

## Expected value of discrete random variables

**Example 1** The expected value of the degenerate distribution is  $E(X) = c \cdot P(X = c) = c$ .

**Example 2** The expected value of a Bernoulli random variable  $X$  is  $E(X) = 1 \cdot P(X = 1) + 0 \cdot P(X = 0) = p$ . Remember that  $X$  is the indicator of event  $A$ , which has a probability of  $p$ , and  $X$  equals to 1, if  $A$  occurs, and 0 if not.

**Example 3** Let  $X$  be a random variable, which has a uniform distribution on numbers  $x_1, \dots, x_n$ , i.e., they have the same probability  $\frac{1}{n}$ .  $E(X) = \frac{1}{n} \cdot \sum_{i=1}^n x_i$ , the mean value.

**Example 4** If  $X \sim \text{Binomial}(n, p)$ , the expected value is the product of parameters:

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

**Example 5** If  $X \sim \text{Poisson}(\lambda)$ :

$$E(X) = \sum_{k=1}^{\infty} k \frac{\lambda^k}{k!} e^{-\lambda} = \sum_{k=1}^{\infty} \frac{\lambda^k}{(k-1)!} e^{-\lambda} = \lambda \sum_{k=1}^{\infty} \frac{\lambda^{k-1}}{(k-1)!} e^{-\lambda} = \lambda.$$

**Remark 1** Not all of the random variables have finite expected value. For example, if  $P(X = 2^k) = \frac{1}{2^k}$  ( $k = 1, 2, \dots$ ),  $E(X) = 1 + 1 + 1 + \dots$ . The St. Petersburg paradox: a casino offers a game in which a single fair coin is tossed at each stage. The pot starts at 1 dollar, and doubles every time a head appears. The first time a tail appears, the game ends and the player wins the pot. It means, if the first tail appears on the  $k$ th toss, the player wins  $2^{k-1}$  dollars. On the other hand, the probability of winning exactly  $2^{k-1}$  dollars is  $\frac{1}{2^k}$ . Thus the expected value of the pot is  $E(X) = \sum_{k=1}^{\infty} \frac{1}{2^k} 2^{k-1} = \infty$ .

## The variance of random variables

The following definition is designed to measure the fluctuation of random quantities, or how far a set of numbers is spread out.

**Definition 1** The variance of a random variable is the expected value of squared difference between the variable and the variable's expected value, i.e.,  $\text{Var}(X) = E((X - E(X))^2)$ . Sometimes  $\text{Var}(X)$  is denoted by  $D^2(X)$ .

**Remark 2**  $\text{Var}(X) = E(X^2 - 2XE(X) + E^2(X)) = E(X^2) - 2E(X)E(X) + E^2(X)$ . Thus  $\text{Var}(X) = E(X^2) - E^2(X)$ , and in practice we use this formula.

Properties:

1.  $\text{Var}(X) \geq 0$ , because it is the expected value of a nonnegative random variable.
2. Let  $a, b$  be real numbers.  $\text{Var}(aX + b) = a^2 \text{Var}(X)$ , because  $\text{Var}(aX + b) = E((aX + b) - E(aX + b))^2 = E((aX + b - aE(X) - b)^2) = a^2 E((X - E(X))^2)$ .
3. If  $E(X) < \infty$ , it doesn't necessarily follow that  $\text{Var}(X) < \infty$ . As an example, let  $X$  be a discrete random variable with distribution  $P(X = k) = \frac{c}{k^3}$  ( $c$  can be easily calculated). In this case,  $E(X)$  is finite, but  $E(X^2) = c(1 + \frac{1}{2} + \dots + \frac{1}{k} + \dots)$ , which is infinite.

**Example 6** The variance of degenerate distribution is  $\text{Var}(X) = E(X^2) - E^2(X) = c^2 - c^2 = 0$ . Conversely, if the variance of a random variable is 0, the variable is constant with probability 1, because  $(X - E(X))^2 \geq 0$ , and its expected value is 0, thus  $(X - E(X)) = 0$  with probability 1.

**Example 7** The variance of a Bernoulli( $p$ ) variable is  $\text{Var}(X) = p - p^2 = p(1 - p)$ .

**Example 8** The variance of dice throw:  $\text{Var}(X) = E(X^2) - E^2(X) = \frac{1+4+\dots+36}{6} - \left(\frac{7}{2}\right)^2 = \frac{35}{12}$ .

