

Tutorial 2: October 16

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2.1 Independence and Conditional Probability

Let us first recall the definition of independent events.

Let $(\Omega, \mathcal{F}, \mathbb{P})$ be a given probability space [The mandatory preamble]

Definition (Independence of Events). A family of events $\{A_i : i \in I\}$ s.t. $A_i \in \mathcal{F}, \forall i \in I$ is said to be *independent* if for any finite set $J \subseteq I$,

$$\mathbb{P}\left(\bigcap_{i \in J} A_i\right) = \prod_{i \in J} \mathbb{P}(A_i).$$

Further, we had seen the following definition of conditional independence with respect to a given event $C \in \mathcal{F}$:

Definition (Conditional Independence of Events). A family of events $\{A_i \in \mathcal{F} : i \in I\}$ is said to be conditionally independent given an event $C \in \mathcal{F}$ such that $\mathbb{P}(C) > 0$, if for any finite set $J \subseteq I$,

$$\mathbb{P}\left(\bigcap_{i \in J} A_i \mid C\right) = \prod_{i \in J} \mathbb{P}(A_i | C)$$

Let us take a look at some examples of these in action:

Example (Independence $\not\Rightarrow$ Conditional Independence). Let us consider the roll of two dice. Then, $\Omega = \{1, 2, \dots, 6\}^2$, $\mathcal{F} = 2^\Omega$, $\mathbb{P}(\{(i, j)\}) = 1/36 \forall (i, j) \in \Omega$.

- Let A be the event that the first roll results in a 3.
- Let B be the event that the second roll results in a 1.
- Let C be the event that the sum of the two rolls is *even*.

From the definition of the probability measure on the event space, it is immediate that A, B are independent events, i.e.,

$$\mathbb{P}(A \cap B) = \mathbb{P}(A)\mathbb{P}(B).$$

However, it is NOT true that A, B are conditionally independent given C . To see this,

$$\begin{aligned}\mathbb{P}(A \cap B | C) &= \frac{\mathbb{P}(A \cap B)}{\mathbb{P}(C)} \\ \frac{\mathbb{P}(A)\mathbb{P}(B)}{\mathbb{P}(C)} &= \frac{1/36}{1/2} = \frac{1}{18}\end{aligned}$$

On the other hand,

$$\begin{aligned}\mathbb{P}(A | C)\mathbb{P}(B | C) &= \frac{\mathbb{P}(A \cap C)\mathbb{P}(B \cap C)}{(\mathbb{P}(C))^2} \\ &= \frac{\frac{1}{12} \cdot \frac{1}{12}}{\left(\frac{1}{2}\right)^2} = \frac{1}{36} \neq \mathbb{P}(A \cap B | C).\end{aligned}$$

To see an example where this conditional independence does not imply independence of events, consider the experiment designed as follows:

Example (Conditional Independence $\not\Rightarrow$ Independence). I have two coins C_1, C_2 where C_1 is fair (unbiased) and C_2 shows heads with probability 1. I choose a coin uniformly at random from C_1 and C_2 and toss it twice.

Question: What are Ω, \mathcal{F} and \mathbb{P} , here? Is it that $\Omega = \{H, T\}^2$ and $\mathcal{F} = 2^\Omega$? Or does this lead to some difficulty in writing down the probability measure?

Define the following events:

- $A := \{\text{First toss results in a } H\}$
- $B := \{\text{Second toss results in a } H\}$
- $C := \{\text{Coin } C_1 \text{ is selected}\}$

It can be easily be seen that $\mathbb{P}(A \cap B | C) = \mathbb{P}(A | C)\mathbb{P}(B | C)$. However, it must be noted that in this case, events A and B are not independent. To see this, carry out the following computations in a simple exercise:

$$\mathbb{P}(A) = 3/4; \mathbb{P}(B) = 3/4; \mathbb{P}(A \cap B) = 5/8 \neq \mathbb{P}(A)\mathbb{P}(B) = 9/16.$$

The next example is based on a statistical model known as ‘‘Polya’s Urn Model’’. This finds application in population genetics, image recognition, and linguistic analysis.

Example. An urn contains r red balls and b blue balls. A ball is chosen at random from the urn, its colour is noted, and it is returned back to the urn along with d more balls of the same colour. This is repeated indefinitely.

Let us assume a suitably defined $(\Omega, \mathcal{F}, \mathbb{P})$.

