq \emptyset}} (-1)^{|I|+1} \mathbb{P}\left(\bigcap_{i \in I} E_i\right) \\ &= \sum_{\substack{I \subseteq [n] \\ I \neq \emptyset}} (-1)^{|I|+1} \prod_{i \in I} \mathbb{P}(E_i) \\ &= 1 - \prod_{i=1}^n (1 - \mathbb{P}(E_i)) \end{aligned}$$

Alternatively, use De Morgan to turn the union into an intersection:

$$\begin{aligned}
 \mathbb{P}\left(\bigcup_{i=1}^n E_i\right) &= 1 - \mathbb{P}\left(\left(\bigcup_{i=1}^n E_i\right)^C\right) \\
 &= 1 - \mathbb{P}\left(\bigcap_{i=1}^n E_i^C\right) \\
 &= 1 - \prod_{i=1}^n \mathbb{P}(E_i^C) = 1 - \prod_{i=1}^n (1 - \mathbb{P}(E_i))
 \end{aligned}$$

Application. Suppose we have a test with a false negative rate of 1% and a false positive rate rate of 50%.

Suppose we can repeat the test independently.

If actually positive, $\mathbb{P}(\text{pos}, \text{pos}) = 0.99 \times 0.99 \geq 0.98$.

If actually negative, $\mathbb{P}(\text{pos}, \text{pos}) = 0.5 \times 0.5 = 0.25$.

Let $S = (0, 1]$, $z \in S$ be uniformly randomly chosen. That is, $\mathbb{P}(z \in (x, y]) = y - x$.

Let E_1, E_2, \dots be events in the probability space. Let $p_i = \mathbb{P}(E_i)$.

The 1st Borel-Cantelli Lemma states that if $\sum_{n=1}^{\infty} p_n < \infty$, then $\mathbb{P}\left(\limsup_{n \rightarrow \infty} E_n\right) = 0$.

Homework: if $\sum_{n=1}^{\infty} p_n = \infty$, then it is possible that $\mathbb{P}\left(\limsup_{n \rightarrow \infty} E_n\right) = 1$.

Also possible that $\mathbb{P}\left(\limsup_{n \rightarrow \infty} E_n\right) = 0$. For example, $E_n = (0, \frac{1}{n}]$.

Theorem 5.1: 2nd Borel-Cantelli Lemma

If E_1, E_2, \dots are mutually independent events and $\sum_{n=1}^{\infty} \mathbb{P}(E_n) = \infty$, then $\mathbb{P}\left(\limsup_{n \rightarrow \infty} E_n\right) = 1$.

Proof. Recall that $\limsup_{n \rightarrow \infty} E_n = \bigcap_{n=1}^{\infty} \left(\bigcup_{i=n}^{\infty} E_n \right)$.

$$\mathbb{P} \left(\limsup_{n \rightarrow \infty} E_n \right) = 1 \Rightarrow \mathbb{P} \left(\left(\limsup_{n \rightarrow \infty} E_n \right)^C \right) = 1$$

$$\left(\limsup_{n \rightarrow \infty} E_n \right)^C = \left(\bigcap_{n=1}^{\infty} \left(\bigcup_{i=n}^{\infty} E_n \right) \right)^C = \bigcup_{n=1}^{\infty} \left(\bigcup_{i=n}^{\infty} E_n \right)^C = \bigcup_{n=1}^{\infty} \bigcap_{i=n}^{\infty} E_n^C$$

$$\begin{aligned} \mathbb{P} \left(\left(\bigcap_{n=1}^{\infty} \left(\bigcup_{i=n}^{\infty} E_n \right) \right)^C \right) &= \mathbb{P} \left(\bigcup_{n=1}^{\infty} \bigcap_{i=n}^{\infty} E_n^C \right) \\ &= \lim_{n \rightarrow \infty} \mathbb{P} \left(\bigcap_{i=n}^{\infty} E_n^C \right) && \text{(continuity)} \\ &= \lim_{n \rightarrow \infty} \prod_{i=n}^{\infty} \mathbb{P}(E_i^C) && \text{(independence, *)} \\ &= \lim_{n \rightarrow \infty} \prod_{i=n}^{\infty} (1 - \mathbb{P}(E_i)) = \lim_{n \rightarrow \infty} 0 = 0 \end{aligned}$$

by convergence test for infinite product $(\lim_{n \rightarrow \infty} \prod_{i=n}^{\infty} \mathbb{P}(E_i) = \infty)$

$$\begin{aligned} (*) \quad \mathbb{P} \left(\bigcap_{i=1}^{\infty} E_i^C \right) &= \mathbb{P} \left(\lim_{N \rightarrow \infty} \bigcap_{i=n}^N E_i^C \right) \\ &= \lim_{N \rightarrow \infty} \mathbb{P} \left(\bigcap_{i=n}^N E_i^C \right) && \text{(continuity)} \\ &= \lim_{N \rightarrow \infty} \prod_{i=n}^N \mathbb{P}(E_i^C) && \text{(independence)} \\ &= \prod_{i=n}^{\infty} \mathbb{P}(E_i^C) \end{aligned}$$

□

6 Discrete Random Variables

6.1 Discrete Random Variable

Definition 6. Given a probability space (S, \mathbb{P}) , a *random variable* is a function $X : S \rightarrow \mathbb{R}$. It is *discrete* if it only takes countably many values.

Observation. A discrete random variable defines a (simpler) probability space.

Let x_1, x_2, x_3, \dots be the values X can take. i.e. $X(S) = \{x_1, x_2, x_3, \dots\}$. \leftarrow new sample space

$$p(x_i) = \mathbb{P}(X(s) = x_i) = \mathbb{P}(\{s \in S \mid X(s) = x_i\}).$$

Observation.

$$\begin{aligned} \sum_i p(x_i) &= \sum_i \mathbb{P}(X(s) = x_i) \\ &= \sum_i \mathbb{P}(X^{-1}(x_i)) && \text{(pairwise disjoint)} \\ &= \mathbb{P}(\cup_i X^{-1}(x_i)) \\ &= \mathbb{P}(S) = 1 \end{aligned}$$

Example 13. Multiple choice exam

- 5 questions, each question has 4 options, one is correct
- pick uniformly random answer on each question, independently

Q. What is the probability of getting none of them correct?

Solution. Let X = the number of correct answers.

Calculate $\mathbb{P}(X = 0)$:

$$\mathbb{P}(X = 0) = \mathbb{P}(F_1 \cap F_2 \cap \dots \cap F_5), \quad F_i = \{\text{get } i\text{th question wrong}\}. \quad \mathbb{P}(F_i) = \frac{3}{4}.$$

$$\text{independence} \Rightarrow \mathbb{P}\left(\bigcap_{i=1}^5 F_i\right) = \prod_{i=1}^5 \mathbb{P}(F_i) = \left(\frac{3}{4}\right)^5.$$

We can calculate

$$\mathbb{P}(X = 0) = \left(\frac{3}{4}\right)^5$$

$$\begin{aligned}
\mathbb{P}(X = 1) &= \binom{5}{1} \left(\frac{1}{4}\right) \left(\frac{3}{4}\right)^4 \\
\mathbb{P}(X = 2) &= \binom{5}{2} \left(\frac{1}{4}\right)^2 \left(\frac{3}{4}\right)^3 \\
\mathbb{P}(X = 3) &= \binom{5}{3} \left(\frac{1}{4}\right)^3 \left(\frac{3}{4}\right)^2 \\
\mathbb{P}(X = 4) &= \binom{5}{4} \left(\frac{1}{4}\right)^4 \left(\frac{3}{4}\right) \\
\mathbb{P}(X = 5) &= \left(\frac{1}{4}\right)^5
\end{aligned}$$

Example 14. Promotion: n different types of prizes

each attempt \rightarrow get a uniformly random prize, independent of previous attempt.

