- 3.1 Mathematical expectation
  - 3.1.4 Expectations for functions of random variables

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# 3.1.4 Expectations for functions of random variables The expectation of a function of a discrete random variable:

 $\xi$  has the pmf

$$\left(\begin{array}{cccc} x_1 & x_2 & \cdots & x_k & \cdots \\ p_1 & p_2 & \cdots & p_k & \cdots \end{array}\right).$$

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Then for  $\eta = f(\xi)$ ,

$$\left(\begin{array}{cccc} f(x_1) & f(x_2) & \cdots & f(x_k) & \cdots \\ p_1 & p_2 & \cdots & p_k & \cdots \end{array}\right).$$

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$$\begin{pmatrix}
y_1 & y_2 & \cdots & y_i & \cdots \\
p_1^* & p_2^* & \cdots & p_i^* & \cdots
\end{pmatrix}$$

where 
$$p_i^* = \sum_{j:f(x_j)=y_i} p_j$$
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where  $p_i^* = \sum_{j:f(x_j)=y_i} p_j$ . Hence  $E\eta$  exists if and only if

$$\sum_{i} |y_i| p_i^* = \sum_{i} \sum_{j: f(x_j) = y_i} |f(x_j)| p_j$$
$$= \sum_{k} |f(x_k)| p_k < \infty.$$

Further,

$$E\eta = \sum_{i} y_{i} p_{i}^{*} = \sum_{i} \sum_{j:f(x_{j})=y_{i}} f(x_{j}) p_{j} = \sum_{k} f(x_{k}) p_{k}.$$

Further,

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$$Ef(\xi) = \sum_{k} f(x_k)p_k = \sum_{k} f(x_k)P(\xi = x_k).$$

**Theorem** Suppose that  $\xi$  is a discrete random variable with the distribution  $F_{\xi}(x)$  and

$$P(\xi = x_k) = p_k, \ k = 1, 2, \cdots,$$

f(x) a Borel function on the real line. Let  $\eta=f(\xi).$  Then  $Ef(\xi)$  exists if and only if

$$\int_{-\infty}^{\infty} |f(x)| dF_{\xi}(x) = \sum_{k} |f(x_k)| P(\xi = x_k) < \infty$$

and

$$Ef(\xi) = \sum_{k} f(x_k) P(\xi = x_k) = \int_{-\infty}^{+\infty} f(x) dF_{\xi}(x).$$

## In general, we have

**Theorem 1.** Suppose that  $\xi$  is a random variable with the distribution  $F_{\xi}(x)$ , f(x) a Borel function on the real line. Let  $\eta = f(\xi)$ . Then

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$$Ef(\xi) = \int_{-\infty}^{+\infty} y dF_{\eta}(y) = \int_{-\infty}^{+\infty} f(x) dF_{\xi}(x).$$

When  $\xi$  has density p(x), then

$$Ef(\xi) = \int_{-\infty}^{+\infty} f(x)p(x)dx.$$

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When  $\xi$  is a random variable of the general type and f(x) is a general Borel function, the proof of this theorem is due to measure theory. Next, we give a proof for the case when  $\xi$  is a continuous type random variable. Let p(x) be the pdf of  $\xi$ . Then

When  $\xi$  is a random variable of the general type and f(x) is a general Borel function, the proof of this theorem is due to measure theory. Next, we give a proof for the case when  $\xi$  is a continuous type random variable. Let p(x) be the pdf of  $\xi$ . Then

$$E|\eta| = \int_0^\infty P(|\eta| > y) dy = \int_0^\infty P(|f(\xi)| > y) dy$$
$$= \int_0^\infty \int_{x:|f(x)| > y} p(x) dx dy$$
$$= \int_{-\infty}^\infty \int_{y:|f(x)| > y, y \ge 0} p(x) dy dx$$
$$= \int_{-\infty}^\infty |f(x)| p(x) dx.$$

So  $Ef(\xi)$  exists if and only if  $\int_{-\infty}^{\infty} |f(x)| p(x) dx < \infty$ .

#### Further,

$$E\eta = \int_0^\infty P(\eta > y) dy - \int_0^\infty P(-\eta > y) dy$$

$$= \int_0^\infty \int_{x:f(x)>y} p(x) dx dy - \int_0^\infty \int_{x:-f(x)>y} p(x) dx dy$$

$$= \int_{-\infty}^\infty \left[ \int_{y:f(x)>y,y\geq 0} dy - \int_{y:-f(x)>y,y\geq 0} dy \right] p(x) dx$$

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Theorem 1 tells us that if  $\xi$  and  $\eta$  have the same distribution function, then

$$Ef(\xi) = Ef(\eta).$$

On the contrary, if the above equality holds for any bounded continuous function f, then  $\xi$  and  $\eta$  have the same distribution function.

