

**Theorem 6.5** If  $X$  and  $Y$  are random variables with finite population variances and covariance, then

$$V[X + Y] = V[X] + V[Y] + 2\text{Cov}(X, Y).$$

**Proof** Using the definition of the population variance, Theorem 6.2, and the fact that expected value is a linear operator,

$$\begin{aligned} V[X + Y] &= E \left[ ((X + Y) - E[X + Y])^2 \right] \\ &= E \left[ ((X - \mu_X) + (Y - \mu_Y))^2 \right] \\ &= E \left[ (X - \mu_X)^2 + (Y - \mu_Y)^2 + 2(X - \mu_X)(Y - \mu_Y) \right] \\ &= E \left[ (X - \mu_X)^2 \right] + E \left[ (Y - \mu_Y)^2 \right] + 2E \left[ (X - \mu_X)(Y - \mu_Y) \right] \\ &= V[X] + V[Y] + 2\text{Cov}(X, Y), \end{aligned}$$

which proves the result.  $\square$

**Example 6.34** A fair coin is tossed twice. Let  $X$  be the number of heads that appear and  $Y$  be the number of tails that appear. Find the population variance of  $X + Y$ .

Since  $X \sim \text{binomial}(2, 1/2)$  and  $Y \sim \text{binomial}(2, 1/2)$ , the population variances of the two random variables are

$$V[X] = 2 \cdot \frac{1}{2} \cdot \frac{1}{2} = \frac{1}{2}$$

and

$$V[Y] = 2 \cdot \frac{1}{2} \cdot \frac{1}{2} = \frac{1}{2}$$

because the population variance of a binomial( $n, p$ ) random variable is  $np(1 - p)$ . Using Theorem 6.5, the population variance of the sum of  $X$  and  $Y$  is

$$V[X + Y] = V[X] + V[Y] + 2\text{Cov}(X, Y) = \frac{1}{2} + \frac{1}{2} - 2 \cdot \frac{1}{2} = 0,$$

where the population covariance was calculated as  $\text{Cov}(X, Y) = -1/2$  in Examples 6.31 and 6.32. The population variance of the sum of  $X$  and  $Y$  must be zero because the sum of the heads and tails tossed in the random experiment is always 2, and the population variance of a constant is zero.

The next result concerns the population covariance between independent random variables.

**Theorem 6.6** If  $X$  and  $Y$  are independent random variables, then  $\text{Cov}(X, Y) = 0$ .

**Proof** Since  $X$  and  $Y$  are independent random variables,  $E[XY] = E[X]E[Y]$  by Theorem 6.3. Using the shortcut formula for the population covariance from Theorem 6.4,  $\text{Cov}(X, Y) = E[XY] - E[X]E[Y] = 0$ , which proves the result.  $\square$

One question that arises from Theorem 6.6 is whether the converse is true. That is, does a joint distribution of random variables  $X$  and  $Y$  with a population covariance of 0 imply that the random variables are independent? The converse is not true in general, and this is best established with a counterexample. The particular counterexample given next is not unique. There are many similar examples for both discrete and continuous probability distributions for  $X$  and  $Y$ .