

# Basic properties of expectations

## Basic properties of expectations of discrete random variables

**Property 1** (*Absolute integrability*): Suppose  $\xi$  is a discrete random variable. Then  $E\xi$  is finite if and only if  $E|\xi| < \infty$ . Further

$$E\xi = E\xi^+ - E\xi^-, \quad E|\xi| = E\xi^+ + E\xi^-.$$

**Property 2** (*Linearity*): Suppose  $\xi$  and  $\eta$  are discrete random variables. If  $E\xi$  and  $E\eta$  exist, then

$$E(a\xi + b\eta) = aE\xi + bE\eta.$$

**Property 3** (*Monotonicity*): Suppose  $\xi$  and  $\eta$  are discrete random variables. If  $\xi \leq \eta$  and the expectations of  $\xi$  and  $\eta$  exist, then  $E\xi \leq E\eta$ .

## Corollary

*Suppose  $\xi$  and  $\eta$  are discrete random variables,  $|\xi| \leq \eta$ . If the expectation  $E\eta$  exists, then the expectation  $E\xi$  exists, and  $|E\xi| \leq E|\xi| \leq E\eta$ .*

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**Proof.** Suppose  $\xi = \sum_{k=1}^{\infty} x_k I\{\xi = x_k\}$ . Write  $\bar{\xi} = \sum_{k=1}^N x_k I\{\xi = x_k\}$ . Then  $|\bar{\xi}| = \sum_{k=1}^N |x_k| I\{\xi = x_k\} \leq |\xi| \leq \eta$ , the expectations of  $|\bar{\xi}|$  and  $\eta$  exist. By Property 3,  $E|\bar{\xi}| \leq E\eta$ .

So,

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$$E|\xi| = \sum_{i=1}^{\infty} |x_i| P(\xi = x_i) \leq E\eta.$$

Hence, the expectation  $E\xi$  exists. Note  
 $-|\xi| \leq \xi \leq |\xi|$ .

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**Property 4** Suppose  $\xi$  and  $\eta$  are discrete random variables and  $E\xi$  and  $E\eta$  exists. Then  $E[\xi\eta]$  exists and

$$E[\xi\eta] = E\xi \cdot E\eta.$$

# Properties of Mathematical expectation for general random variables

For a random variable  $\xi$ . Define

$$\xi^{(m)} = \frac{k}{2^m} \quad \text{if} \quad \frac{k}{2^m} < \xi \leq \frac{k+1}{2^m}.$$

Then

- If  $\xi \geq 0$ , then  $0 \leq \xi_m \nearrow \xi$  and  $0 \leq \xi - \xi^{(m)} \leq \frac{1}{2^m}$ .
- In general,  $|\xi - \xi^{(m)}| \leq \frac{1}{2^m}$ .

## Theorem

$E\xi$  exists if and only if  $E\xi^{(m)}$  exists for one  $m$  (and then all  $m$ ). Further,

$$E\xi = \lim_{m \rightarrow \infty} E\xi^{(m)}.$$

Suppose  $\xi$  has cdf  $F(x)$ . Write  $x_{m,k} = \frac{k}{2^m}$ . Then

$$\xi^{(m)} = \sum_{k=-\infty}^{\infty} x_{m,k} I\{x_{m,k} < \xi \leq x_{m,k+1}\},$$

and

$$\begin{aligned} & \sum_{k=-\infty}^{\infty} |x_{m,k}| P(x_{m,k} < \xi \leq x_{m,k+1}) \\ &= \sum_{k=-\infty}^{\infty} |x_{m,k}| \Delta F(x_{m,k}) \\ &= \sum_{k=-\infty}^{\infty} \int_{x_{m,k} < x \leq x_{m,k+1}} |x_{m,k}| dF(x), \end{aligned}$$

where  $\Delta F(x_{m,k}) = F(x_{m,k+1}) - F(x_{m,k})$ .

For  $x_{m,k} < x \leq x_{m,k+1}$ , we have  $|x_{m,k} - x| \leq \frac{1}{2^m}$ . So,

$$\begin{aligned} \sum_{k=-\infty}^{\infty} |x_{m,k}| \Delta F(x_{m,k}) &= \sum_{k=-\infty}^{\infty} \int_{x_{m,k} < x \leq x_{m,k+1}} |x_{m,k}| dF(x) \\ &\leq \sum_{k=-\infty}^{\infty} \int_{x_{m,k} < x \leq x_{m,k+1}} \left( |x| + \frac{1}{2^m} \right) dF(x) \\ &= \int_{-\infty}^{\infty} |x| dF(x) + \frac{1}{2^m}. \end{aligned}$$

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Similarly,

$$\sum_{k=-\infty}^{\infty} |x_{m,k}| \Delta F(x_{m,k}) \geq \int_{-\infty}^{\infty} |x| dF(x) - \frac{1}{2^m}.$$

So,  $E\xi$  exists if and only if  $E\xi^{(m)}$  exists.

