

About Homework

- Homework 1 will be posted after today's class and is due on **Feb 4**
- You should clearly justify your answer to each question. It is insufficient to only give the final result
- You may discuss homework problems with your classmates. However, what you turn in must be your own

Discrete Probability: a brief review

CMPS 4750/6750: Computer Networks

Applications of Probability in Computer Science

- Information theory
- Networking
- Machine learning
- Algorithms
- Combinatorics
- Cryptography
- ...

Sample Space

- **Experiment**: a procedure that yields one of a given set of possible outcomes
 - Ex: flip a coin, roll two dice, draw five cards from a deck, etc.
- **Sample space Ω** : the set of possible outcomes
 - We focus on **countable** sample space: Ω is finite or countably infinite
 - In many applications, Ω is uncountable (e.g., a subset of \mathbb{R})
- **Event**: a subset of the sample space
 - Probability is assigned to events
 - For an event $A \subseteq \Omega$, its probability is denoted by **$P(A)$**
 - Describes beliefs about likelihood of outcomes

Discrete Probability

- Discrete Probability Law

- A function $P: \mathcal{P}(\Omega) \rightarrow [0,1]$ that assigns probability to events such that:

- $0 \leq P(\{s\}) \leq 1$ for all $s \in \Omega$ (Nonnegativity)

- $P(A) = \sum_{s \in A} P(\{s\})$ for all $A \subseteq \Omega$ (Additivity)

- $P(\Omega) = \sum_{s \in \Omega} P(\{s\}) = 1$ (Normalization)

- Discrete uniform probability law: $|\Omega| = n, P(A) = \frac{|A|}{n} \forall A \subseteq \Omega$

Examples

- Ex. 1: consider rolling a pair of 6-sided **fair** dice
 - $\Omega = \{(i, j): i, j = 1, 2, 3, 4, 5, 6\}$, each outcome has the same probability of $1/36$
 - $P(\{\text{the sum of the rolls is even}\}) = 18/36 = 1/2$
- Ex. 2: consider rolling a 6-sided **biased** (loaded) die
 - Assume $P(3) = \frac{2}{7}, P(1) = P(2) = P(4) = P(5) = P(6) = \frac{1}{7}$
 - $A = \{1, 3, 5\}, P(A) = \frac{1}{7} + \frac{2}{7} + \frac{1}{7} = \frac{4}{7}$

Properties of Probability Laws

- Consider a probability law, and let A , B , and C be events
 - If $A \subseteq B$, then $P(A) \leq P(B)$
 - $P(\bar{A}) = 1 - P(A)$
 - $P(A \cup B) = P(A) + P(B) - P(A \cap B)$
 - $P(A \cup B) = P(A) + P(B)$ if A and B are disjoint, i.e., $A \cap B = \emptyset$

Conditional Probability

- Conditional probability provides us with a way to reason about the outcome of an experiment, based on **partial information**
- Ex. 3: roll a six-sided fair die. Suppose we are told that the outcome is even. *B*
What is the probability that the outcome is 6? *A*

$$P(A \cap B) = \frac{1}{6} \quad P(B) = \frac{1}{2}$$

$$P(A|B) = \frac{P(A \cap B)}{P(B)} = \frac{1}{3}$$

Independence

- We say that event A is **independent** of event B if $P(A | B) = P(A)$
- Two events A and B are independent if and only if $P(A \cap B) = P(A) P(B)$
- We say that the events A_1, A_2, \dots, A_n are (mutually) independent if and only if
$$P(\bigcap_{i \in S} A_i) = \prod_{i \in S} P(A_i),$$
 for every subset S of $\{1, 2, \dots, n\}$

Bernoulli Trials

- **Bernoulli Trial**: an experiment with two possible outcomes
 - E.g., flip a coin results in two possible outcomes: head (H) and tail (T)
- **Independent Bernoulli Trials**: a sequence of Bernoulli trials that are **mutually independent**
- Ex.4: Consider an experiment involving five **independent** tosses of a biased coin, in which the probability of heads is p .
 - What is the probability of the sequence $HHHTT$?
 - $A_i = \{i\text{-th toss is a head}\}$
 - $P(A_1 \cap A_2 \cap A_3 \cap \bar{A}_4 \cap \bar{A}_5) = P(A_1)P(A_2)P(A_3)P(\bar{A}_4)P(\bar{A}_5) = p^3(1 - p)^2$
 - What is the probability that exactly three heads come up?
 - $P(\text{exactly three heads come up}) = \binom{5}{3}p^3(1 - p)^2$