1. What is the probability that the second ball is blue?

Solution: Let B_2 be the event that the second ball drawn is blue, and let B_1 be the event that the first ball drawn is blue. By an application of the *law of total probability*,

$$\begin{aligned}\mathbb{P}(B_2) &= \mathbb{P}(B_2 | B_1)\mathbb{P}(B_1) + \mathbb{P}(B_2 | B_1^c)\mathbb{P}(B_1^c) \\ &= \left(\frac{b}{b+r+d}\right)\left(\frac{r}{b+r}\right) + \left(\frac{b+d}{b+r+d}\right)\left(\frac{b}{b+r}\right) \\ &= \frac{b}{b+r} \quad \text{[This is not dependent on } d\text{!]} \end{aligned}$$

Remark. In general, let B_n , for $n \geq 1$, $n \in \mathbb{N}$ be the event that the n^{th} ball drawn is blue. Using some sophisticated analysis, it can be shown that

$$\mathbb{P}(B_n) = \mathbb{P}(B_1) = \frac{b}{b+r} \quad \forall n \geq 1, n \in \mathbb{N}.$$

2. Find the probability that the first ball is blue given that the n subsequent balls drawn are all blue. Find the limit of this probability as n tends to ∞ .

Solution: Let us make use of notation from the previous remark. Now,

$$\begin{aligned} \mathbb{P}(B_1 | B_2 \cap B_3 \cap \dots \cap B_n) &= \frac{\mathbb{P}(B_1 \cap B_2 \cap B_3 \cap \dots \cap B_n)}{\mathbb{P}(B_2 \cap B_3 \cap \dots \cap B_n)} \\ &= \frac{\left(\frac{b}{b+r}\right) \left(\frac{b+d}{b+r+d}\right) \dots \left(\frac{b+nd}{b+r+nd}\right)}{\left(\frac{b}{b+r}\right) \left(\frac{b+d}{b+r+d}\right) \dots \left(\frac{b+(n-1)d}{b+r+(n-1)d}\right)} \cdot 1 = \frac{b+nd}{b+r+nd}. \end{aligned}$$

Thus, we have that $\lim_{n \rightarrow \infty} \mathbb{P}(B_1 | B_2 \cap B_3 \cap \dots \cap B_n) = 1$.

Exercise 2.1. Give a probability space $(\Omega, \mathcal{F}, \mathbb{P})$, let $\{A_n\}_{n \geq 1} \in \mathcal{F}$, and $\{B_n\}_{n \geq 1} \in \mathcal{F}$ such that $A_1 \subseteq A_2 \subseteq \dots$, and $B_1 \subseteq B_2 \subseteq \dots$, and $B = \bigcup_{n \in \mathbb{N}} B_n$, $A = \bigcup_{n \in \mathbb{N}} A_n$. Let $\mathbb{P}(B) > 0$ and $\mathbb{P}(B_n) > 0 \forall n \in \mathbb{N}$. Show that

- (a) $\lim_{n \rightarrow \infty} \mathbb{P}(A_n | B) = \mathbb{P}(A | B)$.
- (b) $\lim_{n \rightarrow \infty} \mathbb{P}(A | B_n) = \mathbb{P}(A | B)$.

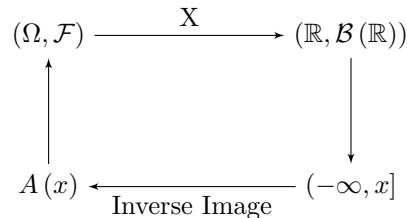
2.2 Random Variables

Let $(\Omega, \mathcal{F}, \mathbb{P})$ be a given probability space.

Definition. A random variable $X : \Omega \rightarrow \mathbb{R}$ is a real-valued function that maps elements in Ω to \mathbb{R} such that for each $x \in \mathbb{R}$, the event

$$A(x) := \{\omega \in \Omega : X(\omega) \leq x\} \in \mathcal{F}.$$

A picture helps cement this idea:



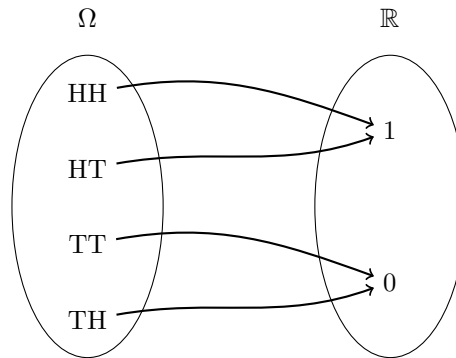
In other words, in order for X to be an \mathcal{F} -measurable RV, the inverse image (this is a set inverse!) of $(-\infty, x]$, called $A(x) \subset \Omega$, must belong to \mathcal{F} .