Q. How many attempts do we need to get all types of prizes?

Solution. Let $S = \{(s_1, s_2, s_3, \dots) \mid 1 \leq s_i \leq n\}$, and

$X((s_1, s_2, s_3, \dots)) = \min \{t \mid (s_1, s_2, s_3, \dots) \text{ has all numbers from 1 to } n\}$.

If $t < n$, $\mathbb{P}(X = t) = 0$.

$$\mathbb{P}(X = n) = \frac{n!}{n^n} \simeq \frac{1}{(e + o(1))^n}$$

If $t > n$, $\mathbb{P}(X = t) = ?$

$$\mathbb{P}(X > t) = \mathbb{P}\left(\bigcup_{i=1}^n E_i\right) \text{ where } E_i = \{\text{ith prize is missing after } t \text{ attempts}\}$$

$$\mathbb{P}(E_i) = \left(\frac{n-1}{n}\right)^t \leftarrow \frac{n-1}{n} \text{ probability for each independent try}$$

$$\mathbb{P}\left(\bigcup_{i=1}^n E_i\right) \stackrel{\text{inc-exc}}{=} \sum_{\emptyset \neq I \subseteq [n]} (-1)^{|I|+1} \mathbb{P}\left(\bigcap_{i \in I} E_i\right)$$

$$\mathbb{P}\left(\bigcap_{i \in I} E_i\right) = \left(\frac{n-|I|}{n}\right)^t \leftarrow n-|I| \text{ bid options for each attempt}$$

$$\mathbb{P}\left(\bigcup_{i=1}^n E_i\right) = \sum_{I \neq \emptyset} (-1)^{|I|+1} \mathbb{P}\left(\bigcap_{i \in I} E_i\right) = \sum_{r=1}^n (-1)^{r+1} \binom{n}{r} \left(\frac{n-r}{n}\right)^t$$

Therefore

$$\mathbb{P}(X = t) = \mathbb{P}(X > t - 1) - \mathbb{P}(X > t) = \sum_{r=1}^n (-1)^{r+1} \binom{n}{r} \left(\frac{n-r}{n}\right)^{t-1} \left(1 - \frac{n-r}{n}\right)$$

6.2 Expectation

Definition 7. Given a probability space (S, \mathbb{P}) and a discrete random variable $X : S \rightarrow \mathbb{R}$ which takes values x_1, x_2, \dots , the *expectation* of X is

$$\mathbb{E}[X] = \sum_i x_i p(x_i) = \sum_i x_i \mathbb{P}(X = x_i).$$

Example 15. (See Example 13.) Multiple choice exam

- 2 questions, each question has 4 options
- pick uniformly random answer on each question, independently

Q. What is the expected number of correct answers?

Solution. X takes values 0, 1, or 2.

$$p(0) = \left(\frac{3}{4}\right)^2 = \frac{9}{16}, p(1) = \binom{2}{1} \left(\frac{1}{4}\right) \left(\frac{3}{4}\right) = \frac{6}{16}, p(2) = \left(\frac{1}{4}\right)^2 = \frac{1}{16}$$

$$\mathbb{E}[X] = 0 \cdot \frac{9}{16} + 1 \cdot \frac{6}{16} + 2 \cdot \frac{1}{16} = \frac{8}{16} = \frac{1}{2}$$

Multiple choice, +1 point if answer correct and -1 point if answer is incorrect.

Let Y = score. What is the expectation of Y ?

X	Y	$p(Y)$
0	-2	$\frac{9}{16}$
1	0	$\frac{6}{16}$
2	2	$\frac{1}{16}$

$$Y = X - (2 - X) = 2X - 2$$

$$\mathbb{E}[Y] = \frac{9}{16} \cdot (-2) + \frac{6}{16} \cdot 0 + \frac{1}{16} \cdot 2 = -1 = 2 \cdot \frac{1}{2} - 2$$

Lemma 6.1: Linearity of Expectation

Let X_1, X_2, \dots, X_n be random variables in a probability space (S, \mathbb{P}) .

Let $Y = \sum_{i=1}^n \alpha_i X_i$ for some $\alpha_i \in \mathbb{R}$. Then $\mathbb{E}[Y] = \sum_{i=1}^n \alpha_i \mathbb{E}[X_i]$.

Proof. **Claim.** $\mathbb{E}[X] = \sum_{s \in S} X(s) \mathbb{P}(s)$.

Proof. (claim) By definition, if $X(S) = \{x_1, x_2, \dots\}$,

$$\begin{aligned} \mathbb{E}[X] &= \sum_i x_i p(x_i) \\ &= \sum_i x_i \mathbb{P}(\{s \in S \mid X(s) = x_i\}) \\ &= \sum_i x_i \mathbb{P}\left(\bigcup_{s \in X^{-1}(x_i)} \{s\}\right) \\ &= \sum_i x_i \sum_{s \in X^{-1}(x_i)} \mathbb{P}(s) \\ &= \sum_{s \in S} X(s) \mathbb{P}(s) \end{aligned}$$

□

$$\begin{aligned} \Rightarrow \mathbb{E}[Y] &= \sum_{x \in S} Y(s) \mathbb{P}(s) \\ &= \sum_{x \in S} \left(\sum_{i=1}^n \alpha_i X_i(s) \right) \mathbb{P}(s) \\ &= \sum_{x \in S} \sum_{i=1}^n \alpha_i X_i(s) \mathbb{P}(s) \end{aligned}$$

$$\begin{aligned}
&= \sum_{i=1}^n \alpha_i \sum_{x \in S} X_i(s) \mathbb{P}(s) \\
&= \sum_{i=1}^n \alpha_i \mathbb{E}[x_i]
\end{aligned}$$

□

Example 16. (See Example 13.) Multiple choice exam

- n questions, each question has k options
- pick uniformly random answer on each question, independently

Q. What is the expectation number of correct answers?

Solution. Let X = number of correct answers. Let

$$X_i = \begin{cases} 1 & \text{if the } i\text{th question is right} \quad \left(\frac{1}{k}\right) \\ 0 & \text{otherwise} \quad \left(\frac{k-1}{k}\right). \end{cases}$$

Then $X = \sum_{i=1}^n X_i$.

$$\stackrel{\text{LoE}}{\Rightarrow} \mathbb{E}[X] = \sum_{i=1}^n \mathbb{E}[X_i] = \sum_{i=1}^n \frac{1}{k} = \boxed{\frac{n}{k}}$$

Example 17. (See Example 13.) Multiple choice exam

- first 10 questions have 3 options
- last 5 questions have 5 options
- pick uniformly random answer on each question, independently

Q. What is

(a) the probability of getting exactly k correct?

(b) the expected number of correct answers?

Solution.

(a) Suppose we get l correct from the first 10, $0 \leq l \leq 10$.