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In fact, for any z and  $\epsilon>0$ , let f(x) be a continuous function such that f(x)=1,  $0\leq f(x)\leq 1$  and f(x)=0 on  $(-\infty,z]$ ,  $(z,z+\epsilon]$  and  $(z+\epsilon,\infty)$ , respectively. Then

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$$\begin{split} F_{\xi}(z) &= \int_{-\infty}^{z} f(x) dF_{\xi}(x) \leq \int_{-\infty}^{\infty} f(x) dF_{\xi}(x) \\ &= \int_{-\infty}^{\infty} f(x) dF_{\eta}(x) = \int_{-\infty}^{z+\epsilon} f(x) dF_{\eta}(x) \\ &\leq \int_{-\infty}^{z+\epsilon} dF_{\eta}(x) = F_{\eta}(z+\epsilon). \end{split}$$

Letting  $\epsilon \to 0$  yields  $F_{\xi}(z) \le F_{\eta}(z)$ .

In fact, for any z and  $\epsilon>0$ , let f(x) be a continuous function such that f(x)=1,  $0\leq f(x)\leq 1$  and f(x)=0 on  $(-\infty,z]$ ,  $(z,z+\epsilon]$  and  $(z+\epsilon,\infty)$ , respectively. Then

$$\begin{split} F_{\xi}(z) &= \int_{-\infty}^{z} f(x) dF_{\xi}(x) \leq \int_{-\infty}^{\infty} f(x) dF_{\xi}(x) \\ &= \int_{-\infty}^{\infty} f(x) dF_{\eta}(x) = \int_{-\infty}^{z+\epsilon} f(x) dF_{\eta}(x) \\ &\leq \int_{-\infty}^{z+\epsilon} dF_{\eta}(x) = F_{\eta}(z+\epsilon). \end{split}$$

Letting  $\epsilon \to 0$  yields  $F_{\xi}(z) \le F_{\eta}(z)$ . Similarly,  $F_{\eta}(z) \le F_{\xi}(z)$ . So  $\xi$  and  $\eta$  have the same distribution function.

Example. (Stein's Lemma) (i) Let  $\xi \sim N(0,1)$ , and g be differentiable function satisfying  $|g(x)| \leq c_1 e^{c_2|x|}$  and  $|g'(x)| \leq c_1 e^{c_2|x|}$  for some  $c_1 > 0, c_2 > 0$ . Prove

$$E[g(\xi)\xi] = Eg'(\xi).$$

(ii)\* On the contrary, if the above equality holds for any bounded continuous function g(x) with bounded derivation, then  $\xi \sim N(0,1)$ .

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# Proof. For (i), we have

$$E[g(\xi)\xi] = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} g(x)x \exp\left\{-\frac{x^2}{2}\right\} dx$$

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$$= \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} g(x)d\left[-\exp\left\{-\frac{x^2}{2}\right\}\right].$$

## Use integration by parts to get

$$E[g(\xi)\xi)]$$

$$= \frac{1}{\sqrt{2\pi}} \left[ -g(x) \exp\left\{-\frac{x^2}{2}\right\} \right]_{-\infty}^{\infty}$$

$$+ \int_{-\infty}^{\infty} g'(x) \exp\left\{-\frac{x^2}{2}\right\} dx$$

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For (ii), Let  $\eta \sim N(0,1).$  It is sufficient to show that  $Eh(\xi)=Eh(\eta)$  holds for any bounded continuous function h(x) .

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$$h(x) - Eh(\eta) = g'(x) - xg(x).$$

The above equation is called Stein's equation.

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$$h(x) - Eh(\eta) = g'(x) - xg(x).$$

The above equation is called Stein's equation. It can be verified that

$$g(x) = e^{\frac{x^2}{2}} \int_{-\infty}^{x} [h(u) - Eh(\eta)] e^{-\frac{u^2}{2}} du$$

is a solution of the equation, and, both g(x) and g'(x) are bounded continuous function.

So

$$Eh(\xi) = \int_{-\infty}^{\infty} [g'(x) - xg(x) + Eh(\eta)] dF_{\xi}(x)$$

$$= \int_{-\infty}^{\infty} g'(x) dF_{\xi}(x) - \int_{-\infty}^{\infty} xg(x) dF_{\xi}(x) + Eh(\eta) \int_{-\infty}^{\infty} dF_{\xi}(x)$$

$$= Eg'(\xi) - E[\xi g(\xi)] + Eh(\eta) = Eh(\eta).$$

The proof is completed. In the second equality above, the linearity of the Stieltjes integral.