Let us look at some examples now.

Example. 1. $\Omega = \{H, T\}^2$, $\mathcal{F} = 2^\Omega$
 $X : \Omega \rightarrow \mathbb{R}$ is given by:

- $X(HH) = 1$,
- $X(HT) = 1$,
- $X(TH) = 0$, and
- $X(TT) = 0$.

X is the RV “heads on the first toss”.



We then have

$$X^{-1}(\mathbb{R}) = \Omega, \text{ and}$$

$$X^{-1}((-\infty, x]) = \begin{cases} \emptyset, & \text{if } x < 0, \\ \{HH, HT\}, & \text{if } 0 \leq x < 1, \\ \Omega, & \text{if } x \geq 1. \end{cases}$$

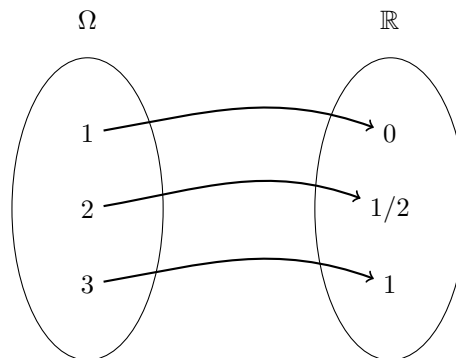
Note that X is an \mathcal{F} -measurable RV

$\Omega = 1, 2, 3, \mathcal{F} = \Omega, \emptyset, 1, 2, 3$

We define X as follows

$$X(1) = 0, \quad X(2) = 1/2, \quad X(3) = 1.$$

Pictorially, the mapping X is given below:



Now,

$$X^{-1}(\mathbb{R}) = \Omega, \text{ and}$$

$$X^{-1}((-\infty, x]) = \begin{cases} \emptyset & x < 0, \\ \{1\} & 0 \leq x < 1/2, \\ \{1, 2\} & 1/2 \leq x < 1, \\ \Omega & x \geq 1. \end{cases}$$

But note that $X^{-1}((-\infty, 2/3]) = \{1, 2\} \notin \mathcal{F}$.
Hence X is not \mathcal{F} -measurable.

Example (Constructing RVs from σ -algebras). Let $\Omega = \{1, 2, 3\}$

1. $\mathcal{F} = \{\Omega, \emptyset\}$. Here, the only \mathcal{F} -measurable RVs are constant RVs, i.e.,

$$X(\omega) = c, \forall \omega \in \Omega, c \in \mathbb{R}$$

2. $\mathcal{F} = \{\Omega, \emptyset, \{1\}, \{2, 3\}\}$.

Here, the \mathcal{F} -measurable RVs look like

$$X(\omega) = \begin{cases} c_1, & \text{if } \omega = 1, \\ c_2, & \text{if } \omega \in \{2, 3\}. \end{cases} \quad \text{for } c_1, c_2 \in \mathbb{R}.$$

2.2.1 Types of Random Variables, CDF, PMFs, and PDFs

Recall that the cumulative distribution function $F : \mathbb{R} \rightarrow [0, 1]$ satisfies

- (a) for any $x, y \in \mathbb{R}$ s.t. $x \leq y$, $F(x) \leq F(y)$,
- (b) $F(\cdot)$ is right-continuous,
- (c) $\lim_{x \rightarrow \infty} F(x) = 1$, and $\lim_{x \rightarrow -\infty} F(x) = 0$.

This definition also happens to be the sufficient conditions for any function F to be a CDF.

2.2.1.1 Discrete Random Variables

1. Bernoulli Random Variables: $X \sim \text{Ber}(p)$.

In the above, read \sim as “drawn according to”. p is a parameter of the distribution.

$$X : \Omega \rightarrow \{0, 1\}, \text{ such that } F_X(x) = \begin{cases} 0, & x < 0, \\ 1 - p, & 0 \leq x < 1, \\ 1, & x \geq 1. \end{cases}$$

Example: The outcome of a coin toss can be thought of as a Bernoulli RV, with suitably defined $p \in [0, 1]$.