$\Rightarrow k - l$ correct from last 5. Then the answer would be

$$\sum_{l=0}^{10} \binom{10}{l} \binom{5}{k-l} \left(\frac{1}{3}\right)^l \left(\frac{2}{3}\right)^{10-l} \left(\frac{1}{5}\right)^{k-l} \left(\frac{4}{5}\right)^{5-k+l}.$$

(Define $\binom{n}{r} = 0$ for $r > n$.)

(b) Let X_i be the indicator random variable for the event that we got the i -th question right.

$$X_i = \begin{cases} 1 & \text{if } i\text{-th question correct} \\ 0 & \text{if not} \end{cases}$$

Then if X = the number of correct answers, $X = \sum_{i=1}^{15} X_i$.

By linearity of expectation,

$$\begin{aligned} \mathbb{E}[X] &= \sum_{i=1}^{15} \mathbb{E}[X_i] = \sum_{i=1}^{15} \mathbb{P}(X_i = 1) \\ &= \sum_{i=1}^{10} \mathbb{P}(i\text{-th question correct}) + \sum_{i=11}^{15} \mathbb{P}(i\text{-th question correct}) \\ &= \sum_{i=1}^{10} \frac{1}{3} + \sum_{i=11}^{15} \frac{1}{5} = \boxed{\frac{13}{3}} \end{aligned}$$

Theorem 6.1: Markov's Inequality

If X is a discrete random variable taking nonnegative values, then for any $t \in \mathbb{R}_{>0}$,

$$\mathbb{P}(X \geq t) \leq \frac{\mathbb{E}[X]}{t}.$$

Remark.

(a) Nonnegativity is necessary. Consider

$$X = \begin{cases} 1 & \text{with probability } \frac{1}{2} \\ -1 & \text{with probability } \frac{1}{2} \end{cases}$$

Then $\mathbb{E}[X] = 0$, but for $t \leq 1$, $\mathbb{P}(X \geq t) \geq \frac{1}{2} > 0$.

(b) Inequality is useless for $t \leq \mathbb{E}[X]$, but useful for saying a random variable is unlikely to be much bigger than its expectation.

Proof.

$$\begin{aligned} \mathbb{E}[X] &= \sum_x xp(x) \\ &= \sum_{x:x < t} xp(x) + \sum_{x:x \geq t} xp(x) \\ &\geq \sum_{x:x < t} 0 + \sum_{x:x \geq t} tp(x) && (X \text{ is nonnegative}) \\ &= t \sum_{x:x \geq t} p(x) \\ &= t \sum_{x:x \geq t} \mathbb{P}(\{X = x\}) \\ &= t\mathbb{P}\left(\bigcup_{x:x \geq t} \{X = x\}\right) && (\text{disjoint events}) \\ &= t\mathbb{P}(X \geq t) \end{aligned}$$

□

From Markov's inequality, we can know that if $\mathbb{E}[X]$ is low, X is likely to be low.

Is the converse true? if $\mathbb{E}[X]$ is high, is X likely to be high?

This is in general not true. For example, let

$$X = \begin{cases} 1000000 & \text{with probability } \frac{1}{1000} \\ 0 & \text{with probability } \frac{999}{1000} \end{cases}$$

Then $\mathbb{E}[X] = 1000000 \cdot \frac{1}{1000} + 0 \cdot \frac{999}{1000} = 1000$. But $\mathbb{P}(X > 0) = \frac{1}{1000}$.

Fun question. There are 3 investment option. Which one would you take?

$$\begin{aligned} X_1 &= 1 \text{ with probability } 1 & \mathbb{E}[X_1] &= 1 \\ X_2 &= \begin{cases} 1000 & \text{with probability } \frac{1}{1000} \\ 0 & \text{with probability } \frac{999}{1000} \end{cases} & \mathbb{E}[X_2] &= 1 \\ X_3 &= \begin{cases} \frac{2000}{999} & \text{with probability } \frac{999}{1000} \\ -1000 & \text{with probability } \frac{1}{1000} \end{cases} & \mathbb{E}[X_3] &= 1 \end{aligned}$$

6.3 Variance

We want to know that how far from the expectation are we on average.

Definition 8. The *variance* of a random variable X with expectation μ is

$$\text{Var}(X) = \mathbb{E}[(X - \mu)^2].$$

Proposition 6.1

$$\text{Var}(X) = \mathbb{E}[X^2] - \mathbb{E}[X]^2.$$

Proof.

$$\begin{aligned} \text{Var}(X) &= \mathbb{E}[(X - \mu)^2] \\ &= \sum_x (x - \mu)^2 p(x) \\ &= \sum_x (x^2 - 2\mu x + \mu^2) p(x) \\ &= \sum_x x^2 p(x) - 2\mu \sum_x x p(x) + \mu^2 \sum_x p(x) \\ &= \mathbb{E}[X^2] - 2\mu^2 + \mu^2 \\ &= \mathbb{E}[X^2] - \mu^2 \end{aligned}$$

□

Example 18. Let X_1, X_2, X_3 be the investment strategies from before.

$$\text{Var}(X_1) = \mathbb{E}[(X_1 - 1)^2] = 0$$

$$\begin{aligned} \text{Var}(X_2) &= \mathbb{E}[(X_2 - 1)^2] = 999^2 \cdot \frac{1}{1000} + (-1)^2 \cdot \frac{999}{1000} \\ &= \frac{999}{1000}(999 + 1) = 999 \\ &= \mathbb{E}[X_2^2] - \mathbb{E}[X_2]^2 = \left(1000^2 \cdot \frac{1}{1000} + 0^2 \cdot \frac{999}{1000}\right) - 1^2 \\ &= 1000 - 1 = 999 \end{aligned}$$

$$\begin{aligned} \text{Var}(X_3) &= \mathbb{E}[(X_3 - 1)^2] = \mathbb{E}[X_3^2] - \mathbb{E}[X_3]^2 \\ &= \left(\left(\frac{2000}{999}\right)^2 \cdot \frac{999}{1000} + (-1000)^2 \frac{1}{1000} \right) - 1 \\ &= \left(\frac{4000}{999} + 1000 \right) - 1 = 1003 \frac{4}{999} \end{aligned}$$

Definition 9. The *standard deviation* of a random variable is the square root of its variance, often denoted by $\sigma(X)$.

Theorem 6.2: Chebychev's Inequality

Let X be a random variable with expectation $E[X] = \mu$. Then for any $t > 0$,

$$\mathbb{P}(|X - \mu| \geq t) \leq \frac{\text{Var}(X)}{t^2}.$$

Proof. Apply Markov's inequality to the nonnegative random variable $(X - \mu)^2$. Observe that

$$\{|X - \mu| \geq t\} = \{(X - \mu)^2 \geq t^2\}.$$

By Markov,

$$\mathbb{P}((X - \mu)^2 \geq t^2) \leq \frac{\mathbb{E}[(X - \mu)^2]}{t^2} = \frac{\text{Var}(X)}{t^2}.$$

□

Corollary 6.1

The probability that X is at least k standard deviations away from its expectation is $\leq \frac{1}{k^2}$.

Remark. Let X be a random variable, $a, b \in \mathbb{R}$. Define $Y = aX + b$.

By linearity, $\mathbb{E}[Y] = \mathbb{E}[aX + b] = a\mathbb{E}[X] + b$.

