

## 1 Chapter 1

## 2 Chapter 2

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## 4 Chapter 4

### 4.1 Random Variables

**Definition 4.1:** A **random variable**,  $X$ , is a mapping from the sample space to real numbers.

### 4.2 Discrete Random Variables

**Definition 4.2:** A random variable is said to be **discrete** if range of  $X$  is either **finite** or **countably infinite**.

**Definition 4.3:** The **probability mass function** (pmf) of a discrete random variable  $X$  is defined by

$$p_X(x) = \begin{cases} P(X = x), & \text{if } x = x_1, x_2, \dots \\ 0, & \text{otherwise.} \end{cases}$$

Note that  $\sum_{i=1}^{\infty} p_X(x_i) = 1$ .

**Definition 4.4:** The **cumulative distribution function** (cdf) of a discrete random variable  $X$  is defined as  $F_X : \mathbb{R} \rightarrow \mathbb{R}^T$  where  $F_X(x) = P(X \leq x)$ , for  $x \in \mathbb{R}$ .

### 4.3 Expected Value

**Definition 4.5:** If  $X$  is a discrete random variable having a probability mass function  $p_X$ , the **expectation** or **expected value** of  $X$  is defined by

$$E(X) = \sum_x x p_X(x).$$

**Tail Sum Formula:** For **nonnegative integer-valued** random variable  $X$ , we have

$$E(X) = \sum_{k=1}^{\infty} P(X \geq k) = \sum_{k=0}^{\infty} P(X > k).$$

### 4.4 Expectation of a Function of a Random Variable

**Proposition 4.1** If  $X$  is a **discrete random variable** that takes values  $x_i$ ,  $i \geq 1$ , with respective probabilities  $p_X(x_i)$ , then for any real value function  $g$ ,

$$\begin{aligned} E[g(X)] &= \sum_i g(x_i) p_X(x_i) \quad \text{or equivalently} \\ &= \sum_x g(x) p_X(x). \end{aligned}$$

**Corollary 4.2** Let  $a$  and  $b$  be constants, then

$$E[aX + b] = aE(X) + b.$$

### 4.5 Variance and Standard Deviation

**Definition 4.6** If  $X$  is a random variable with mean  $\mu$ , then the **variance** of  $X$ , denoted by  $\text{Var}(X)$ , is defined by

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

**Definition 4.7** The **standard deviation** of  $X$ , denoted by  $\sigma_X$  or  $\text{SD}(X)$ , is defined by

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

**Scaling and shifting:**

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

### 4.6 Discrete Random Variables Arising from Repeated Trials

**Bernoulli Random Variable:**  $\text{Be}(p)$ , define

$$X = \begin{cases} 1, & \text{if it is a success;} \\ 0 & \text{if it is a failure.} \end{cases}$$

- $P(X = 1) = p;$
- $P(X = 0) = 1 - p;$
- $E(X) = p;$
- $\text{Var}(X) = p(1 - p).$

**Binomial Random Variable:**  $\text{Bin}(n, p)$ , define  $X$  as **number of successes** in  $n$  **Bernoulli** ( $p$ ) trials.

Therefore,  $X$  takes values  $0, 1, 2, \dots, n$ .

- $P(X = k) = \binom{n}{k} p^k (1 - p)^{n-k};$
- $E(X) = np;$
- $\text{Var}(X) = np(1 - p);$

**Geometric Random Variable:**  $\text{Geom}(p)$ , define  $X$  as **number of trials** until the first success in a sequence of independent **Bernoulli** ( $p$ ) trials.

- $P(X = k) = p q^{k-1};$
- $E(X) = \frac{1}{p};$
- $\text{Var}(X) = \frac{1 - p}{p^2};$

**Alternative Geometric Distribution:** Let  $X'$  be the **number of failures** in the **Bernoulli** ( $p$ ) trials in order to obtain the first success. Here,

$$X = X' + 1$$

- $P(X' = k) = p q^k;$
- $E(X') = \frac{1 - p}{p};$
- $\text{Var}(X') = \frac{1 - p}{p^2};$

**Negative Binomial Random Variable:**  $\text{NB}(r, p)$ , define  $X$  to be **number of Bernoulli** ( $p$ ) **trials** required to obtain  $r$  **successes**. For  $k \geq r$ , we have:

- $P(X = k) = \binom{k-1}{r-1} p^r (1 - p)^{k-r};$
- $E(X) = \frac{r}{p};$
- $\text{Var}(X) = \frac{r(1 - p)}{p^2};$

**Remark:**  $\text{Geom}(p) = \text{NB}(1, p)$ .

### 4.7 Poisson Random Variable

**Poisson:** A random variable  $X$  is said to have a **Poisson** distribution with parameter  $\lambda$  if  $X$  takes values  $0, 1, 2, \dots$  with probabilities given as:

$$P(X = k) = \frac{e^{-\lambda} \lambda^k}{k!}, \quad \text{for } k = 0, 1, 2, \dots$$

- $E(X) = \lambda;$
- $\text{Var}(X) = \lambda.$

When  $n$  is large and  $\lambda$  is moderate, we can use **poisson** to approximate **binomial**:

$$\text{Bin}(n, p) \approx \text{Poisson}(np).$$

I.e.  $P(X = k) \approx e^{-\lambda} \frac{\lambda^k}{k!}$ .

**Examples obeying Poisson distribution:**

- Number of misprints on a page;
- Number of people in a community living to 100 years;
- Number of wrong telephone numbers that are dialled in a day;
- Number of people entering a store on a given day;
- Number of particles emitted by a radioactive source.

These are approximately Poisson **because of the Poisson approximation to the binomial distribution**.