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# Similarly,

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$$E\left[\xi g(\xi-1)\right] = E[\lambda g(\xi)], \; \forall g(\mathsf{bounded}) \Leftrightarrow \xi \sim P(\lambda).$$

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Stein-Chen method.

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  - 3.1.4 Expectations for functions of random variables

In general, suppose  $(\xi_1, \cdots, \xi_n) \sim F(x_1, \cdots, x_n)$ . Also, assume that  $g(x_1, \cdots, x_n)$  is a Borel function, then

$$Eg(\xi_1,\cdots,\xi_n)=\int_{-\infty}^{\infty}\cdots\int_{-\infty}^{\infty}g(x_1,\cdots,x_n)dF(x_1,\cdots,x_n).$$

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$$Eg(\xi_1,\cdots,\xi_n)=\int_{-\infty}^{\infty}\cdots\int_{-\infty}^{\infty}g(x_1,\cdots,x_n)dF(x_1,\cdots,x_n).$$

If 
$$(\xi_1, \xi_2, \dots, \xi_n)$$
 has pmf

$$P(\xi_1 = x_1(i_1), \xi_2 = x_2(i_2), \dots, \xi_n = x_n(i_n)) = p_{i_1 i_2 \dots i_n}$$
, then

$$Eg(\xi_1, \xi_2, \dots, \xi_n) = \sum_{i_1, i_2, \dots, i_n} g(x_1(i_1), x_2(i_2), \dots, x_n(i_n)) p_{i_1 i_2 \dots i_n};$$

If  $(\xi_1, \xi_2, \dots, \xi_n)$  has pdf  $p(x_1, x_2, \dots, x_n)$ , then

$$Eg(\xi_1,\xi_2,\ldots,\xi_n)$$

$$= \int_{-\infty}^{\infty} \cdots \int_{-\infty}^{\infty} g(x_1, x_2, \dots, x_n) p(x_1, x_2, \dots, x_n) dx_1 \cdots dx_n.$$

Here, the multi-variable Stieltjes integral is defined similarly as in the one-variable case. For example

$$\int_{a_1}^{b_1} \cdots \int_{a_n}^{b_n} g(x_1, \dots, x_n) dF(x_1, \dots, x_n)$$

$$= \lim \sum_{k_1, \dots, k_n} g(x_1(k_1), \dots, x_n(k_n)) \Delta F(x_1(k_1), \dots, x_n(k_n)),$$

where 
$$x_i(1), x_i(2), \ldots$$
 is a partition of  $(a_i, b_i]$ , 
$$\Delta F(x_1(k_1), \ldots, x_n(k_n))$$
 is the probability that  $(\xi_1, \ldots, \xi_n)$  falls in  $(x_1(k_1), x_1(k_1+1)] \times \cdots \times (x_n(k_n), x_n(k_n+1)]$ .

## In particular, we have

$$E\xi_i = \int_{-\infty}^{\infty} \cdots \int_{-\infty}^{\infty} x_i dF(x_1, \cdots, x_n) = \int_{-\infty}^{\infty} x dF_i(x),$$

where  $F_i(x)$  is the distribution function of  $\xi_i$ .

3.1.4 Expectations for functions of random variables

# For F(x,y) it follows

$$E\xi\eta = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} xy dF(x,y)$$

and

$$E\xi^2 = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} x^2 dF(x, y),$$

etc.

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Example. Suppose R and  $\Theta$  are indept.,  $\Theta \sim U(0, 2\pi)$ ,  $R \sim Rayleigh$ . Find  $Ee^{R\sin\Theta}$ . Solution.



- 3.1 Mathematical expectation
  - 3.1.4 Expectations for functions of random variables

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$$Ee^{R\sin\Theta} = \int_0^\infty \int_0^{2\pi} e^{r\sin\theta} r e^{-r^2/2} \frac{1}{2\pi} d\theta dr$$

- 3.1 Mathematical expectation
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3.1.4 Expectations for functions of random variables

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$$= \int_{-\infty}^{\infty} e^{x} \frac{1}{\sqrt{2\pi}} e^{-\frac{x^{2}}{2}} dx$$

$$= e^{\frac{1}{2}} \int_{-\infty}^{\infty} \frac{1}{\sqrt{2\pi}} e^{-\frac{(x-1)^{2}}{2}} dx = e^{\frac{1}{2}}.$$

- 3.1 Mathematical expectation
  3.1.5 Basic properties of expectations
  - 3.1.5 Basic properties of expectations-examples

- 3.1 Mathematical expectation
  - 3.1.5 Basic properties of expectations

- $\mathbf{Q} \ E\xi_1, \cdots, E\xi_n \ \text{exist} \implies$

$$E(\sum_{i=1}^{n} c_i \xi_i + b) = \sum_{i=1}^{n} c_i E \xi_i + b.$$

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 $\bullet$   $\xi_1, \cdots, \xi_n$  indept. and expectations exist  $\Longrightarrow$ 

$$E(\xi_1\cdots\xi_n)=E\xi_1\cdots E\xi_n.$$

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$$E(\xi_1\cdots\xi_n)=E\xi_1\cdots E\xi_n.$$

• If  $\xi \leq \eta$  and the exceptions of  $\xi$  and  $\eta$  exist, then  $E\xi \leq E\eta$ .

