Chapter 7

Probability.

7.1 Probability Spaces.

Definition 7.1.1. A probability space defined by a tuple (Ω, P) such that:

- 1. Ω is a set, called the sample space. Any element $\omega \in \Omega$ is named an atomic event. Conceptually, we think of atomic events as possible outcomes of our experiment. Any subset $A \subset \Omega$ is an event.
- 2. P, called the probability function, is a function that assigns a number in [0,1] to any event, denoted as $P:2^{\Omega} \to [0,1]$, and satisfies:
 - (a) For any event $A \subset \Omega$, $P(A) = \sum_{w \in A} P(w)$.
 - (b) Normalization, over the atomic events, to 1, which means $\sum_{\omega \in \Omega} P(\omega) = 1$.

Example 7.1.1. [COMMENT] Add dice roll, as an example.

Claim 7.1.1. *Probability function satisfies the following properties:*

- 1. $P(\emptyset) = 0$.
- 2. Monotonic, If $A \subset B \subset \Omega$ then $P(A) \leq P(B)$.
- 3. Union Bound, $P(A \cup B) \leq P(A) + P(B)$.
- 4. Additivity for disjointness events. If $A \cap B = \emptyset$ then $P(A \cup B) = P(A) + P(B)$.
- 5. Denote by \bar{A} the complementary event of A, which means $A \cup \bar{A} = \Omega$. Then, $P(\bar{A}) = 1 P(A)$.

Example 7.1.2. Let's proof the additivity of disjointness property. Let A, B disjointness events, so $A \cap B = \emptyset$ then

$$\begin{split} P(A \cup B) &= \sum_{w \in A \cup B} P(w) \\ &= \underbrace{\sum_{w \in A, w \notin B} P(w)}_{P(A)} + \underbrace{\sum_{w \in B, w \notin A} P(w)}_{P(B)} + \underbrace{\sum_{w \in A, w \in B} P(w)}_{Q(A)} \\ &= P(A) + P(B) \end{split}$$

Definition 7.1.2. Let (Ω, P) be a probability space. A random variable X on (Ω, P) is a function $X: \Omega \to \mathbb{R}$. An indicator, is a random variable defined by an event $A \subset \Omega$ as follows

$$X(\omega) = \begin{cases} 1 & \omega \in A \\ 0 & \omega \notin A \end{cases}$$

Sometimes, we will use the notation $\{X = x\}$ to denote the event A such:

$$A = \{\omega : X(\omega) = x\} := \{X = x\}$$

Example 7.1.3. [COMMENT] Add dice roll, as an example.

Definition 7.1.3. We will say that two random variable $X, Y : \Omega \to \mathbb{R}$ are independent if for any $x \in \text{Iamge } X$ and $y \in \text{Iamge } Y$:

$$P(X = x \cap Y = y) = P(X = x) \cdot P(Y = y)$$

7.2 [COMMENT] Throw Keys to Cells.

[COMMENT] Add the description of throwing keys to cells. Define the random variable X_i^j .

Definition 7.2.1. Let $X : \Omega \to \mathbb{R}$ be a random variable, the expectation of X is

$$\mathbf{E}\left[X\right] = \sum_{\omega \in \Omega} X(\omega) P(\omega) = \sum_{x \in \text{Iamge } X} x P(X = x)$$

Observes that if P is distributed uniformly, then the expectation of X is just the arithmetic mean:

$$\mathbf{E}[X] = \sum_{\omega \in \Omega} X(\omega) P(\omega) = \frac{1}{|\Omega|} \sum_{\omega \in \Omega} X(\omega)$$

Claim 7.2.1. The expectation satisfies the following properties:

- 1. Monotonic, If X < Y (for any $\omega \in \Omega$) then $\mathbf{E}[X] < \mathbf{E}[Y]$.
- 2. Linearity, for $a, b \in \mathbb{R}$ it holds that $\mathbf{E}[aX + by] = a\mathbf{E}[X] + b\mathbf{E}[Y]$.
- 3. Independently, if X, Y are independent, then $\mathbf{E}[X \cdot Y] = \mathbf{E}[X] \cdot \mathbf{E}[Y]$.
- 4. For any constant $a \in \mathbb{R}$ we have that $\mathbf{E}[a] = a$.

Proof.

Monotonic, if $X \leq Y$ then $\mathbf{E}[X] = \sum_{\omega \in \Omega} X(\omega) P(\omega) \leq \sum_{\omega \in \Omega} Y(\omega) P(\omega) = \mathbf{E}[Y]$.

Linearity,

$$\begin{aligned} \mathbf{E}\left[aX+bY\right] &= \sum_{\omega \in \Omega} \left(aX(\omega) + bY(\omega)\right) P(\omega) \\ &= a \sum_{\omega \in \Omega} X(\omega) P(\omega) + b \sum_{\omega \in \Omega} Y(\omega) P(\omega) \end{aligned}$$

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Result: Sorting A_1, A_2, ...A_n
1 for i \in [n] do
2 | for j \in [n] do
3 | if A_i < A_j then
4 | swap A_i \leftrightarrow A_j
5 | end
6 | end
7 end
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Algorithm 1: "ICan'tBelieveItCanSort" alg.