What about the variance?

$$\begin{aligned}\text{Var}(Y) &= \mathbb{E}[(Y - \mathbb{E}[Y])^2] \\ &= \mathbb{E}[(aX + b - (a\mathbb{E}[X] + b))^2] \\ &= \mathbb{E}[(a(X - \mathbb{E}[X]))^2] \\ &= a^2 \mathbb{E}[(X - \mathbb{E}[X])^2] = a^2 \text{Var}(X)\end{aligned}$$

7 Famous Distributions

7.1 Binomial Distribution

Setting:

- run n independent trial of a random experiment
- each trial is a success with probability p
- count the number of successes

Denoted by $\text{Bin}(n, p)$.

Distribution: The possible values are $0, 1, 2, \dots, n$. The probability that we get k successes is

$$p(k) = \binom{n}{k} p^k (1-p)^{n-k}.$$

Observation.

$$\sum_k p(k) = \sum_{k=0}^n \binom{n}{k} p^k (1-p)^{n-k} = (p + (1-p))^n = 1$$

Remark. When $n = 1$, we get a Bernoulli distribution, defined by

$$X = \begin{cases} 1 & \text{with probability } p \\ 0 & \text{with probability } 1-p. \end{cases}$$

Denoted by $\text{Ber}(p)$.

Therefore

$\text{Bin}(n, p)$ = sum of n independent Bernoulli random variables.

Statistics. Let $Y \sim \text{Ber}(p)$ (Y be a $\text{Ber}(p)$ random variable). Then

$$\mathbb{E}[Y] = 1 \cdot p + 0 \cdot (1 - p) = p.$$

Let $X \sim \text{Bin}(n, p)$. Then $X = \sum_{i=1}^n X_i$ where each $X_i \sim \text{Ber}(p)$ independently.

$$\mathbb{E}[X] = \mathbb{E}\left[\sum_{i=1}^n X_i\right] = \sum_{i=1}^n \mathbb{E}[X_i] = \sum_{i=1}^n p = \boxed{np}$$

To calculate the expectation of the binomial distribution manually, we use the binomial theorem.

$$\sum_{k=0}^n \binom{n}{k} x^k y^{n-k} = (x + y)^n \quad (\text{binomiral theorem})$$

$$\xRightarrow{\frac{d}{dx}} \sum_{k=0}^n k \binom{n}{k} x^{k-1} y^{n-k} = n(x + y)^{n-1}$$

Multiply both side by x ,

$$\sum_{k=0}^n k \binom{n}{k} x^k y^{n-k} = nx(x + y)^{n-1}.$$

Substitute $x = p$, $y = 1 - p$, and we can get

$$\mathbb{E}[X] = \sum_{k=0}^n k \binom{n}{k} p^k (1 - p)^{n-k} = np(p + (1 - p))^{n-1} = \boxed{np}.$$

Now, to calculate the variance of the binomial distribution, we need to compute $\mathbb{E}[X^2]$.

Observe

$$\sum_{k=0}^n k \binom{n}{k} k x^k y^{n-k} = nx(x + y)^{n-1}$$

$$\xRightarrow{\frac{d}{dx}} \sum_{k=0}^n k^2 \binom{n}{k} k x^{k-1} y^{n-k} = n(x + y)^{n-1} + n(n - 1)x(x + y)^{n-2}$$

Multiply both side by x ,

$$\sum_{k=0}^n k^2 \binom{n}{k} k x^k y^{n-k} = nx(x + y)^{n-1} + n(n - 1)x^2(x + y)^{n-2}$$

Substitute $x = p$, $y = 1 - p$, and we can get

$$\begin{aligned}\mathbb{E}[X^2] &= \sum_{k=0}^n k^2 \binom{n}{k} p^k (1-p)^{n-k} \\ &= np(p + (1-p))^{n-1} + n(n-1)p^2(p + (1-p))^{n-2} = \boxed{np + n(n-1)p^2}.\end{aligned}$$

Therefore

$$\begin{aligned}\text{Var}(X) &= \mathbb{E}[X^2] - \mathbb{E}[X]^2 \\ &= np + n(n-1)p^2 - n^2p^2 \\ &= np - np^2 = \boxed{np(1-p)}\end{aligned}$$

Also, We can calculate the variance of Bernoulli distribution:

$$\begin{aligned}X &= \begin{cases} 1 & \text{with probability } p \\ 0 & \text{with probability } 1-p. \end{cases} \\ X^2 &= \begin{cases} 1 & \text{with probability } p \\ 0 & \text{with probability } 1-p. \end{cases} \\ \Rightarrow \mathbb{E}[X^2] &= \mathbb{E}[X] = p\end{aligned}$$

$$\begin{aligned}\text{Var}(X) &= \mathbb{E}[X^2] - \mathbb{E}[X]^2 \\ &= p - p^2 = \boxed{p(1-p)}\end{aligned}$$

Remark. We have the following observation:

(a) Let $X \sim \text{Bin}(n, p)$. Then $\mathbb{E}[X] = np$ and $\text{Var}(X) = np(1-p)$.

By Chebychev we can know that $\mathbb{P}(|X - np| \geq t) \leq \frac{np(1-p)}{t^2}$.

That is, even though there are $n + 1$ values the distribution can take, the probability it is outside an interval of with $\Theta(\sqrt{n})$ around the expectation is very small.

(b) $\mathbb{E}[X^2] = \underbrace{\mathbb{E}[X(X-1)]}_{\sum_k k(k-1)p(k)} + \mathbb{E}[X]$.

7.2 Poisson Distribution

Setting:

- the number of earthquakes in Taiwan in a month
- on average, there are λ earthquakes in a month
- divide into n equal time intervals \rightarrow expect $\frac{\lambda}{n}$ earthquakes in each interval

Assumption:

- At most one earthquakes per interval.
- Each interval is independent of the others.

The number of earthquakes $\sim \text{Poi}(n, \frac{\lambda}{n})$.

Distribution:

$$\mathbb{P}(k \text{ earthquakes in a month}) \simeq \binom{n}{k} \left(\frac{\lambda}{n}\right)^k \left(1 - \frac{\lambda}{n}\right)^{n-k}$$

Take $n \rightarrow \infty$,

$$\begin{aligned} \binom{n}{k} \left(\frac{\lambda}{n}\right)^k &= \frac{n(n-1)\cdots(n-k+1)}{k!} \left(\frac{\lambda}{n}\right)^k \rightarrow \frac{\lambda^k}{k!} \\ \left(1 - \frac{\lambda}{n}\right)^{n-k} &= \frac{\left(1 - \frac{\lambda}{n}\right)^n}{\left(1 - \frac{\lambda}{n}\right)^k} \rightarrow \frac{e^{-\lambda}}{1} \end{aligned}$$

Therefore the Poisson distribution with parameter $\lambda > 0$, $\text{Poi}(\lambda)$ has distribution

$$p(k) = \frac{\lambda^k e^{-\lambda}}{k!} \quad \text{for } k = 0, 1, 2, \dots$$

Fun fact. This is a distribution $p(k) \geq 0$ for all $k \geq 0$.

$$\begin{aligned} \sum_{k=0}^{\infty} p(k) &= \sum_{k=0}^{\infty} \frac{\lambda^k e^{-\lambda}}{k!} \\ &= e^{-\lambda} \sum_{k=0}^{\infty} \frac{\lambda^k}{k!} \\ &= e^{-\lambda} e^{\lambda} = 1 \end{aligned}$$

Remark. $\text{Poi}(\lambda)$ is a good approximation for $\text{Bin}(n, \frac{\lambda}{n})$ when n is large.