3.1 Mathematical expectation
3.1.5 Basic properties of expectations

Example 12. Suppose that  $\xi$  follows the binomial distribution B(n,p), find  $E\xi$ .

Example 12. Suppose that  $\xi$  follows the binomial distribution B(n, p), find  $E\xi$ . Solution. Consider a Bernoulli trial and set

p = P(A) and

$$\xi_i = \left\{ \begin{array}{l} 1, \quad A \text{ occurs in the } i\text{-th trial }, \\ 0, \quad A \text{ does not occur in the } i\text{-th trial }. \end{array} \right.$$

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Thus  $\xi_i$  follows 0-1 distribution,  $E\xi_i=p$  and  $\xi=\sum_{i=1}^n \xi_i$ . Hence  $E\xi=np$ .

$$P(\xi = m) = \frac{\binom{M}{m} \binom{N-M}{n-m}}{\binom{N}{n}}, \quad m = 0, 1, \dots, n.$$

$$(n \le M \le N)$$
. Find  $E\xi$ .

Solution. Design a sampling without replacement.

$$P(\xi = m) = \frac{\binom{M}{m} \binom{N-M}{n-m}}{\binom{N}{n}}, \quad m = 0, 1, \dots, n.$$

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**Solution.** Design a sampling without replacement. Let  $\xi_i$  be the number of defective goods in the i-th draw. Then  $\xi = \sum_{i=1}^n \xi_i$ .

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**Solution.** Design a sampling without replacement. Let  $\xi_i$  be the number of defective goods in the i-th draw. Then  $\xi = \sum_{i=1}^n \xi_i$ . It is known that  $P(\xi_i = 1) = M/N$ , so  $E\xi_i = M/N$ .

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$$E\xi = \sum_{i=1}^{n} E\xi_i = \frac{nM}{N}.$$

Example 14. Suppose that  $\xi_1, \dots, \xi_n$  are independent identically distributed positive random variables with a common density function f(x). Show for any  $1 \le k \le n$ ,

$$E\frac{\xi_1 + \dots + \xi_k}{\xi_1 + \dots + \xi_n} = \frac{k}{n}.$$

3.1 Mathematical expectation
3.1.5 Basic properties of expectations

Proof.

- 3.1 Mathematical expectation
  - 3.1.5 Basic properties of expectations

**Proof.**Notice that  $\frac{\xi_k}{\xi_1 + \dots + \xi_n}$  is positive and

$$E\frac{\xi_k}{\xi_1 + \dots + \xi_n}$$

$$= \int_0^\infty \dots \int_0^\infty \frac{x_k}{x_1 + \dots + x_n} f(x_1) \dots f(x_n) dx_1 \dots dx_n$$

**Proof.**Notice that  $\frac{\xi_k}{\xi_1 + \dots + \xi_n}$  is positive and

$$E\frac{\xi_k}{\xi_1 + \dots + \xi_n}$$

$$= \int_0^\infty \dots \int_0^\infty \frac{x_k}{x_1 + \dots + x_n} f(x_1) \dots f(x_n) dx_1 \dots dx_n$$

$$= \int_0^\infty \dots \int_0^\infty \frac{y_1}{y_1 + \dots + y_n} f(y_1) \dots f(y_n) dy_1 \dots dy_n$$

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$$E\frac{\xi_k}{\xi_1 + \dots + \xi_n}$$

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$$= \int_0^\infty \dots \int_0^\infty \frac{y_1}{y_1 + \dots + y_n} f(y_1) \dots f(y_n) dy_1 \dots dy_n$$

$$= E\frac{\xi_1}{\xi_1 + \dots + \xi_n}.$$

- 3.1 Mathematical expectation
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$$E\frac{\xi_1}{\xi_1+\cdots+\xi_n}+\cdots+E\frac{\xi_n}{\xi_1+\cdots+\xi_n}$$