Random Variables

- A **random variable (r.v.)** is a real-valued function of the experimental outcome.
- Ex. 5: Consider an experiment involving three **independent** tosses of a fair coin.
 - $\Omega = \{HHH, HHT, HTH, HTT, THH, THT, TTH, TTT\}$
 - $X(s)$ = the number of heads that appear for $s \in \Omega$.
 - $P(X = 2) = P(\{HHT, HTH, THH\}) = 3/8$
 - $P(X < 2) = P(\{HTT, THT, TTH, TTT\}) = 4/8 = 1/2$
- A **discrete** random variable is a **real-valued** function of the outcome of the experiment that can take a **finite or countably infinite** number of values

Probability Mass Functions

- Let X be a discrete r.v. Then the **probability mass function (PMF)**, $p_X(\cdot)$ of X , is defined as:

$$p_X(x) = P(X = x) = P(s \in \Omega: X(s) = x)$$

$$- \sum_x p_X(x) = 1$$

$$- P(X \in S) = \sum_{x \in S} p_X(x)$$

- The **cumulative distribution function (CDF)** of X is defined as

$$F_X(a) = P(X \leq a) = \sum_{x \leq a} p_X(x)$$

Bernoulli Distribution

- Consider a Bernoulli trial with probability of success p . Let X be a r.v. where $X = 1$ if “success” and $X = 0$ if “failure”

$$X = \begin{cases} 1 & \text{w/prob } p \\ 0 & \text{otherwise} \end{cases}$$

We write $X \sim \text{Bernoulli}(p)$. The PMF of X is defined as:

$$p_X(1) = p$$

$$p_X(0) = 1 - p$$

Binomial Distribution

- Consider an experiment of n independent Bernoulli trials, with the probability of success p . Let the r.v. X be the number of successes in the n trials.
- The PMF of X is defined as:

$$\begin{aligned} p_X(k) &= P(X = k) \\ &= \binom{n}{k} p^k (1 - p)^{n-k}, \text{ where } k = 0, 1, 2, \dots, n \end{aligned}$$

We write $X \sim \text{Binomial}(n, p)$.

Geometric Distribution

- Consider an experiment of independent Bernoulli trials, with probability of success p . Let X be the number of trials to get one success.
- Then the PMF of X is:

$$P(X = k) = (1 - p)^{k-1}p, \text{ where } k = 1, 2, 3 \dots$$

We write $X \sim \text{Geometric}(p)$.

Expected Value

- The **expected value** (also called the **expectation** or the **mean**) of a random variable X on the sample space Ω is equal to

$$\begin{aligned} E(X) &= \sum_{s \in \Omega} X(s) P(\{s\}) \\ &= \sum_x x p_X(x) \end{aligned}$$

Ex. 6: If $X \sim \text{Bernoulli}(p)$, $E(X) = 1 \cdot p + 0 \cdot (1 - p) = p$

Ex. 7: If $X \sim \text{Geometric}(p)$, $E(X) = \sum_{k=1}^{\infty} k(1-p)^{k-1}p = \frac{1}{p}$

Linearity of Expectations

- If $X_i, i = 1, 2, \dots, n$ are random variables on Ω , and a and b are real numbers, then

$$- E(X_1 + X_2 + \dots + X_n) = E(X_1) + E(X_2) + \dots + E(X_n)$$

$$- E(aX + b) = aE(X) + b$$

- Ex. 8: $X \sim \text{Binomial}(n, p)$

$$- E(X) = \sum_{k=0}^n k \binom{n}{k} p^k (1-p)^{n-k} = np$$

Variance

- The **variance** of a random variable X on the sample space Ω is equal to

$$\begin{aligned}\text{Var}(X) &= \text{E} \left[(X - \text{E}(X))^2 \right] \\ &= \text{E}(X^2) - \text{E}(X)^2\end{aligned}$$

- The variance provides a measure of dispersion of X around its mean
- Another measure of dispersion is the **standard deviation** of X :

$$\sigma(X) = \sqrt{\text{Var}(X)}$$

Moment-Generating Functions

- The moment-generating function of a r.v. X is

$$M_X(t) = E(e^{tX}), t \in \mathbb{R}$$

$$e^{tX} = 1 + tX + \frac{t^2 X^2}{2!} + \frac{t^3 X^3}{3!} + \dots + \frac{t^n X^n}{n!} + \dots$$

$$\Rightarrow M_X(t) = 1 + tE(X) + \frac{t^2 E(X^2)}{2!} + \frac{t^3 E(X^3)}{3!} + \dots + \frac{t^n E(X^n)}{n!} + \dots$$

$$\Rightarrow \frac{d^n M_X(0)}{dt^n} = E(X^n)$$

Joint Probability and Independence

- The **joint probability mass function** between discrete r.v.'s X and Y is defined by

$$p_{X,Y}(x, y) = P\{X = x \text{ and } Y = y\}$$

- We say two discrete r.v.'s X and Y are **independent** if

$$p_{X,Y}(x, y) = p_X(x) \cdot p_Y(y), \quad \forall x, y$$

- **Theorem:** If two r.v.'s X and Y are independent, then $E(XY) = E(X)E(Y)$