That is to say, Poisson distribution is appropriate when we have many independent events, each with small probability.

For example,

- number of customers in a shop in an hour.
- number of people who will die in a day.
- radioactive decay.

Statistics. Let $X \sim \text{Poi}(\lambda)$. The expectation is

$$\begin{aligned}
 \mathbb{E}[X] &= \sum_{k=0}^{\infty} kp(k) \\
 &= \sum_{k=0}^{\infty} k \cdot \frac{\lambda^k e^{-\lambda}}{k!} \\
 &= \sum_{k=1}^{\infty} \frac{\lambda^k e^{-\lambda}}{(k-1)!} \\
 &= \sum_{k=0}^{\infty} \frac{\lambda^{k+1} e^{-\lambda}}{k!} \\
 &= \lambda \sum_{k=0}^{\infty} \frac{\lambda^k e^{-\lambda}}{k!} \\
 &= \lambda \sum_{k=0}^{\infty} p(k) = \boxed{\lambda}
 \end{aligned}$$

The variance is

$$\begin{aligned}
 \text{Var}(X) &= \mathbb{E}[X^2] - \mathbb{E}[X]^2 \\
 &= \mathbb{E}[X(X-1)] + \mathbb{E}[X] - \mathbb{E}[X]^2 \\
 &= \mathbb{E}[X(X-1)] + \lambda - \lambda^2
 \end{aligned}$$

where

$$\begin{aligned}
 \mathbb{E}[X(X-1)] &= \sum_{k=0}^{\infty} k(k-1)p(k) \\
 &= \sum_{k=0}^{\infty} k(k-1) \frac{\lambda^k e^{-\lambda}}{k!} \\
 &= \sum_{k=2}^{\infty} k(k-1) \frac{\lambda^k e^{-\lambda}}{k!} \\
 &= \sum_{k=2}^{\infty} \frac{\lambda^k e^{-\lambda}}{(k-2)!}
 \end{aligned}$$

$$= \sum_{k=0}^{\infty} \frac{\lambda^{k+2} e^{-\lambda}}{k!} = \lambda^2$$

Therefore

$$\begin{aligned} \text{Var}(X) &= \mathbb{E}[X(X-1)] + \lambda - \lambda^2 \\ &= \lambda^2 + \lambda - \lambda^2 = \boxed{\lambda} \end{aligned}$$

Like what we mentioned above, $\text{Poi} \simeq \text{Bin}(n, \frac{\lambda}{n})$, which has expectation $np = \lambda$ and variance $np(1-p) = n \cdot \frac{\lambda}{n} \left(1 - \frac{\lambda}{n}\right) \simeq \lambda$.

The Poisson Paradigm. The Poisson distribution is more widely applicable: if we have n events $E_1, E_2, E_3, \dots, E_n$ such that

- $p_i = \mathbb{P}(E_i)$ is small for every i , and
- the events are “weakly independent”: for $j \neq i$, $\mathbb{P}(E_i|E_j) \simeq p_i$,

then if $\lambda = p_1 + p_2 + \dots + p_n$, $\text{Poi}(\lambda)$ is a good approximation to the number of events that occur.

Example 19. (See Example 4.) There are a party with n people and n hats. What is the probability that nobody gets their own hat?

Solution. Let $E_i = \{i\text{-th person gets own hat}\}$. Then $\mathbb{P}(E_i) = \frac{1}{n}$, $\mathbb{P}(E_i|E_j) = \frac{1}{n-1}$. Therefore the Poisson paradigm applies. The number of correct hats $\simeq \text{Poi}(1)$.

$$\mathbb{P}(\text{nobody gets own hat}) \simeq \frac{1^0 e^{-1}}{0!} = \frac{1}{e}.$$

$$\mathbb{P}(\text{exactly } k \text{ gets own hat}) \simeq \frac{1^k e^{-1}}{k!} = \frac{1}{k!e}.$$

Example 20. Toss a fair coin n times. Let L_n denote the length of longest sequence of consecutive heads.

$$\begin{aligned} E &= \{\text{there is a sequence of } k \text{ heads in a row}\} \\ &= \{L_n \geq k\} \end{aligned}$$

$$= \bigcup_{i=1}^{n-k+1} E_i, \text{ where } E_i = \{\text{tosses } i, i+1, \dots, i+k-1 \text{ are all heads}\}$$

We have $\mathbb{P}(E_i) = \frac{1}{2^k}$. However, these events are far from independence:

$$\mathbb{P}(E_i|E_j) = \frac{1}{2^k} \text{ if } i-j \geq k,$$

but $\mathbb{P}(E_i|E_{i-1}) = \frac{1}{2}$. So the Poisson paradigm does not apply in this setting. ☹

Fortunately, we can fix the problem by letting $E = \bigcup_{i=1}^{n-k+1} E'_i$, where

$$E'_i = \begin{cases} \text{tosses } i, i+1, \dots, i+k-1 \text{ are all heads AND } i+k \text{ is tail} & \text{if } 1 \leq i \leq n-k \\ \text{tosses } n-k+1, n-k+2, \dots, n \text{ are all heads} & \text{if } i = n-k+1. \end{cases}$$

Then

$$\mathbb{P}(E'_i) = \begin{cases} \frac{1}{2^{k+1}} & \text{if } 1 \leq i \leq n-k \text{ (fix outcome of } k+1 \text{ tosses)} \\ \frac{1}{2^k} & \text{if } i = n-k+1 \text{ (same as before)} \end{cases}$$

Hence we have

$$\mathbb{P}(E'_i|E'_j) = \begin{cases} \mathbb{P}(E_i) & \text{if } i, j \text{ are far apart} \\ 0 & \text{if sequence overlap} \rightarrow \text{close to } \mathbb{P}(E'_i). \end{cases}$$

Then Poisson paradigm applies. ☺

\Rightarrow The number of k heads followed by a tail at the end of tosses is

$$X_k \sim \text{Poi}\left(\frac{n-k}{2^{k+1}} + \frac{1}{2^k}\right) = \text{Poi}\left(\frac{n-k+2}{2^{k+1}}\right).$$

$$\{L_n \leq k\} = \{X_{k+1} = 0\}$$

By the Poisson paradigm,

$$\begin{aligned} \mathbb{P}(X_{k+1} = 0) &\simeq \frac{\lambda_{k+1}^0 e^{-\lambda_{k+1}}}{0!} \\ &= e^{-\lambda_{k+1}}, \text{ where } \lambda_{k+1} = \frac{n-k+1}{2^{k+2}} \end{aligned}$$

$$\begin{aligned}\mathbb{P}(L_n \leq k) &\simeq e^{-\frac{n-k+1}{2^{k+2}}} \\ &\simeq e^{-\frac{n}{2^{k+2}}}\end{aligned}$$

Finally,

$$\begin{aligned}\mathbb{P}(L_n = k) &= \mathbb{P}(L_n \leq k) - \mathbb{P}(L_n \leq k-1) \\ &= e^{-\frac{n}{2^{k+2}}} - e^{-\frac{n}{2^{k+1}}} \\ &= e^{-\frac{n}{2^{k+2}}} \left(1 - e^{-\frac{n}{2^{k+2}}}\right)\end{aligned}$$

In order to have $\mathbb{P}(L_n = k) \not\rightarrow 0$, we need $e^{-\frac{n}{2^{k+2}}} \not\rightarrow 0$ and $e^{-\frac{n}{2^{k+2}}} \not\rightarrow 1$.