- 3.1 Mathematical expectation
  - 3.1.5 Basic properties of expectations

$$E\frac{\xi_1}{\xi_1 + \dots + \xi_n} + \dots + E\frac{\xi_n}{\xi_1 + \dots + \xi_n}$$

$$= E\frac{\xi_1 + \dots + \xi_n}{\xi_1 + \dots + \xi_n} = 1.$$

- 3.1 Mathematical expectation
  - 3.1.5 Basic properties of expectations

$$E\frac{\xi_1}{\xi_1 + \dots + \xi_n} + \dots + E\frac{\xi_n}{\xi_1 + \dots + \xi_n}$$

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It follows that

$$E\frac{\xi_1}{\xi_1 + \dots + \xi_n} = \dots = E\frac{\xi_n}{\xi_1 + \dots + \xi_n} = \frac{1}{n}.$$

3.1.5 Basic properties of expectations

#### On the other hand,

$$E\frac{\xi_1}{\xi_1 + \dots + \xi_n} + \dots + E\frac{\xi_n}{\xi_1 + \dots + \xi_n}$$

$$= E\frac{\xi_1 + \dots + \xi_n}{\xi_1 + \dots + \xi_n} = 1.$$

It follows that

$$E\frac{\xi_1}{\xi_1 + \dots + \xi_n} = \dots = E\frac{\xi_n}{\xi_1 + \dots + \xi_n} = \frac{1}{n}.$$

Hence

$$E\frac{\xi_1 + \dots + \xi_k}{\xi_1 + \dots + \xi_n}$$

$$E\frac{\xi_1}{\xi_1 + \dots + \xi_n} + \dots + E\frac{\xi_n}{\xi_1 + \dots + \xi_n}$$

$$= E\frac{\xi_1 + \dots + \xi_n}{\xi_1 + \dots + \xi_n} = 1.$$

It follows that

$$E\frac{\xi_1}{\xi_1+\cdots+\xi_n}=\ldots=E\frac{\xi_n}{\xi_1+\cdots+\xi_n}=\frac{1}{n}.$$

Hence

$$E\frac{\xi_1 + \dots + \xi_k}{\xi_1 + \dots + \xi_n}$$

$$= E\frac{\xi_1}{\xi_1 + \dots + \xi_n} + \dots + E\frac{\xi_k}{\xi_1 + \dots + \xi_n} = \frac{k}{n}.$$

# Example

A grove of 52 trees is arranged in a circular fashion. If a total of 15 chipmunks (花栗鼠) live in these tress, show that there is a group of 7 consecutive trees that together house at least 3 chipmunks.

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**解**: 给定树j,记它连同它旁边按顺时针方向排列的6颗构成一个邻域 $U_j$ , 生活在 $U_j$ 中的chipmunks个数记为 $Y_j$ .

# Example

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解: 给定树j,记它连同它旁边按顺时针方向排列的6颗构成一个邻域 $U_j$ ,生活在 $U_j$ 中的chipmunks个数记为 $Y_j$ .我们只要证明 $EY_j > 2$   $\forall j$ ,就说明了存在一个树,使得至少有3个chipmunks 生活在此树的邻域中.

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事实上, 如果 $Y_j \le 2 \ \forall j$ , 那么 $\sum_{j=1}^{52} Y_j \le 2 * 52$ .

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事实上, 如果 $Y_j \le 2 \ \forall j$ , 那么 $\sum_{j=1}^{52} Y_j \le 2 * 52$ . 从

$$E\left[\sum_{j=1}^{52} Y_j\right] \le 2 * 52.$$

这与

$$\sum_{j=1}^{52} EY_j > 2 * 52$$

矛盾.

3.1.5 Basic properties of expectations

下面求
$$EY_j$$
.

$$\diamondsuit \ \, X_i = \begin{cases} 1, & \text{if chipmunk i live in } U_j, \\ 0, & \text{otherwise.} \end{cases}$$

则
$$Y_j = \sum_{i=1}^{15} X_i$$
.

# 下面求 $EY_j$ .

$$\label{eq:Xi} \diamondsuit \ \ X_i = \begin{cases} 1, & \text{if chipmunk i live in } U_j, \\ 0, & \text{otherwise}. \end{cases}$$

则
$$Y_j = \sum_{i=1}^{15} X_i$$
. 因为

$$EX_i = P(X_i = 1) = \frac{7}{52}.$$

# 下面求 $EY_j$ .

$$\diamondsuit \ \, X_i = \begin{cases} 1, & \text{if chipmunk i live in } U_j, \\ 0, & \text{otherwise.} \end{cases}$$

则
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. 因为

$$EX_i = P(X_i = 1) = \frac{7}{52}.$$

所以
$$EY_j = \sum_{i=1}^{15} EX_i = \frac{105}{52} > 2.$$

Example 15. Make a census on some kind of disease in a community with large population. Now check blood for N citizens in two ways: (1) each person each time, so need check N times. (2) check the mixture of bloods of a group of k people. If the outcome reports no virus, that means all these k people are not of this disease; while if the outcome reports virus, then each person from this group is checked again, so k people need check k+1 times in this way. Which way may decrease the number of checks?

