

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 $P : 2^\Omega \rightarrow [0, 1]$, and satisfies:
 - (a) For any event $A \subset \Omega$, $P(A) = \sum_{\omega \in A} P(\omega)$.
 - (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

$$\begin{aligned} P(A \cup B) &= \sum_{w \in A \cup B} P(w) \\ &= \overbrace{\sum_{w \in A, w \notin B} P(w)}^{P(A)} + \overbrace{\sum_{w \in B, w \notin A} P(w)}^{P(B)} + \overbrace{\sum_{w \in A, w \in B} P(w)}^0 \\ &= P(A) + P(B) \end{aligned}$$

Definition 7.1.2. Let (Ω, P) be a probability space. A random variable X on (Ω, P) is a function $X : \Omega \rightarrow \mathbb{R}$. 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 $X, Y : \Omega \rightarrow \mathbb{R}$ are independent if for any $x \in \text{Im } X$ and $y \in \text{Im } Y$:

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

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 $X : \Omega \rightarrow \mathbb{R}$ be a random variable, the expectation of X is

$$\mathbf{E}[X] = \sum_{\omega \in \Omega} X(\omega)P(\omega) = \sum_{x \in \text{Im } X} xP(X = x)$$

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 $X \leq Y$ (for any $\omega \in \Omega$) then $\mathbf{E}[X] \leq \mathbf{E}[Y]$.
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. 1. Monotonic, if $X \leq Y$ then :

$$\mathbf{E}[X] = \sum_{\omega \in \Omega} X(\omega)P(\omega) \leq \sum_{\omega \in \Omega} Y(\omega)P(\omega) = \mathbf{E}[Y]$$

2. Linearity,

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

3. Independently,

$$\begin{aligned}
 \mathbf{E}[XY] &= \sum_{x,y \in \text{Im } X \times \text{Im } Y} xyP(X = x \cap Y = y) \\
 &= \sum_{x,y \in \text{Im } X \times \text{Im } Y} xyP(X = x)P(Y = y) \\
 &= \sum_{x \in \text{Im } X} \sum_{y \in \text{Im } Y} xyP(X = x)P(Y = y) \\
 &= \sum_{x \in \text{Im } X} xP(X = x) \sum_{y \in \text{Im } Y} yP(Y = y) \\
 &= \sum_{x \in \text{Im } X} xP(X = x)\mathbf{E}[Y] \\
 &= \mathbf{E}[X]\mathbf{E}[Y]
 \end{aligned}$$

4. Let X be the random variable which is also the constant function $X(\omega) = a$ for any $\omega \in \Omega$. Then we have that

$$\begin{aligned}
 \mathbf{E}[X] &= \sum_{\omega \in \Omega} X(\omega)P(\omega) \\
 &= \sum_{\omega \in \Omega} aP(\omega) = a \cdot 1 = a
 \end{aligned}$$

□

Example 7.2.1. [COMMENT] *Expectation of indicators and their multiplication.*

Example 7.2.2. [COMMENT] *How many keys trowed into the same cell as the first key thrown to?*

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1 let B[0 : n - 1] be a new array
2 for i ← [0, n-1] do
3   | make Bi an empty list
4 end
5 for i ← [1, n] do
6   | insert Ai into list B[nAi]
7 end
8 for i ← [0, n-1] do
9   | sort list Bi
10 end
11 concatenate the lists B0, B1, ..., Bn-1 together and
12 return the concatenated lists

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Algorithm 1: bucket-sort(A, n)

Denote by $X_i : [n] \rightarrow [n]$ then random variable that counts the number of elements fallen in the i th bucket. The Expectation of the sorting running time is:

$$\begin{aligned}
\mathbf{E}[T] &= \mathbf{E} \left[\text{Inserting into buckets} + \sum_i \text{Sorting } i\text{th bucket} \right] \\
&= \mathbf{E} \left[\Theta(n) + \sum_i X_i^2 \right] = \Theta(n) + \sum_i \mathbf{E}[X_i^2] \\
\mathbf{E}[X_i^2] &= \mathbf{E} \left[\left(\sum X_i^j \right)^2 \right] = \mathbf{E} \left[\sum_{j,j'} X_i^j X_i^{j'} \right] \\
&= \sum_{j,j'} \mathbf{E}[X_i^j X_i^{j'}] = \sum_{j \neq j'} \mathbf{E}[X_i^j X_i^{j'}] + \sum_j \mathbf{E}[X_i^j X_i^j] \\
&= \sum_{j \neq j'} \mathbf{E}[X_i^j X_i^{j'}] + \sum_j \mathbf{E}[X_i^j] \\
&= 2 \binom{n}{2} \left(\frac{1}{n} \right)^2 + n \cdot \frac{1}{n} \\
&= \frac{n-1}{n} + 1
\end{aligned}$$