

## **Probability and Statistics (IT302)**

**2<sup>nd</sup> September 2020 Wednesday 11:15 AM - 11:45AM Class 13**

# Introduction to Variance of Random Variables

- The mean, or expected value, of a random variable  $X$  is of special importance in statistics because it describes where the probability distribution is centered. By itself, however, the mean does not give an adequate description of the shape of the distribution. We also need to characterize the variability in the distribution.
- In below Figure shows the histograms of two discrete probability distributions that have the same mean,  $\mu = 2$ , but differ considerably in variability, or the dispersion of their observations about the mean.

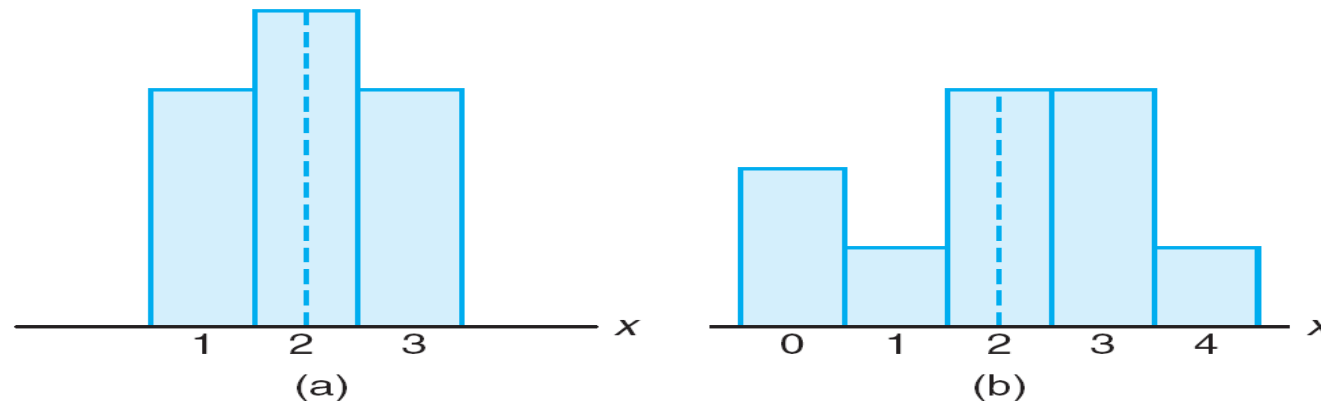


Figure 4.1: Distributions with equal means and unequal dispersions.

# Variance of the Random Variable $X$

The most important measure of variability of a random variable  $X$  is obtained by applying Theorem 4.1 with  $g(X) = (X - \mu)^2$ . The quantity is referred to as the **variance of the random variable  $X$**  or the **variance of the probability distribution of  $X$**  and is denoted by  $\text{Var}(X)$  or the symbol  $\sigma^2_X$  or simply by  $\sigma^2$ .

## Definition 4.3:

Let  $X$  be a random variable with probability distribution  $f(x)$  and mean  $\mu$ . The variance of  $X$  is

$$\sigma^2 = E[(X - \mu)^2] = \sum_x (x - \mu)^2 f(x), \quad \text{if } X \text{ is discrete, and}$$

$$\sigma^2 = E[(X - \mu)^2] = \int_{-\infty}^{\infty} (x - \mu)^2 f(x) dx, \quad \text{if } X \text{ is continuous.}$$

The positive square root of the variance,  $\sigma$ , is called the **standard deviation** of  $X$ .

# Variance of the Random Variable X Contd.

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The positive square root of the variance,  $\sigma$ , is called the **standard deviation** of  $X$ .

The quantity  $x - \mu$  in Definition 4.3 is called the **deviation of an observation** from its mean. Since the deviations are squared and then averaged,  $\sigma^2$  will be much smaller for a set of  $x$  values that are close to  $\mu$  than it will be for a set of values that vary considerably from  $\mu$ .

## Example 4.8

Let the random variable  $X$  represent the number of automobiles that are used for official business purposes on any given workday. The probability distribution for company A

$x$	1	2	3
$f(x)$	0.3	0.4	0.3

and that for company B

$x$	0	1	2	3	4
$f(x)$	0.2	0.1	0.3	0.3	0.1

Show that the variance of the probability distribution for company B is greater than that for company A.

**Solution :** For company A, we find that  $\mu_A = E(X) = (1)(0.3) + (2)(0.4) + (3)(0.3) = 2.0$ , and then

$$\sigma_A^2 = \sum_{x=1}^3 (x - 2)^2 = (1 - 2)^2(0.3) + (2 - 2)^2(0.4) + (3 - 2)^2(0.3) = 0.6.$$

## Example 4.8 Contd.

For company  $B$ , we have

$$\mu_B = E(X) = (0)(0.2) + (1)(0.1) + (2)(0.3) + (3)(0.3) + (4)(0.1) = 2.0,$$

and then

$$\begin{aligned}\sigma_B^2 &= \sum_{x=0}^4 (x - 2)^2 f(x) \\ &= (0 - 2)^2(0.2) + (1 - 2)^2(0.1) + (2 - 2)^2(0.3) \\ &\quad + (3 - 2)^2(0.3) + (4 - 2)^2(0.1) = 1.6.\end{aligned}$$

Clearly, the variance of the number of automobiles that are used for official business purposes is greater for company  $B$  than for company  $A$ .