2. Poisson Random Variable: $X \sim \text{Poi}(\lambda)$, if $X : \Omega \rightarrow \mathbb{N} \cup \{0\}$ such that

$$P_X(x) = \frac{e^{-\lambda} \lambda^x}{x!}, \quad x \in \mathbb{N} \cup \{0\}, \quad \text{and}$$

$$F_X(x) = \sum_{k=0}^x \frac{e^{-\lambda} \lambda^k}{k!}, \quad x \in \mathbb{N} \cup \{0\}.$$

Question: Why are we writing $P_X(x)$? Is it enough if we define the probability measure over such singletons?

Example: The arrival process of customers in a bank can be modelled as a $\text{Poi}(\lambda)$ random variable.

3. Geometric random variables: $X \sim \text{Geo}(p)$, if $X : \Omega \rightarrow \mathbb{N}$, and

$$P_X(x) = p(1-p)^{x-1}, \quad x \in \mathbb{N}$$

$$F_X(x) = \sum_{k=1}^{\infty} p(1-p)^{k-1}, \quad x \in \mathbb{N}.$$

Exercise 2.2. Show that the RV $X \sim \text{Geo}(p)$ satisfies the memoryless property, i.e.,

$$\mathbb{P}\{X > k+n \mid X > n\} \text{ does not depend on } n.$$

2.2.1.2 Continuous Random Variables

Recall that we can specify a continuous random variable X by its density (probability density function, pdf), if it exists.

1. Uniform Random Variable: $X \sim \text{Unif}([a, b])$ if $X : \Omega \rightarrow [a, b]$, and

$$f_X(x) = \begin{cases} \frac{1}{b-a}, & x \in [a, b], \\ 0, & \text{o.w.} \end{cases}$$

2. Exponential Random Variable: $X \sim \text{Exp}(\lambda)$ if $X : \Omega \rightarrow [0, \infty)$ and

$$f_X(x) = \begin{cases} \lambda e^{-\lambda x}, & x \geq 0, \\ 0, & \text{o.w.} \end{cases}$$

Exercise 2.3. Show that the memoryless property holds for an $\text{Exp}(\lambda)$ random variable X :

$$\mathbb{P}\{X > t+s \mid X > s\} = \mathbb{P}\{X > t\} = e^{-\lambda t}.$$

3. Normal Random Variables: $X \sim \mathcal{N}(\mu, \sigma^2)$ if $X : \Omega \rightarrow \mathbb{R}$ and

$$f_X(x) = \frac{1}{\sigma\sqrt{2\pi}} \exp\left(-\frac{(x-\mu)^2}{2\sigma^2}\right), \quad x \in \mathbb{R}.$$

Exercise 2.4. 1. Suppose that a coin of bias p (probability of a head is $p \in [0, 1]$) is tossed once. Define Ω and the largest possible \mathcal{F} . Consider the events:

$$A = \{\text{The coin shows up heads}\},$$

$$B = \{\text{The coin shows up tails}\}.$$

Are events A and B independent?

2. Let us modify the experiment as follows.

Let N be the RV corresponding to a random number of tosses of the coin. Further, let $N \sim \text{Poi}(\lambda)$. Now, let X denote the number of heads in N (random) tosses, and let Y denote the number of tails. Show (by a law of total probability argument) that:

(a) $\mathbb{P}(\{X = x\}) = \frac{(\lambda p)^x e^{-\lambda p}}{x!}$, $x \in \mathbb{N} \setminus \{0\}$ [**Hint: Try conditioning on $\{N = n\}$**].

(b) $\mathbb{P}(\{Y = y\}) = \frac{\lambda(1-p)^y e^{-\lambda(1-p)}}{y!}$, $y \in \mathbb{N} \cup \{0\}$.

(c) What is $\mathbb{P}(\{X = x\} \cap \{Y = y\})$?

[**Hint: Notice that $\mathbb{P}(\{X = x\} \cap \{Y = y\}) = \mathbb{P}(\{X = x\} \cap \{Y = y\} \cap \{N = x + y\})$].**

Exercise 2.5. Consider a continuous RV X with $\Omega = \mathbb{R}$ and $\mathcal{F} = \mathcal{B}(\mathbb{R})$. Show that if X and $-X$ have the same CDF, then

$$f_X(x) = f_X(-x), \forall x \in \mathbb{R}.$$

Exercise 2.6. Consider the Normal RV $Y \sim \mathcal{N}(\mu, \sigma^2)$. Can you write the density function of $Z = aY + b$?
Hint: Start from the CDF of Z and massage it to obtain a CDF of Y .