Therefore we need $k \simeq \log_2 n - 2$.

7.3 Geometric Distribution

Setting:

- Independent trials, successful with probability p .
- How many trials until our first success?

Denoted by $\text{Geom}(p)$.

Distribution: $\mathbb{P}(X = k) = \mathbb{P}(\overbrace{FFF \dots F}^{\text{first } k-1 \text{ trials failed}} \underbrace{S}_{\substack{k\text{-th trial} \\ \text{success}}}) = (1-p)^{k-1}p$

Verify this is a valid distribution:

$$\begin{aligned}\sum_{k=1}^{\infty} \mathbb{P}(X = k) &= \sum_{k=1}^{\infty} (1-p)^{k-1}p \\ &= p \sum_{k=1}^{\infty} (1-p)^{k-1} \\ &= p \cdot \frac{1}{1 - (1-p)} = \frac{p}{p} = 1\end{aligned}$$

Statistics. To calculate the expectation of the geometry distribution, we observe

$$\sum_{k=1}^{\infty} x^k = \frac{x}{1-x} \quad (\text{geometric series})$$

$$\stackrel{\frac{d}{dx}}{\Rightarrow} \sum_{k=1}^n kx^{k-1} = (1-x)^{-1} + x(1-x)^{-2} = \frac{1}{(1-x)^2}$$

Substitute $x = 1 - p$, and we can get

$$\mathbb{E}[X] = p \sum_{k=1}^{\infty} k(1-p)^{k-1} = \boxed{\frac{1}{p}}.$$

Example 21. A casino has a game where you have a 50% chance of winning.

If you bet $\$x$, then if you win, you get $\$2x$.

If you lose, you get $\$0$.

Q1. What is your expected profit/loss?

Solution. Let X = profit. Then

$$X = \begin{cases} \$x & \text{if we win, } \mathbb{P} = \frac{1}{2} \\ -\$x & \text{if we lose, } \mathbb{P} = \frac{1}{2}. \end{cases}$$

We have $\mathbb{E}[X] = \frac{1}{2}\$x + \frac{1}{2}(-\$x) = \0 .

Q2. You aren't happy with losing, so your strategy is to keep betting $\$1$ until you win.

What is your expected profit/loss?

Solution.

$$\begin{aligned} X &= \$1 - (\text{number of losses}) \cdot \$1 \\ &= \$2 - \underbrace{(\text{number of trials})}_{\text{Geom}(\frac{1}{2})} \cdot \$1 \end{aligned}$$

Let Y = number of trials until first win. Then $Y \sim \text{Geom}(\frac{1}{2})$. Compute

$$\mathbb{E}[X] = \mathbb{E}[2 - Y] = 2 - \mathbb{E}[Y] = 2 - \frac{1}{\frac{1}{2}} = \boxed{0}.$$

Q3. You have a new strategy: every time we lose, we double our bet and go again. Repeat until we win.

number of games	profit	how much money we need
1	+\$1	\$1
2	-\$1 + \$2 = +\$1	\$1 + \$2 = \$3
3	-\$1 - \$2 + \$4 = +\$1	\$1 + \$2 + \$4 = \$7
\vdots	\vdots	\vdots
k	$-\$1 - \$2 - \dots - \$2^{k-2} + \$2^{k-1} = +\$1$	$\$1 + \$2 + \$4 + \dots + \$2^{k-1} = \$2^k - 1$

Note that no matter how many times you lose before you win, you win \$1 back.

Therefore $\mathbb{E}[X] = \$1$ since $\mathbb{P}(X = 1) = 1$.

However,

$$\begin{aligned}
 \mathbb{E}[\text{amount of money needed}] &= \sum_{k=1}^{\infty} (2^k - 1) \left(\frac{1}{2}\right)^k \\
 &= \sum_{k=1}^{\infty} 1^k - \sum_{k=1}^{\infty} \left(\frac{1}{2}\right)^k \\
 &= \infty - 1
 \end{aligned}$$

Example 22. Coupon collector (See Homework 3.2.)

There are n types of coupons. Every coupon we get is uniformly random, independent of previous coupons.

Q. How many coupon do we need to collect them all?

Solution. Let X_i be the number of coupons we need to get the i -th new coupon after we got the $(i - 1)$ -th. The answer we want is $X_1 + X_2 + \dots + X_n$.

$$X_1 = 1 \quad (\text{first coupon is always new})$$

$$X_2 \sim \text{Geom}\left(\frac{n-1}{n}\right)$$

→ each coupon is independent

→ probability of being new = $\frac{n-1}{n}$

→ repeat until we get a new one

$$X_i \sim \text{Geom}\left(\frac{n-i+1}{n}\right)$$

Therefore

$$\begin{aligned}
 \mathbb{E}[X] &= \mathbb{E}\left[\sum_{i=1}^n X_i\right] = \sum_{i=1}^n \mathbb{E}[X_i] & (\text{LoE}) \\
 &= \sum_{i=1}^n \frac{1}{\frac{n-i+1}{n}} = \sum_{i=1}^n \frac{n}{n-i+1} \\
 &= \sum_{i=1}^n \frac{n}{i} = n \sum_{i=1}^n \frac{1}{i} \\
 &= nH_n \simeq n \log n
 \end{aligned}$$

Calculate the variance of $\text{Geom}(p)$:

$$\begin{aligned}
 \text{Var}(X) &= \mathbb{E}[X^2] - \mathbb{E}[X]^2 \\
 &= \mathbb{E}[X(X-1)] + \underbrace{\mathbb{E}[X]}_{\frac{1}{p}} - \underbrace{\mathbb{E}[X]^2}_{\frac{1}{p^2}}
 \end{aligned}$$

To calculate $\mathbb{E}[X(X-1)]$, observe

$$\begin{aligned}
 \sum_{k=1}^{\infty} kx^{k-1} &= \frac{1}{(1-x)^2} \\
 \xRightarrow{\frac{d}{dx}} \sum_{k=1}^{\infty} k(k-1)x^{k-2} &= \frac{2}{(1-x)^3}
 \end{aligned}$$

Multiply both side by x ,

$$\sum_{k=1}^{\infty} k(k-1)x^{k-1} = \frac{2x}{(1-x)^3}.$$

Substitute $x = 1 - p$, and we can get

$$\begin{aligned}
 \mathbb{E}[X(X-1)] &= \sum_{k=1}^{\infty} k(k-1)(1-p)^{k-1}p \\
 &= p \frac{2(1-p)}{(1-(1-p))^3} = \frac{2(1-p)}{p^2}
 \end{aligned}$$

Therefore

$$\begin{aligned}
 \text{Var}(X) &= \mathbb{E}[X(X-1)] + \mathbb{E}[X] - \mathbb{E}[X]^2 \\
 &= \frac{2(1-p)}{p^2} + \frac{1}{p} - \frac{1}{p^2} = \boxed{\frac{1-p}{p^2}}.
 \end{aligned}$$

Example 23. Estimate X = the number of dice rolls until the first 6.