# Alternative and Preferred Formula for Finding $\sigma^2$

**Theorem 4.2:** The variance of a random variable  $X$  is  $\sigma^2 = E(X^2) - \mu^2$ .

*Proof:* For the discrete case, we can write

$$\begin{aligned}\sigma^2 &= \sum_x (x - \mu)^2 f(x) = \sum_x (x^2 - 2\mu x + \mu^2) f(x) \\ &= \sum_x x^2 f(x) - 2\mu \sum_x x f(x) + \mu^2 \sum_x f(x).\end{aligned}$$

Since  $\mu = \sum_x x f(x)$  by definition, and  $\sum_x f(x) = 1$  for any discrete probability distribution, it follows that

$$\sigma^2 = \sum_x x^2 f(x) - \mu^2 = E(X^2) - \mu^2.$$

For the continuous case the proof is step by step the same, with summations replaced by integrations. 

## Example 4.9

Let the random variable  $X$  represent the number of defective parts for a machine when 3 parts are sampled from a production line and tested. The following is the probability distribution of  $X$ .

$x$	0	1	2	3
$f(x)$	0.51	0.38	0.10	0.01

calculate  $\sigma^2$

**Solution:** First, we compute

$$\mu = (0)(0.51) + (1)(0.38) + (2)(0.10) + (3)(0.01) = 0.61.$$

Now,

$$E(X^2) = (0)(0.51) + (1)(0.38) + (4)(0.10) + (9)(0.01) = 0.87.$$

Therefore,

$$\sigma^2 = 0.87 - (0.61)^2 = 0.4979.$$



## Example 4.10

The weekly demand for a drinking-water product, in thousands of liters, from a local chain of efficiency stores is a continuous random variable  $X$  having the probability density

$$f(x) = \begin{cases} 2(x - 1), & 1 < x < 2, \\ 0, & \text{elsewhere.} \end{cases}$$

Find the mean and variance of  $X$ .

## Example 4.10 Contd.

**Solution:** Calculating  $E(X)$  and  $E(X^2)$ , we have

$$\mu = E(X) = 2 \int_1^2 x(x-1) dx = \frac{5}{3}$$

and

$$E(X^2) = 2 \int_1^2 x^2(x-1) dx = \frac{17}{6}.$$

Therefore,

$$\sigma^2 = \frac{17}{6} - \left(\frac{5}{3}\right)^2 = \frac{1}{18}.$$

## Theorem 4.3

Let  $X$  be a random variable with probability distribution  $f(x)$ . The variance of the random variable  $g(X)$  is

$$\sigma_{g(X)}^2 = E\{[g(X) - \mu_{g(X)}]^2\} = \sum_x [g(x) - \mu_{g(X)}]^2 f(x)$$

if  $X$  is discrete, and


$$\sigma_{g(X)}^2 = E\{[g(X) - \mu_{g(X)}]^2\} = \int_{-\infty}^{\infty} [g(x) - \mu_{g(X)}]^2 f(x) dx$$

if  $X$  is continuous.

## Proof of Theorem 4.3

**Proof:** Since  $g(X)$  is itself a random variable with mean  $\mu_{g(X)}$  as defined in Theorem 4.1, it follows from Definition 4.3 that

$$\sigma_{g(X)}^2 = E\{[g(X) - \mu_{g(X)}]^2\}.$$

Now, applying Theorem 4.1 again to the random variable  $[g(X) - \mu_{g(X)}]^2$  completes the proof. 

## Example 4.11

Calculate the variance of  $g(X) = 2X + 3$ , where  $X$  is a random variable with probability distribution

$x$	0	1	2	3
$f(x)$	$\frac{1}{4}$	$\frac{1}{8}$	$\frac{1}{2}$	$\frac{1}{8}$

**Solution:** First, we find the mean of the random variable  $2X + 3$ . According to Theorem 4.1,

$$\mu_{2X+3} = E(2X + 3) = \sum_{x=0}^3 (2x + 3)f(x) = 6.$$

Now, using Theorem 4.3, we have

$$\begin{aligned}\sigma_{2X+3}^2 &= E\{[(2X + 3) - \mu_{2x+3}]^2\} = E[(2X + 3 - 6)^2] \\ &= E(4X^2 - 12X + 9) = \sum_{x=0}^3 (4x^2 - 12x + 9)f(x) = 4.\end{aligned}$$

## Example 4.12

Let  $X$  be a random variable having the density function given is  $f(x) = \begin{cases} \frac{x^2}{3}, & -1 < x < 2, \\ 0, & \text{elsewhere.} \end{cases}$

Find the variance of the random variable  $g(X) = 4X + 3$ .