**Solution.** Consider the second way. Denote by  $\xi$  the number of times each person needs check in a group of k people in the second way. Then

$$\xi = \begin{cases} 1/k, & \text{none of } k \text{ people is sick} \\ (k+1)/k, & \text{at least one of } k \text{ people is sick}. \end{cases}$$

So

**Solution.** Consider the second way. Denote by  $\xi$  the number of times each person needs check in a group of k people in the second way. Then

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So 
$$P(\xi = \frac{1}{k}) = (1 - p)^k$$
,  $P(\xi = 1 + \frac{1}{k}) = 1 - (1 - p)^k$ .

**Solution.** Consider the second way. Denote by  $\xi$  the number of times each person needs check in a group of k people in the second way. Then

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So 
$$P(\xi = \frac{1}{k}) = (1 - p)^k$$
, 
$$P(\xi = 1 + \frac{1}{k}) = 1 - (1 - p)^k$$
. Hence 
$$E\xi = \frac{1}{k}(1 - p)^k + (1 + \frac{1}{k})(1 - (1 - p)^k)$$
$$= 1 - (1 - p)^k + \frac{1}{k}.$$

3.1.5 Basic properties of expectations

## Basic properties of expectations (continue)

## Corollary

Suppose 
$$|\xi| \le \eta$$
,  $E\eta < \infty$ . Then  $E\xi$  exists and  $|E\xi| \le E|\xi| \le E\eta$ .

3.1.5 Basic properties of expectations

## Basic properties of expectations (continue)

### Corollary

Suppose  $|\xi| \le \eta$ ,  $E\eta < \infty$ . Then  $E\xi$  exists and  $|E\xi| \le E|\xi| \le E\eta$ .

**Proof.** For M>0, let  $\xi_M=|\xi|$  if  $|\xi|\leq M$ , and 0 if  $|\xi|>M$ . Then  $0\leq \xi_M\leq M$ . By Property 1,  $0\leq E\xi_M\leq M$ .

## Basic properties of expectations (continue)

#### Corollary

Suppose  $|\xi| \le \eta$ ,  $E\eta < \infty$ . Then  $E\xi$  exists and  $|E\xi| \le E|\xi| \le E\eta$ .

**Proof.** For M>0, let  $\xi_M=|\xi|$  if  $|\xi|\leq M$ , and 0 if  $|\xi|>M$ . Then  $0\leq \xi_M\leq M$ . By Property 1,  $0\leq E\xi_M\leq M$ . So  $E\xi_M$ ,  $E\eta$  exist, and  $\xi_M\leq \eta$ . It follows that  $\int_{-M}^{M} |\xi|^{2} d\xi = \int_{-M}^{M} |\xi|^{2} d\xi$ 

$$\int_{-M}^{M} |x| dF_{\xi}(x) = E\xi_M \le E\eta$$

by Property 4.

3.1.5 Basic properties of expectations

# Basic properties of expectations (continue)

#### Corollary

Suppose  $|\xi| \le \eta$ ,  $E\eta < \infty$ . Then  $E\xi$  exists and  $|E\xi| \le E|\xi| \le E\eta$ .

**Proof.** For M>0, let  $\xi_M=|\xi|$  if  $|\xi|\leq M$ , and 0 if  $|\xi|>M$ . Then  $0\leq \xi_M\leq M$ . By Property 1,  $0\leq E\xi_M\leq M$ . So  $E\xi_M$ ,  $E\eta$  exist, and  $\xi_M\leq \eta$ . It follows that

$$\int_{-M}^{M} |x| dF_{\xi}(x) = E\xi_M \le E\eta$$

by Property 4. Hence  $E|\xi| = \int_{-\infty}^{\infty} |x| dF_{\xi}(x) \le E\eta < \infty$ .

# Basic properties of expectations (continue)

#### Corollary

Suppose  $|\xi| \le \eta$ ,  $E\eta < \infty$ . Then  $E\xi$  exists and  $|E\xi| \le E|\xi| \le E\eta$ .

**Proof.** For M>0, let  $\xi_M=|\xi|$  if  $|\xi|\leq M$ , and 0 if  $|\xi|>M$ . Then  $0\leq \xi_M\leq M$ . By Property 1,  $0\leq E\xi_M\leq M$ .

