

Expectation of a function of a random variable

Theorem 1.8

Let X be a random variable and let a and b be constants. Then

① $\mathbf{E}(aX + b) = a\mathbf{E}(X) + b$ (note $a=0 \Rightarrow \mathbf{E}(b) = b$)

② If $\mathbf{P}(a < X \leq b) = 1$, then $a < \mathbf{E}(X) \leq b$

③ If $g(X)$ and $h(X)$ have (finite) means, then

$$\mathbf{E}(g(X) + h(X)) = \mathbf{E}(g(X)) + \mathbf{E}(h(X))$$

① $\mathbf{E}(aX + b) = \sum_x (ax + b) f(x) = a \sum_x x \cdot f(x) + b \sum_x f(x)$
 $= a \cdot \mathbf{E}(X) + b \cdot 1 = a \mathbf{E}(X) + b$

② $\mathbf{E}(X) = \sum_x x \cdot f_x(x) = \sum_{x < a} x \cdot f_x(x) + \sum_{a \leq x \leq b} x \cdot f_x(x) + \sum_{x > b} x \cdot f_x(x)$
 $a = a \sum_x f_x(x) \leq \sum_{a \leq x \leq b} x \cdot f_x(x) \leq b \cdot \sum_x f_x(x) = b$

Expectation of the indicator random variable

Example 1.9

Suppose that X is the indicator random variable of an event A . That is

$$X(\omega) = \begin{cases} 1, & \text{if } \omega \in A \\ 0, & \text{if } \omega \notin A \end{cases}$$

Then $\mathbf{E}(X) = 0 \cdot f_X(0) + 1 \cdot f_X(1) = \mathbf{P}(A)$

$$\begin{aligned} P(X=1) &= P(\{\omega \in S : X(\omega) = 1\}) \\ &= P(A) \end{aligned}$$

Exercise

Exercise 1.9

Let X have the p.d.f

$$f_X(x) = a \frac{1}{x(x+1)(x+2)}, \quad x = 1, 2, \dots$$

$$\sum_{x=1}^{\infty} \frac{1}{x(x+1)(x+2)} = S_1$$
$$a = 1/S_1$$

and let Y have the p.d.f

$$f_Y(x) = b \frac{1}{x(x+1)}, \quad x = 1, 2, \dots$$

$$\sum_{x=1}^{\infty} \frac{1}{x(x+1)} = S_2$$
$$b = 1/S_2$$

for some constants a and b . Which of these have an expected value.

$$\sum_{x=1}^{\infty} \frac{1}{(x+1)(x+2)} < \infty$$

but

$$\sum_{x=1}^{\infty} \frac{1}{(x+1)} \neq \infty.$$

Variance

Theorem 1.10

If $\mathbf{E}(X)$ and $\mathbf{E}(X^2)$ exist, then $(\mathbf{E}(X))^2 \leq (\mathbf{E}(|X|))^2 \leq \mathbf{E}(X^2)$

Proof

First, note that $(|X| - \mathbf{E}(|X|))^2 \geq 0$. Hence, Theorem 1.8

$$0 \leq \mathbf{E}((|X| - \mathbf{E}(|X|))^2) = \mathbf{E}(|X|^2 + \mathbf{E}(|X|)^2 - 2|X| \cdot \mathbf{E}(|X|))$$

$$= \mathbf{E}(X^2) - (\mathbf{E}(|X|))^2$$

which proves the second inequality. Also, $|X| - X \geq 0$, hence,
 $\mathbf{E}(X) \leq \mathbf{E}(|X|)$

$$\mathbf{E}(X)^2 \geq \mathbf{E}(X)^2$$

$$\mathbf{E}(|X| - X) \geq 0$$

$$\mathbf{E}(|X|) - \mathbf{E}(X) \geq 0$$

$$\Leftarrow \mathbf{E}(|X|) \geq \mathbf{E}(X)$$

Variance

Definition 1.12

If X is a random variable with $\mathbf{E}(X^2) < \infty$, its variance is defined as

$$\sigma^2(X) = \mathbf{E}((X - \mathbf{E}(X))^2) = \mathbf{E}(X^2) - (\mathbf{E}(X))^2.$$

Its square root $\sigma(X)$ is called the standard deviation of X .

$$\begin{aligned}\sigma^2(X) &= \mathbf{E}((X - \mu)^2) = \mathbf{E}(X^2 + \mu^2 - 2\mu X) \\ &= \mathbf{E}(X^2) + \mu^2 - 2\mu \mathbf{E}(X) = \mathbf{E}(X^2) + \mu^2 - 2\mu^2 \\ &= \mathbf{E}(X^2) - \mu^2 = \mathbf{E}(X^2) - (\mathbf{E}(X))^2\end{aligned}$$

Variance

Theorem 1.11

If $\mathbf{E}(X^2) < \infty$, and a and b are constants then

$$\text{var}(aX + b) = a^2 \text{var}(X)$$

Proof

Using Theorem 1.8 we get,

$$\begin{aligned}\text{var}(aX + b) &= \mathbf{E} \left((aX + b - \mathbf{E}(aX + b))^2 \right) = \mathbf{E} \left((a(X - \mathbf{E}(X)) + b - b)^2 \right) \\ &= \mathbf{E} \left(a^2 (X - \mathbf{E}(X))^2 \right) = a^2 \text{var}(X)\end{aligned}$$

Geometric distribution

Definition 1.13

The number X of Bernoulli trials needed to get one success, follows the geometric distribution with p.d.f.

$$0 < p < 1$$

$$f(x) = (1 - p)^{x-1} p; \quad x = 1, 2, \dots$$

Theorem 1.12

If X follows the geometric distribution with parameter p ,

$$E(X) = \frac{1}{p}, \quad \text{var}(X) = \frac{1-p}{p^2}$$

Proof $E(X)$!

$$\sum_{x=1}^{\infty} (1-p)^{x-1} p = 1$$
$$\sum_{x=1}^{\infty} x \cdot p (1-p)^{x-1} = \frac{1}{p}$$
$$E(X^2) = \sum_{x=1}^{\infty} x^2 p (1-p)^{x-1} = ?$$