**Solution :** using Theorem 4.3

$$\begin{aligned}\sigma_{4X+3}^2 &= E\{[(4X + 3) - 8]^2\} = E[(4X - 5)^2] \\ &= \int_{-1}^2 (4x - 5)^2 \frac{x^2}{3} dx = \frac{1}{3} \int_{-1}^2 (16x^4 - 40x^3 + 25x^2) dx = \frac{51}{5}.\end{aligned}$$

If  $g(X, Y) = (X - \mu_X)(Y - \mu_Y)$ , where  $\mu_X = E(X)$  and  $\mu_Y = E(Y)$ , Definition 4.2 yields an expected value called the **covariance** of  $X$  and  $Y$ , which we denote by  $\sigma_{XY}$  or  $\text{Cov}(X, Y)$ .

## Definition 4.4

Let  $X$  and  $Y$  be random variables with joint probability distribution  $f(x, y)$ . The covariance of  $X$  and  $Y$  is

$$\sigma_{XY} = E[(X - \mu_X)(Y - \mu_Y)] = \sum_x \sum_y (x - \mu_X)(y - \mu_Y) f(x, y)$$

if  $X$  and  $Y$  are discrete, and

$$\sigma_{XY} = E[(X - \mu_X)(Y - \mu_Y)] = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} (x - \mu_X)(y - \mu_Y) f(x, y) \, dx \, dy$$

if  $X$  and  $Y$  are continuous.

## Theorem 4.4

The covariance of two random variables  $X$  and  $Y$  with means  $\mu_X$  and  $\mu_Y$ , respectively, is given by

$$\sigma_{XY} = E(XY) - \mu_X \mu_Y.$$

**Proof:** For the discrete case, we can write

$$\begin{aligned}\sigma_{XY} &= \sum_x \sum_y (x - \mu_X)(y - \mu_Y) f(x, y) \\ &= \sum_x \sum_y xy f(x, y) - \mu_X \sum_x \sum_y y f(x, y) \\ &\quad - \mu_Y \sum_x \sum_y x f(x, y) + \mu_X \mu_Y \sum_x \sum_y f(x, y).\end{aligned}$$



## Theorem 4.4 Contd.

Since

$$\mu_X = \sum_x x f(x, y), \quad \mu_Y = \sum_y y f(x, y), \quad \text{and} \quad \sum_x \sum_y f(x, y) = 1$$

for any joint discrete distribution, it follows that

$$\sigma_{XY} = E(XY) - \mu_X \mu_Y - \mu_Y \mu_X + \mu_X \mu_Y = E(XY) - \mu_X \mu_Y.$$

For the continuous case, the proof is identical with summations replaced by integrals. 

## Example 4.13

a situation involving the number of blue refills  $X$  and the number of red refills  $Y$ . Two refills for a ballpoint pen are selected at random from a certain box, and the following is the joint probability distribution:

$f(x, y)$		$x$			$h(y)$
		0	1	2	
$y$	0	$\frac{3}{28}$	$\frac{9}{28}$	$\frac{3}{28}$	$\frac{15}{28}$
	1	$\frac{3}{14}$	$\frac{3}{14}$	0	$\frac{3}{7}$
	2	$\frac{1}{28}$	0	0	$\frac{1}{28}$
$g(x)$		$\frac{5}{14}$	$\frac{15}{28}$	$\frac{3}{28}$	1

Find the covariance of  $X$  and  $Y$ .

## Example 4.13 Contd.

**Solution:** From Example 4.6, we see that  $E(XY) = 3/14$ . Now

$$\mu_X = \sum_{x=0}^2 xg(x) = (0) \left(\frac{5}{14}\right) + (1) \left(\frac{15}{28}\right) + (2) \left(\frac{3}{28}\right) = \frac{3}{4},$$

and

$$\mu_Y = \sum_{y=0}^2 yh(y) = (0) \left(\frac{15}{28}\right) + (1) \left(\frac{3}{7}\right) + (2) \left(\frac{1}{28}\right) = \frac{1}{2}.$$

Therefore,

$$\sigma_{XY} = E(XY) - \mu_X \mu_Y = \frac{3}{14} - \left(\frac{3}{4}\right) \left(\frac{1}{2}\right) = -\frac{9}{56}.$$

## Exercise Problem 4.34

Let  $X$  be a random variable with the following probability distribution:

$x$	$-2$	$3$	$5$
$f(x)$	$0.3$	$0.2$	$0.5$

Find the standard deviation of  $X$ .

**Solution:**

$$\mu = (-2)(0.3) + (3)(0.2) + (5)(0.5) = 2.5 \text{ and}$$

$$E(X^2) = (-2)^2(0.3) + (3)^2(0.2) + (5)^2(0.5) = 15.5.$$

$$\text{So, } \sigma^2 = E(X^2) - \mu^2 = 9.25 \text{ and } \sigma = 3.041.$$