Then $X \sim \text{Geom}(\frac{1}{6})$.

$$\mathbb{E}[X] = \frac{1}{\frac{1}{6}} = 6$$

$$\text{Var}(X) = \frac{1 - \frac{1}{6}}{\frac{1}{36}} = 30$$

7.4 Other Distributions

Negative Binomial Distribution.

- Repeat independent trials, each with success probability p , until r -th success.
- How many trials do we need?

Observation. When $r = 1$, this is just $\text{Geom}(p)$.

In general, this is sum of r independent $\text{Geom}(p)$ variables.

Distribution: $\mathbb{P}(X = n) = \binom{n-1}{r-1} p^r (1-p)^{n-r}$.

Hypergeometric Distribution.

- Bucket with N balls, m of which are good.
- We draw n balls from the bucket.
- How many are good?

Distribution: $\mathbb{P}(X = k) = \frac{(\text{choice of } k \text{ good balls})(\text{choice of } N - k \text{ bad balls})}{(\text{choice of } N \text{ balls})} = \frac{\binom{m}{k} \binom{N-m}{n-k}}{\binom{N}{n}}$.

Statistics. We try to find the expectation of X .

Imagine we draw the balls one at a time. Let X_i be the indicator of the i -th ball being good.

Then $X = \sum_{i=1}^n X_i$.

$$\mathbb{E}[X] = \sum_{i=1}^n \mathbb{E}[X_i] \tag{LoE}$$

$$\begin{aligned}
&= \sum_{i=1}^n \mathbb{P}(X_i = 1) \\
&= \sum_{i=1}^n \mathbb{P}(i\text{-th ball is good})
\end{aligned}$$

By careful observation, we can find that any of the N balls is equally likely to be the i -th ball. Therefore we can view the i -th ball as uniformly distributed.

Then $\mathbb{P}(i\text{-th ball is good}) = \frac{m}{N}$. Hence $\mathbb{E}[X] = \boxed{\frac{nm}{N}}$.

In conclusion,

Distribution	Definition	Expectation	Variance
$\text{Bin}(n, p)$	number of successes in n trials, each is independent with success probability p	np	$np(1 - p)$
$\lim_{n \rightarrow \infty} \text{Bin}(n, \frac{\lambda}{n}) = \text{Poi}(\lambda)$	number of rare independent events occurring in a fixed time frame	λ	λ
$\text{NB}(1, p) = \text{Geom}(p)$	number of trials needed, each is independent with success probability p , until first success	$\frac{1}{p}$	$\frac{1 - p}{p^2}$
$\text{NB}(r, p)$	number of trials needed, each is independent with success probability p , until r -th success	$\frac{r(1 - p)}{p}$	$\frac{r(1 - p)}{p^2}$
$\text{Hypergeometric}(N, m, n)$	N outcomes, m of which are good, select n without replacement, number of good outcomes	$\frac{nm}{N}$	$\frac{nK(N - K)(N - n)}{N^2(N - 1)}$

8 Continuous Random Variables

8.1 Cumulative Distribution Function

Definition 10. Let X be a random variable. We define the *cumulative distribution function* $F_X : \mathbb{R} \rightarrow [0, 1]$ as

$$F_X(x) = \mathbb{P}(X \leq x).$$

Observation. Given F_X , we have $\mathbb{P}(a < X \leq b) = F_X(b) - F_X(a)$.

This can be obtained from the identity $\{X \leq b\} = \{X \leq a\} \cup \{a < X \leq b\}$ and thus $\mathbb{P}(X \leq b) = \mathbb{P}(X \leq a) + \mathbb{P}(a < X \leq b)$.

Some other properties:

- $F_X(x)$ is increasing in x .
- $\lim_{x \rightarrow \infty} F_X(x) = 1$. This is obtained from

$$\lim_{x \rightarrow \infty} \mathbb{P}(\{X \leq x\}) \stackrel{\text{continuity}}{=} \mathbb{P}\left(\bigcup_{x \rightarrow \infty} \{X \leq x\}\right) = \mathbb{P}(X \in \mathbb{R}) = 1.$$

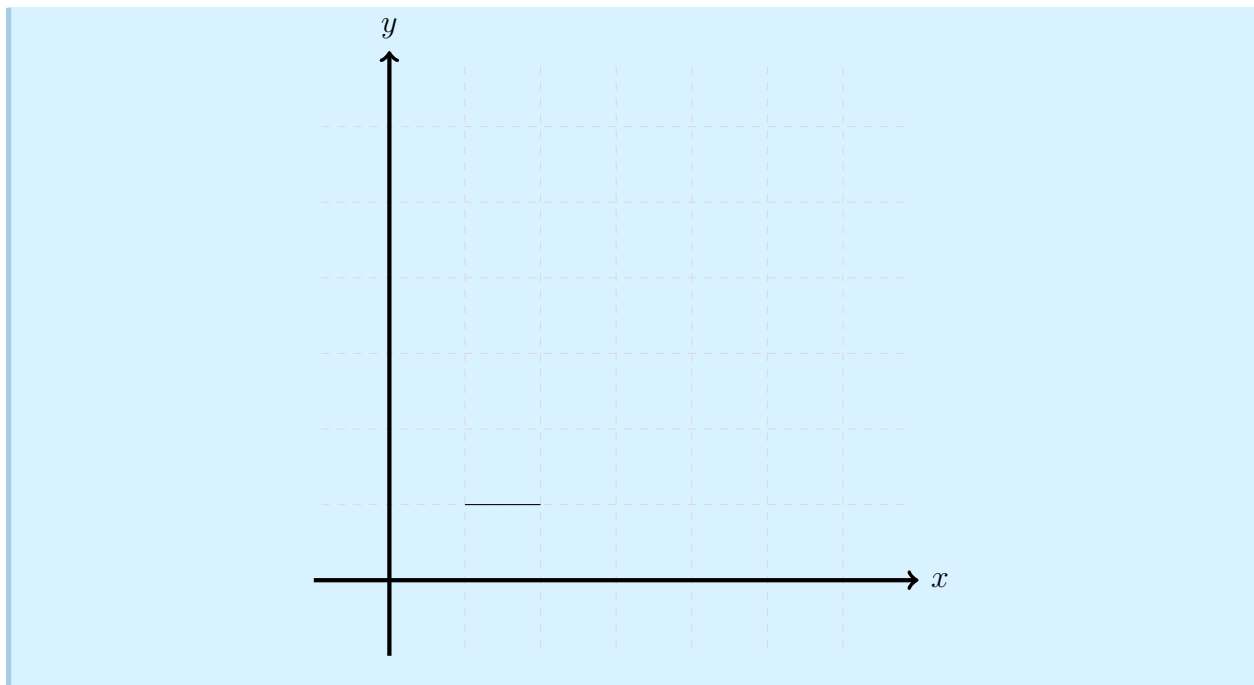
- $\lim_{x \rightarrow -\infty} F_X(x) = 0$.
- If $x_n \searrow x$, then $\lim_{n \rightarrow \infty} F_X(x_n) = F_X(x)$. (right continuity)

This is obtained from $\bigcap_n \{X \leq x_n\} = \{X \leq x\}$.

Remark. If $x_n \nearrow x$, then $\bigcup_n \{X \leq x_n\} = \{X < x\}$, so

$$\lim_{n \rightarrow \infty} F_X(x_n) = F_X(x) - \mathbb{P}(X = x).$$

Example 24. Let X be the outcome of a roll of a die.