Similarly,

$$\begin{aligned} E\xi^{(m)} &= \sum_{k=-\infty}^{\infty} x_{m,k} P(x_{m,k} < \xi \leq x_{m,k+1}) \\ &= \sum_{k=0}^{\infty} x_{m,k} \Delta F(x_{m,k}) \\ &= \sum_{k=-\infty}^{\infty} \int_{x_{m,k} < x \leq x_{m,k+1}} |x_{m,k}| dF(x) \end{aligned}$$

and

$$\int_{-\infty}^{\infty} x dF(x) - \frac{1}{2^m} \leq E\xi^{(m)} \leq \int_{-\infty}^{\infty} x dF(x) + \frac{1}{2^m}.$$

The proof is completed.

## 3.1.5 Basic properties of expectations

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In fact,

$$E\xi = \int_{-\infty}^{\infty} x dF(x) = \int_a^b x dF(x).$$

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$$E\xi \geq a \int_a^b dF(x) = a \int_{-\infty}^{\infty} dF(x) = a.$$

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**Proof.** Note  $|X - X^{(m)}| \leq \frac{1}{2^m}$ . So

$$\begin{aligned} & |(a\xi + b\eta)^{(m)} - (a\xi^{(m)} + b\eta^{(m)})| \\ & \leq |(a\xi + b\eta)^{(m)} - (a\xi + b\eta)| + |a| |\xi^{(m)} - \xi| + |b| |\eta^{(m)} - \eta| \\ & \leq \frac{1 + |a| + |b|}{2^m}. \end{aligned}$$

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It follows that

$$|E[(a\xi + b\eta)^{(m)}] - (aE\xi^{(m)} + bE\eta^{(m)})| \leq \frac{1 + |a| + |b|}{2^m}.$$

Taking the limit  $m \rightarrow \infty$  completes the proof.

## Corollary

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## Proof

$$E\eta - E\xi = E[\eta - \xi] \geq 0.$$

- 3 Suppose that  $\xi$  and  $\eta$  are independent, and expectations  $E\xi$  and  $E\eta$  exists. Then

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**Proof.** Note that  $E\xi^{(m)}$  and  $E\eta^{(m)}$  both exist.

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**Proof.** Note that  $E\xi^{(m)}$  and  $E\eta^{(m)}$  both exist. So,  $E(\xi^{(m)}\eta^{(m)})$  exists and

$$E(\xi^{(m)}\eta^{(m)}) = E\xi^{(m)} E\eta^{(m)} \rightarrow E\xi E\eta.$$

On the other hand,

$$|(\xi\eta)^{(m)} - \xi\eta| \leq \frac{1}{2^m},$$

$$\begin{aligned} \xi^{(m)}\eta^{(m)} - \xi\eta &= (\xi^{(m)} - \xi)\eta^{(m)} + \xi(\eta^{(m)} - \eta) \\ &= (\xi^{(m)} - \xi)\eta^{(m)} + \xi^{(m)}(\eta^{(m)} - \eta) \\ &\quad + (\xi - \xi^{(m)})(\eta^{(m)} - \eta). \end{aligned}$$

It follows that

$$|\xi^{(m)}\eta^{(m)} - (\xi\eta)^{(m)}| \leq \frac{1}{2^m}|\eta^{(m)}| + \frac{1}{2^m}|\xi^{(m)}| + \frac{2}{2^m}.$$

Note that  $\xi^{(m)}\eta^{(m)}$ ,  $(\xi\eta)^{(m)}$ ,  $|\eta^{(m)}|$ ,  $|\xi^{(m)}|$  are discrete random variables, and  $E[\xi^{(m)}\eta^{(m)}]$ ,  $E[|\eta^{(m)}|]$ ,  $E[|\xi^{(m)}|]$  exist.

So  $E[(\xi\eta)^{(m)}]$  exists and

$$\begin{aligned} & |E[\xi^{(m)}\eta^{(m)}] - E[(\xi\eta)^{(m)}]| \\ & \leq \frac{1}{2^m} E[|\eta^{(m)}|] + \frac{1}{2^m} E[|\xi^{(m)}|] + \frac{2}{2^m} \\ & \leq \frac{1}{2^m} E[|\eta|] + \frac{1}{2^m} E[|\xi|] + \frac{4}{2^m} \rightarrow 0. \end{aligned}$$

Hence,  $E[\xi\eta]$  exists and

$$\begin{aligned} E[\xi\eta] &= \lim_{m \rightarrow \infty} E[(\xi\eta)^{(m)}] \\ &= \lim_{m \rightarrow \infty} E[\xi^{(m)}\eta^{(m)}] \\ &= \lim_{m \rightarrow \infty} E[\xi^{(m)}]E[\eta^{(m)}] \\ &= E[\xi]E[\eta]. \square \end{aligned}$$

## Integral with respect to a probability measure

The random variable  $\xi(\omega)$  is a  $\mathcal{F}$ -measurable function on the probability space  $(\Omega, \mathcal{F}, P)$ . The expectation of  $\xi$  is the integral of  $\xi$  with respect to  $P$ .

$$E\xi = \int \xi(\omega)dP(\omega) = \int \xi dP.$$

- If  $\xi(\omega) = \sum_i x_i I_{A_i}$ , then

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- $\int \xi dP = \int \xi^+ dP - \int \xi^- dP.$

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Then

$$\int_{A+B} \xi dP = \int_A \xi dP + \int_B \xi dP.$$