So  $E\xi_M$ ,  $E\eta$  exist, and  $\xi_M \leq \eta$ . It follows that

$$\int_{-M}^{M} |x| dF_{\xi}(x) = E\xi_M \le E\eta$$

by Property 4. Hence  $E|\xi| = \int_{-\infty}^{\infty} |x| dF_{\xi}(x) \le E\eta < \infty$ .

Finally, since  $-|\xi| \le \xi \le |\xi|$ , by Property 4 we have

$$-E|\xi| \le E\xi \le E|\xi|$$
. The proof is completed.

3.1 Mathematical expectation
3.1.5 Basic properties of expectations

## Corollary

Let p > 1. If  $E|\xi|^p$  exists, then  $E|\xi|$  exists.

#### Corollary

Let p > 1. If  $E|\xi|^p$  exists, then  $E|\xi|$  exists.

**Proof.** Since  $|\xi| \le 1 + |\xi|^p$ ,  $E|\xi| \le 1 + E|\xi|^p$ .

- 3.1 Mathematical expectation
  - 3.1.5 Basic properties of expectations
    - **Markov** inequality: If  $E|\xi|$  exists, then

$$P(|\xi| \ge \epsilon) \le \frac{E|\xi|}{\epsilon}, \ \forall \epsilon > 0.$$

- 3.1 Mathematical expectation
  - 3.1.5 Basic properties of expectations
    - **Markov** inequality: If  $E|\xi|$  exists, then

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## **1** Markov inequality: If $E|\xi|$ exists, then

$$P(|\xi| \ge \epsilon) \le \frac{E|\xi|}{\epsilon}, \ \forall \epsilon > 0.$$

In fact, let

$$\eta = \begin{cases} 1, & \text{if } |\xi| \ge \epsilon, \\ 0, & \text{for otherwise.} \end{cases} \quad \text{Then } \eta \le \frac{|\xi|}{\epsilon}.$$

By Property 4, we have

$$P(|\xi| \ge \epsilon) = E\eta \le E\left[\frac{|\xi|}{\epsilon}\right] = \frac{E|\xi|}{\epsilon}.$$

**o** 
$$P(\xi = 0) = 1$$
 if and only if  $E|\xi| = 0$ .

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**1** 
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 if and only if  $E|\xi| = 0$ .

In fact, the "only if" part is obvious. For the "if" part, by Property 5 we have

$$P(|\xi| \ge \epsilon) = 0$$
 for all  $\epsilon > 0$ .

So 
$$P(|\xi| > 0) = 0$$
.

#### Convergence theorems

(Monotone convergence theorem). If  $0 \le \xi_n(\omega) \nearrow \xi(\omega)$ , then

$$\lim_{n \to \infty} E\xi_n = E\xi. \tag{*}$$

If  $0 \le \xi_n(\omega) \searrow 0$ , and  $E\xi_n$ s are finite, then

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**(** Dominated convergence theorem). If  $\xi_n(\omega) \to \xi(\omega)$ ,  $|\xi_n| \le \eta$  and  $E\eta < \infty$ , then (\*) holds.

#### Convergence theorems

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- **(** *(Dominated convergence theorem*). If  $\xi_n(\omega) \to \xi(\omega)$ ,  $|\xi_n| \le \eta$  and  $E\eta < \infty$ , then (\*) holds.
- **(**Bounded convergence theorem). If  $\xi_n(\omega) \to \xi(\omega)$  and  $|\xi_n| \leq M < \infty$ , then (\*) holds.

3.1 Mathematical expectation
3.1.5 Basic properties of expectations

证明: 先证明有界收敛定理.

首先, 已知 $|\xi_n| \le M$ ,  $|\xi| \le M$ . 由性质1,  $E\xi_n$ ,  $E\xi$ 存在, 并且 $|E\xi_n - E\xi| \le E|\xi_n - \xi|$ .

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首先, 已知 $|\xi_n| \le M$ ,  $|\xi| \le M$ . 由性质1,  $E\xi_n$ ,  $E\xi$ 存在, 并且 $|E\xi_n - E\xi| \le E|\xi_n - \xi|$ . 对任给的 $\epsilon > 0$ , 记 $A_n = \{|\xi_n - \xi| > \epsilon\}$ . 在 $A_n^c$ 上有 $|\xi_n - \xi| \le \epsilon$ . 而在 $A_n$ 上有 $|\xi_n - \xi| \le 2M$ .

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$$|\xi_n - \xi| \le \epsilon + 2MI_{A_n}.$$

因此

$$|E\xi_n - E\xi| \le E|\xi_n - \xi| \le \epsilon + 2MP(A_n).$$

- 3.1 Mathematical expectation
  - 3.1.5 Basic properties of expectations

另一方面, 由于
$$\xi_n(\omega) \to \xi(\omega)$$
, 所以 $\lim_{n\to\infty} A_n = \emptyset$ .