8.2 Continuous Random Variable

Many random situation have uncountably many possible outcomes. For example,

- How long over time will this lecture run?
- How many seconds will it take for the first student to fall asleep?

Definition 11. A random variable X is said to be (*absolutely*) *continuous* if there is a function $f : \mathbb{R} \rightarrow \mathbb{R}_{\geq 0}$ such that the cumulative distribution function is given by

$$\mathbb{P}(X \leq x) = F_X(x) = \int_{-\infty}^x f(t) dt.$$

f is called the *probability density function* (pdf).

Q. What does the pdf represent?

Observe that

$$\frac{d}{dx} F_X(x) = f_X(x).$$

If f_X is continuous, then

$$\mathbb{P}(x - \varepsilon \leq X \leq x + \varepsilon) = \mathbb{P}(x + \varepsilon) - \mathbb{P}(x - \varepsilon)$$

$$\begin{aligned}
&= F_X(x + \varepsilon) - F_X(x - \varepsilon) \\
&= \int_{x-\varepsilon}^{x+\varepsilon} f_X(t) \, dt
\end{aligned}$$

More generally, for any event $E \subseteq \mathbb{R}$, $\mathbb{P}(E) = \int_E f_X(t) \, dt$.

Since

$$\int_{x-\varepsilon}^{x+\varepsilon} f_X(t) \, dt \stackrel{f_X \text{ is continuous}}{\simeq} f_X(x) \, dt = 2\varepsilon f_X(x),$$

therefore $f_X(x)$ represents the likelihood

Example 25. Let

$$f(x) = \begin{cases} \frac{C}{x^3} & \text{if } x \geq 1 \\ 0 & \text{if } x < 1 \end{cases}$$

for some constant c .

Q. What is C ? What is $F(X)$?

Solution.

$$F(x) = \int_{-\infty}^x f(t) \, dt = \begin{cases} 0 & \text{if } x < 1 \\ \int_1^x \frac{C}{t^3} \, dt = \frac{-C}{2t^2} = \frac{C}{2} - \frac{C}{2x^2} & \text{if } x \geq 1 \end{cases}$$

Since the total probability is 1, we have

$$\begin{aligned}
1 &= \lim_{x \rightarrow \infty} F(x) = \lim_{x \rightarrow \infty} \frac{C}{2} - \frac{C}{2x^2} = \frac{C}{2} \\
&\Rightarrow C = 2.
\end{aligned}$$

Therefore we have

$$F(x) = \begin{cases} 1 - \frac{1}{x^2} & \text{if } x \geq 1 \\ 0 & \text{if } x \leq 1. \end{cases}$$

8.3 Expectation

In the discrete setting, $\mathbb{E}[X] = \sum_i x_i \cdot \mathbb{P}(X = x_i)$.

For a continuous random variable, observe

$$\mathbb{P}(x - \varepsilon \leq X < x + \varepsilon) \simeq 2\varepsilon f_X(x).$$

Therefore we define

$$\mathbb{E}[X] = \int_{-\infty}^{\infty} t f_X(t) dt.$$

Example 26. Let X have pdf

$$f(x) = \begin{cases} 0 & \text{if } x \leq 1 \\ \frac{2}{x^3} & \text{if } x \geq 1. \end{cases}$$

Q. What is $\mathbb{E}[X]$?

Solution.

$$\begin{aligned} \mathbb{E}[X] &= \int_{-\infty}^{\infty} t f(t) dt \\ &= \int_1^{\infty} t \frac{2}{t^3} dt \\ &= \int_1^{\infty} \frac{2}{t^2} dt \\ &= \left. \frac{-2}{t} \right|_1^{\infty} = \boxed{2} \end{aligned}$$

Example 27. The lecturer walks from their office to the lecture hall. The time of the walk is a random variable W with pdf f_W .

- If the lecturer arrives early, they incur a cost of c per minute.
- If the lecturer arrives late, then they incur a cost of k per minute.

Q1. If the lecturer leaves the office t before the lecture starts, what is the expected cost?

Q2. When should they leave to minimize the cost?

Solution.

The cost if the walk takes w minute is

$$g_t(w) := \begin{cases} c(t - w) & \text{if } w \leq t \\ k(w - t) & \text{if } w \geq t \end{cases}$$

The expectation cost is

$$\begin{aligned} \mathbb{E}[g_t(w)] &= \int_{-\infty}^{\infty} g_t(w) f_W(w) \, dw \\ &= \int_0^{\infty} g_t(w) f_W(w) \, dw \\ &= \int_0^t g_t(w) f_W(w) \, dw + \int_t^{\infty} g_t(w) f_W(w) \, dw \\ &= \int_0^t c(t - w) f_W(w) \, dw + \int_t^{\infty} k(w - t) f_W(w) \, dw \\ &=: C(t) \end{aligned}$$

To minimize the expected cost, differentiate with respect to t .

$$\begin{aligned} \frac{dC}{dt} &= \frac{d}{dt} \left(\int_0^t c(t - w) f_W(w) \, dw + \int_t^{\infty} k(w - t) f_W(w) \, dw \right) \\ &= \cancel{c(t - w) f(w) \Big|_{w=t}} + \int_0^t c f_W(w) \, dw - \int_t^{\infty} k f_W(w) \, dw - \cancel{k(w - t) f(w) \Big|_{w=t}} \\ &= \int_0^t (c + k) f_W(w) \, dw - \int_0^{\infty} k f_W(w) \, dw \\ &= (c + k) F_W(t) - k \end{aligned}$$

Setting the derivative equal to 0,

$$\begin{aligned} \frac{dC}{dt} = 0 &\iff (c + k) F_W(t) - k \\ &\iff F_W(t) = \frac{k}{c + k} \end{aligned}$$

Therefore the optimal t is $F_W^{-1} \left(\frac{k}{c + k} \right)$.

Observe that the linearity of expectation still works for continuous random variables (by the linearity of integral).

8.4 Variance

We define the variance as before

$$\text{Var}(X) = \mathbb{E}[(X - \mathbb{E}[X])^2] = \int_{-\infty}^{\infty} (t - \mathbb{E}[X])^2 f(t) dt.$$

Alternatively, $\text{Var}(X) = \mathbb{E}[X^2] - \mathbb{E}[X]^2$.

Example 28. Let

$$f_X(x) = \begin{cases} \frac{2}{x^3} & \text{if } x \geq 1 \\ 0 & \text{if } x \leq 1 \end{cases}$$

We saw that $\mathbb{E}[X] = 2$. What is $\text{Var}(X)$?

Compute

$$\begin{aligned} \mathbb{E}[X^2] &= \int_{-\infty}^{\infty} t^2 f(t) dt \\ &= \int_1^{\infty} t^2 \cdot \frac{2}{x^3} dt \\ &= \int_1^{\infty} \frac{2}{t} dt \\ &= 2 \ln t \Big|_1^{\infty} \\ &= \infty \end{aligned} \tag{!!}$$

Example 29. Game show

Two envelopes are with $\$x$ and one with $\$y$, and $1 \leq x < y$.

First choose an envelope and open it. Then decide whether to take it or take the other.

Q. What strategy can we use to maximize the chance of getting the more valuable envelope?

Solution. Attempts to give a lower bound:

50%. Choose a random envelope and keep it no matter what.