**Example 9** Let  $X$  be a  $\text{Poisson}(\lambda)$  random variable.  $E(X^2) = \sum_{k=1}^{\infty} k^2 \frac{\lambda^k}{k!} e^{-\lambda} = \lambda \sum_{k=1}^{\infty} (k-1+1) \frac{\lambda^{k-1}}{(k-1)!} = \lambda^2 + \lambda$ , and  $\text{Var}(X) = E(X^2) - E^2(X) = \lambda^2 + \lambda - \lambda^2 = \lambda$ .

**Definition 2** The standard deviation of a random variable is the squareroot of the variance, i.e.,  $D(X) = \sqrt{\text{Var}(X)}$ .

The variance of sum of two random variables is  $\text{Var}(X+Y) = E((X+Y - E(X+Y))^2) = E((X - E(X) + Y - E(Y))^2) = E((X - E(X))^2) + E((Y - E(Y))^2) + 2E((X - E(X))(Y - E(Y))) = \text{Var}(X) + \text{Var}(Y) + 2E((X - E(X))(Y - E(Y)))$ . For example, if  $X = Y$ ,  $\text{Var}(X+Y) = 4\text{Var}(X)$ .

**Proposition 1** Suppose that  $X$  and  $Y$  are independent discrete random variables, and  $E(X)$ ,  $E(Y)$  are finite values. Then  $E(XY) = E(X)E(Y)$ .

PROOF: Let the range of  $X$  and  $Y$  be  $(x_1, x_2, \dots)$  and  $(y_1, y_2, \dots)$ .  $E(XY) = \sum_{k,l} x_k y_l P(X = x_k, Y = y_l)$ . Because of independence, this is equal to  $\sum_k x_k P(X = x_k) \sum_l y_l P(Y = y_l) = E(X)E(Y)$ .  $\square$

**Remark 3** If  $X$  and  $Y$  are independent,  $\text{Var}(X+Y) = \text{Var}(X) + \text{Var}(Y)$ . Moreover, it can be proved by induction that for pairwise independent random variables  $X_1, \dots, X_n$ , the variance of the sum equals to the sum of variances:  $\text{Var}(X_1 + \dots + X_n) = \text{Var}(X_1) + \dots + \text{Var}(X_n)$ . It follows that the variance of a binomial random variable is  $np(1-p)$ , i.e., the sum of  $n$  Bernoulli variances.

## Distribution functions

**Definition 3 (distribution function)** Let  $F_X(z) : \mathbb{R} \rightarrow \mathbb{R}$  denote the (*cumulative*) *distribution function* of random variable  $X$ , defined as  $F_X(z) := P(X < z)$ .

**Proposition 2** The following properties hold for distribution functions.

1.  $0 \leq F_X(z) \leq 1$
2. monotonically increasing (non-decreasing)
3.  $\lim_{z \rightarrow -\infty} F_X(z) = 0$  and  $\lim_{z \rightarrow \infty} F_X(z) = 1$
4. left-continuous and the right hand limits exist

**Example 10** The distribution function of degenerate distribution is  $F(z) = \begin{cases} 0 & \text{if } z \leq c \\ 1 & \text{if } z > c \end{cases}$ .  
(Remember: in this case  $P(X = c) = 1$ .)

**Example 11** The d.f. of a Bernoulli random variable is  $F(z) = \begin{cases} 0 & z \leq 0 \\ 1-p & 0 < z \leq 1 \\ 1 & z > 1 \end{cases}$ .

**Definition 4** If the distribution function of a random variable  $X$  is continuous, the variable is called *continuous*.

**Remark 4** The range of continuous random variables is uncountably infinite.

**Example 12** Uniform distribution on interval  $[a, b]$ .  $F(z) = \begin{cases} 0 & z \leq a \\ \frac{z-a}{b-a} & a < z \leq b \\ 1 & z > b \end{cases}$ . Notation:  $X \sim U(a, b)$ .

**Example 13** The exponential distribution with parameter  $\lambda > 0$  is defined by d.f.  $F(z) = \begin{cases} 0 & z \leq 0 \\ 1 - e^{-\lambda z} & 0 < z \end{cases}$ .

**Remark 5**  $P(a \leq X < b) = F(b) - F(a)$ ,  $P(a < X < b) = F(b) - F(a+0)$ ,  $P(a \leq X \leq b) = F(b+0) - F(a)$ ,  $P(X = a) = F(a+0) - F(a)$  (last equality means, if  $F$  is continuous, each point has probability 0).