

# Probability and Random Process (SWE3026)

## Discrete Random Variables

**JinYeong Bak**

**jy.bak@skku.edu**

**College of Computing, SKKU**

# Expectation

Expected value (= mean=average):

$$a_1, a_2, \dots, a_n \Rightarrow \bar{a} = \frac{a_1 + a_2 + \dots + a_n}{n}.$$

**Definition.** Let  $X$  be a discrete random variable with range  $R_X = \{x_1, x_2, x_3, \dots\}$ . The **expected value** of  $X$ , denoted by  $EX$  is defined as

$$EX = \mu_X = \sum_{x_k \in R_X} x_k P(X = x_k) = \sum_{x_k \in R_X} x_k P_X(x_k).$$

# Expectation

Repeat the experiment  $N$  times ( $N$  large).

$$P(X = x_k) = P_X(x_k) = \frac{(\text{The number of times } X = x_k)}{N} = \frac{N_k}{N},$$

$$\Rightarrow N_k \approx NP_X(x_k),$$

$$\begin{aligned}\text{Average} &= \frac{N_1x_1 + N_2x_2 + N_3x_3 + \dots}{N} \\ &\approx \frac{x_1NP_X(x_1) + x_2NP_X(x_2) + x_3NP_X(x_3) + \dots}{N} \\ &= x_1P_X(x_1) + x_2P_X(x_2) + x_3P_X(x_3) + \dots \\ &= EX.\end{aligned}$$

# Expectation

**Example.** Let  $X \sim \text{Bernoulli}(p)$ , find  $EX$ .

# Expectation

**Example.** Let  $X \sim \text{Geometric}(p)$ , find  $EX$ .

# Expectation

**Example.** Let  $X \sim \text{Poisson}(\lambda)$ , find  $EX$ .

# Summary

## Discrete RVs:

- **Range:**  $R_X = \{x_1, x_2, x_3, \dots\}$ .
- **PMF:**  $P_X(x_k) = P(X = x_k)$ .
- **CDF:**  $F_X(x) = P(X \leq x)$ , for all  $x \in \mathbb{R}$ .
- **Expected value:**  $\mu_X = E[X] = \sum_{x_k \in R_X} x_k P_X(x_k)$ .

# Summary

- $X \sim \text{Bernoulli}(p), \quad EX = p.$
- $X \sim \text{Geometric}(p), \quad EX = \frac{1}{p}.$
- $X \sim \text{Poisson}(\lambda), \quad EX = \lambda.$



# Functions of Random Variables

If  $X$  is a random variable and  $Y = g(X)$ , then  $Y$  itself is a random variable.

For example:  $Y = X^2$ .

$$R_X = \{x_1, x_2, x_3, \dots\} \rightarrow R_Y = \{g(x) | x \in R_X\} = \{g(x_1), g(x_2), \dots\}.$$

Then,

$$P_Y(y_k) = P(Y = y_k) = P(g(X) = y_k).$$

# Functions of Random Variables

**Example.** Let  $X$  be a discrete random variable uniformly distributed with

$$P_X(k) = \frac{1}{5}, \text{ for } k = \{-2, -1, 0, 1, 2\}. \text{ Let } Y = |X|.$$

a) Find PMF of  $Y$ ,  $P_Y(y)$ .

b) Find  $EY$ .

# Functions of Random Variables

Law of the unconscious statistician (LOTUS) for discrete random variables:

$$E[g(X)] = \sum_{x_k \in R_X} g(x_k) P_X(x_k).$$

In the previous example  $g(X) = |X|$ ,

$$\begin{aligned} E[|X|] &= |-2| \cdot \frac{1}{5} + |-1| \cdot \frac{1}{5} + |0| \cdot \frac{1}{5} + |1| \cdot \frac{1}{5} + |2| \cdot \frac{1}{5} \\ &= \frac{6}{5}. \end{aligned}$$

# Functions of Random Variables

Linearity of expectation:

$$Y = aX + b \Rightarrow E[Y] = aEX + b, \quad a, b \in \mathbb{R}$$

**Proof:** Here  $g(X) = aX + b$ , so using LOTUS we have

$$\begin{aligned} E[Y] &= E[g(X)] = \sum g(x_k)P_X(x_k) = \sum_{x_k \in R_X} (ax_k + b)P_X(x_k) \\ &= a \underbrace{\sum_{x_k \in R_X} x_k P_X(x_k)}_{\substack{\longrightarrow \\ EX}} + b \underbrace{\sum_{x_k \in R_X} P_X(x_k)}_{\substack{\longrightarrow \\ 1}} \\ &= aEX + b. \end{aligned}$$

# Functions of Random Variables

More generally (Linearity of expectation):

$$Y = X_1 + X_2 + \cdots + X_n \Rightarrow E[Y] = E[X_1] + E[X_2] + \cdots + E[X_n].$$

**Example.**  $X \sim \text{Binomial}(n, p)$ ,  $EX$ ?

# Functions of Random Variables

**Example.** Let  $R_X = \{0, \frac{\pi}{4}, \frac{\pi}{2}, \frac{3\pi}{4}, \pi\}$  , such that

$$P_X(0) = P_X(\frac{\pi}{4}) = P_X(\frac{\pi}{2}) = P_X(\frac{3\pi}{4}) = P_X(\pi) = \frac{1}{5}$$

**Find**  $E[\sin(X)]$ .

# Variance

The **variance** is a measure of how spread out the distribution of a random variable is.

$$EX = \mu_X \rightarrow E[X - \mu_X] = E[X] - E[\mu_X] = \mu_X - \mu_X = 0.$$

The **variance** of a random variable  $X$ , with mean  $EX = \mu_X$ , is defined as

$$\text{Var}(X) = E[(X - \mu_X)^2], \quad \mu_X = EX.$$

# Variance

The **standard deviation** of a random variable  $X$  is defined as

$$\text{SD}(X) = \sigma_X = \sqrt{\text{Var}(X)}.$$



# Variance

**Theorem.** Computational formula for the variance:

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

**Proof:**

$$\begin{aligned}\text{Var}(X) &= E[(X - \mu_X)^2] \\ &= E[X^2 - 2\mu_X X + \mu_X^2] \\ &= E[X^2] - 2E[\mu_X X] + E[\mu_X^2] \quad \text{by linearity of expectation.} \\ &= E[X^2] - 2\mu_X^2 + \mu_X^2 \\ &= E[X^2] - \mu_X^2.\end{aligned}$$

# Variance

**Example.**  $X \sim \text{Bernoulli}(p)$ ,  $\text{Var}(X)$ ?

# Variance

**Theorem.** For a random variable  $X$  and real numbers  $a$  and  $b$ ,

$$\text{Var}(aX + b) = a^2 \text{Var}(X).$$

**Proof:**

If  $Y = aX + b$ ,  $EY = aEX + b$ . Thus,

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

# Variance

**Theorem.** If  $X_1, X_2, \dots, X_n$  are **independent** random variables and  $X = X_1 + X_2 + \dots + X_n$ , then

$$\text{Var}(X) = \text{Var}(X_1) + \text{Var}(X_2) + \dots + \text{Var}(X_n).$$

# Variance

**Example.**  $X \sim \text{Binomial}(n, p)$ ,  $\text{Var}(X)$ ?