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3.1.5 Basic properties of expectations

另一方面, 由于 $\xi_n(\omega) \to \xi(\omega)$ , 所以 $\lim_{n\to\infty} A_n = \emptyset$ . 由概率的连续性得

$$\lim_{n \to \infty} P(A_n) = P(\lim_{n \to \infty} A_n) = 0.$$

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所以

$$\limsup_{n \to \infty} |E\xi_n - E\xi| \le \limsup_{n \to \infty} E|\xi_n - \xi| \le \epsilon.$$

由 $\epsilon > 0$ 的任意性得

$$\lim_{n \to \infty} |E\xi_n - E\xi| = \lim_{n \to \infty} E|\xi_n - \xi| = 0.$$

- 3.1 Mathematical expectation
  3.1.5 Basic properties of expectations
  - 现在证明单调收敛定理. 设 $0 \le \xi_n(\omega) \nearrow \xi(\omega)$ . 对任意的M > 0, 令 $\eta_n = \xi_n I\{|\xi_n| \le M\}$ ,  $\eta = \xi I\{|\xi| \le M\}$ . 则 $\eta_n \le \xi_n$ ,  $\eta \le \xi$ ,

$$\eta_n(\omega) \to \eta(\omega), \ \forall \omega$$

并且 $0 \le \eta_n \le M$ . 由有界收敛定理和数学期望的单调性知,

$$\lim_{n \to \infty} E\xi_n \ge \lim_{n \to \infty} E\eta_n = E\eta = \int_0^M x dF_{\xi}(x).$$

 $\diamondsuit M \to \infty$ 得

$$\lim_{n\to\infty} E\xi_n \ge E\xi.$$

如果 $E\xi = \infty$ , 则结论已经得证.

3.1 Mathematical expectation
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现在证明单调收敛定理. 设 $0 \le \xi_n(\omega) \nearrow \xi(\omega)$ . 对任意的M > 0, 令 $\eta_n = \xi_n I\{|\xi_n| \le M\}$ ,  $\eta = \xi I\{|\xi| \le M\}$ . 则 $\eta_n \le \xi_n$ ,  $\eta \le \xi$ ,

$$\eta_n(\omega) \to \eta(\omega), \ \forall \omega$$

并且 $0 \le \eta_n \le M$ . 由有界收敛定理和数学期望的单调性知,

$$\lim_{n \to \infty} E\xi_n \ge \lim_{n \to \infty} E\eta_n = E\eta = \int_0^M x dF_{\xi}(x).$$

 $\diamondsuit M \to \infty$ 得

$$\lim_{n\to\infty} E\xi_n \ge E\xi.$$

如果 $E\xi = \infty$ , 则结论已经得证. 如果 $E\xi < \infty$ , 则由于 $\xi_n \leq \xi$ , 由单调性得 $E\xi_n \leq E\xi$ . 所以

$$\lim_{n \to \infty} E\xi_n = E\xi.$$

## 下设 $0 \le \xi_n(\omega) \setminus 0$ , $E\xi_n$ 存在, 这时

$$0 \le \xi_1 - \xi_n \nearrow \xi_1.$$

所以

$$E(\xi_1 - \xi_n) \to E\xi_1.$$

所以

$$E\xi_n \to 0.$$

- 3.1 Mathematical expectation
  - 3.1.5 Basic properties of expectations

#### 最后证明控制收敛定理. 记

$$\eta_n = \sup_{m \ge n} |\xi_m - \xi|.$$

则
$$0 \le \eta_n(\omega) \searrow 0$$
.

3.1.5 Basic properties of expectations

#### 最后证明控制收敛定理. 记

$$\eta_n = \sup_{m \ge n} |\xi_m - \xi|.$$

则
$$0 \le \eta_n(\omega) \searrow 0$$
. 另一方面, 由于 $0 \le \eta_n \le 2\eta$ , 所以 $0 \le E\eta_n \le 2E\eta < \infty$ .

#### 3.1.5 Basic properties of expectations

#### 最后证明控制收敛定理. 记

$$\eta_n = \sup_{m > n} |\xi_m - \xi|.$$

则 $0 \le \eta_n(\omega) \searrow 0$ . 另一方面, 由于 $0 \le \eta_n \le 2\eta$ , 所以 $0 \le E\eta_n \le 2E\eta < \infty$ . 由单调收敛定理,

$$E\eta_n \to 0.$$

而

$$|E\xi_n - E\xi| \le E|\xi_n - \xi| \le E\eta_n.$$

因此

$$\lim_{n\to\infty} E\xi_n = E\xi.$$