

# Section 3.4 Variance

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Section 3.4  
Variance

- (a) Compute the expected number of gallons produced during a one-hour period.
- (b) The cost (in hundreds of dollars) to produce  $Y$  gallons is given by the cost function  $C(Y) = 3 + 12Y + 2Y^2$ . What is the expected cost in a one-hour period?

SOLUTION: (a) The expected value of  $Y$  is

$$E(Y) = \sum_{y \in R} y p_Y(y) = 0(0.2) + 1(0.3) + 2(0.3) + 3(0.2) = 1.5.$$

That is, we would expect 1.5 gallons of the toxic chemical to be produced per hour. For (b), we first compute  $E(Y^2)$ :

$$E(Y^2) = \sum_{y \in R} y^2 p_Y(y) = 0^2(0.2) + 1^2(0.3) + 2^2(0.3) + 3^2(0.2) = 3.3.$$

Finally,

$$\begin{aligned} E[C(Y)] &= E(3 + 12Y + 2Y^2) \\ &= 3 + 12E(Y) + 2E(Y^2) = 3 + 12(1.5) + 2(3.3) = 27.6. \end{aligned}$$

The expected hourly cost is \$2,760.00.  $\square$

### 3.4 Variance

*TERMINOLOGY:* Let  $Y$  be a discrete random variable with pmf  $p_Y(y)$ , support  $R$ , and expected value  $E(Y) = \mu$ . The **variance** of  $Y$  is given by

$$\sigma^2 \equiv V(Y) \equiv E[(Y - \mu)^2] = \sum_{y \in R} (y - \mu)^2 p_Y(y). \quad \geq 0$$

The standard deviation of  $Y$  is given by the positive square root of the variance; i.e.,

$$\sigma = \sqrt{\sigma^2} = \sqrt{V(Y)}.$$

*FACTS:* The variance  $\sigma^2$  satisfies the following:

- (a)  $\sigma^2 \geq 0$ .  $\checkmark$

- (b)  $\sigma^2 = 0$  if and only if the random variable  $Y$  has a degenerate distribution; i.e., all the probability mass is located at one support point.  $V(C) = 0$
- (c) The larger (smaller)  $\sigma^2$  is, the more (less) spread in the possible values of  $Y$  about the mean  $\mu = E(Y)$ .
- (d)  $\sigma^2$  is measured in (units)<sup>2</sup> and  $\sigma$  is measured in the original units.

VARIANCE COMPUTING FORMULA: Let  $Y$  be a random variable with (finite) mean  $E(Y) = \mu$ . Then

$$V(Y) = E[(Y - \mu)^2] = E(Y^2) - [E(Y)]^2.$$

Proof. Expand the  $(Y - \mu)^2$  term and distribute the expectation operator as follows:

$$\begin{aligned} E[(Y - \mu)^2] &= E(Y^2 - 2\mu Y + \mu^2) = E(Y^2) + E(-2\mu Y) + E(\mu^2) \\ &= E(Y^2) - 2\mu E(Y) + \mu^2 \\ &= E(Y^2) - 2\mu^2 + \mu^2 \\ &= E(Y^2) - \mu^2. \quad \square \end{aligned}$$

Example 3.9. The discrete uniform distribution. Suppose that the random variable  $X$  has pmf

$$p_X(x) = \begin{cases} 1/m, & x = 1, 2, \dots, m \\ 0, & \text{otherwise,} \end{cases} \quad \mu = E[X]$$

where  $m$  is a positive integer larger than 1. Find the variance of  $X$ .

$$V[X] = E[X^2] - \mu^2$$

SOLUTION. We find  $\sigma^2 = V(X)$  using the variance computing formula. In Example 3.7, we computed

$$\mu = E(X) = \frac{m+1}{2}.$$

$$\sum_{x=1}^m x^2 = \frac{m(m+1)(2m+1)}{6}$$

We first find  $E(X^2)$ :

$$\begin{aligned} E(X^2) &= \sum_{x \in R} x^2 p_X(x) = \sum_{x=1}^m x^2 \left(\frac{1}{m}\right) = \frac{1}{m} \left(\sum_{x=1}^m x^2\right) = \frac{1}{m} \left[\frac{m(m+1)(2m+1)}{6}\right] \\ &= \frac{(m+1)(2m+1)}{6} \end{aligned} \quad \sum_{x=1}^m x^3 = \left(\frac{m(m+1)}{2}\right)^2$$

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$$\begin{aligned} E(X^3) &= \sum_{x \in R} x^3 p_X(x) = \sum_{x=1}^m x^3 \left(\frac{1}{m}\right) = \frac{1}{m} \sum_{x=1}^m x^3 = \frac{1}{m} \times \left(\frac{m(m+1)}{2}\right)^2 \\ &= \frac{m(m+1)^2}{4} \end{aligned}$$

We have used the well-known fact that  $\sum_{x=1}^m x^2 = m(m+1)(2m+1)/6$ ; this can be proven by induction. The variance of  $X$  is equal to

$$\begin{aligned} \sigma^2 &= E(X^2) - [E(X)]^2 \\ &= \frac{(m+1)(2m+1)}{6} - \left(\frac{m+1}{2}\right)^2 = \frac{m^2-1}{12}. \quad \square \end{aligned}$$

EXERCISE: Find  $\sigma^2 = V(Y)$  in Examples 3.5 and 3.8 (notes).

IMPORTANT RESULT: Let  $Y$  be a random variable (not necessarily a discrete random variable). Suppose that  $a$  and  $b$  are fixed constants. Then

$$E(a+bY) = a + bE(Y) \quad V(a+bY) = b^2V(Y).$$

REMARK: Taking  $b = 0$  above, we see that  $V(a) = 0$ , for any constant  $a$ . This makes sense intuitively. The variance is a measure of variability for a random variable; a constant (such as  $a$ ) does not vary. Also, by taking  $a = 0$ , we see that  $V(bY) = b^2V(Y)$ .

$$\begin{aligned} & (a+bE(Y))^2 \\ & \text{"} \\ & E((a+bY)^2) - [E(a+bY)]^2 \\ & = E(a^2 + 2abY + b^2Y^2) - (a^2 + 2abE(Y) + b^2[E(Y)]^2) \\ & = a^2 + 2abE(Y) + b^2E(Y^2) - a^2 - 2abE(Y) - b^2[E(Y)]^2 \\ & = b^2(E(Y^2) - [E(Y)]^2) \\ & = b^2V(Y) \end{aligned}$$

### 3.5 Moment generating functions

TERMINOLOGY: Let  $Y$  be a discrete random variable with pmf  $p_Y(y)$  and support  $R$ . The **moment generating function (mgf)** for  $Y$ , denoted by  $m_Y(t)$ , is given by

$$m_Y(t) = E(e^{tY}) = \sum_{y \in R} e^{ty} p_Y(y),$$

provided  $E(e^{tY}) < \infty$  for all  $t$  in an open neighborhood about 0; i.e., there exists some  $h > 0$  such that  $E(e^{tY}) < \infty$  for all  $t \in (-h, h)$ . If  $E(e^{tY})$  does not exist in an open neighborhood of 0, we say that the moment generating function does not exist.

TERMINOLOGY: We call  $\mu'_k \equiv E(Y^k)$  the  **$k$ th moment** of the random variable  $Y$ :

- $E(Y)$  1st moment (mean!)
- $E(Y^2)$  2nd moment
- $E(Y^3)$  3rd moment
- $E(Y^4)$  4th moment
- $\vdots$   $\quad \quad \quad \vdots$

