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3.1.4 Expectations for functions of random variables

The expectation of a function of a discrete random variable:

 ξ 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 $\eta = f(\xi)$,

$$\begin{pmatrix} f(x_1) & f(x_2) & \cdots & f(x_k) & \cdots \\ p_1 & p_2 & \cdots & p_k & \cdots \end{pmatrix}.$$

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So the pmf of η is

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

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

Further.

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

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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 ξ is a discrete random variable with the distribution $F_{\xi}(x)$ and

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

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

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

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

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When ξ has density p(x), then

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

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When ξ 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 ξ is a continuous type random variable. Let p(x) be the pdf of ξ . Then

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When ξ 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 ξ is a continuous type random variable. Let p(x) be the

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

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 ξ and η 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 ξ and η 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

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

$$F_{\xi}(z) = \int_{-\infty}^{z} f(x)dF_{\xi}(x) \le \int_{-\infty}^{\infty} f(x)dF_{\xi}(x)$$
$$= \int_{-\infty}^{\infty} f(x)dF_{\eta}(x) = \int_{-\infty}^{z+\epsilon} f(x)dF_{\eta}(x)$$
$$\le \int_{-\infty}^{z+\epsilon} dF_{\eta}(x) = F_{\eta}(z+\epsilon).$$

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

$$F_{\xi}(z) = \int_{-\infty}^{z} f(x)dF_{\xi}(x) \le \int_{-\infty}^{\infty} f(x)dF_{\xi}(x)$$
$$= \int_{-\infty}^{\infty} f(x)dF_{\eta}(x) = \int_{-\infty}^{z+\epsilon} f(x)dF_{\eta}(x)$$
$$\le \int_{-\infty}^{z+\epsilon} dF_{\eta}(x) = F_{\eta}(z+\epsilon).$$

Letting $\epsilon \to 0$ yields $F_{\xi}(z) \le F_{\eta}(z)$. Similarly, $F_{\eta}(z) \le F_{\xi}(z)$. So ξ and η 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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$$= \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} g(x)d\left[-\exp\left\{-\frac{x^2}{2}\right\}\right].$$

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Use integration by parts to get

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

$$= \frac{1}{\sqrt{2\pi}} \left[-g(x) \exp\left\{-\frac{x^2}{2}\right\} \Big|_{-\infty}^{\infty} + \int_{-\infty}^{\infty} g'(x) \exp\left\{-\frac{x^2}{2}\right\} dx \right]$$

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$$= Eg'(\xi).$$

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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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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). Suppose $|h(x)| \leq M$, then $0 \leq \frac{h(x) + M}{2M} \leq 1$. So without loss of generality, we assume $0 \leq h(x) \leq 1$.

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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. (verify! Note $g(\infty)=0$, $\Phi(x)\leq \frac{1}{|x|\sqrt{2\pi}}e^{-x^2/2}$, $\Phi(x)\leq e^{-x^2/2}$ for all x<0.)

So

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

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

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

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

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Similarly,

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Similarly,

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

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Similarly,

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

Stein-Chen method.

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

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

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

$$P(\xi_1=x_1(i_1),\xi_2=x_2(i_2),\dots,\xi_n=x_n(i_n))=p_{i_1i_2\cdots i_n}$$
, 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

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

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

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 (ξ_1, \ldots, ξ_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 ξ_i .

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

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 $Ee^{R\sin\Theta}$

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

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$$Ee^{R\sin\Theta} = \int_0^\infty \int_0^{2\pi} e^{r\sin\theta} r e^{-r^2/2} \frac{1}{2\pi} d\theta dr$$
$$= \iint e^x \frac{1}{2\pi} e^{-\frac{x^2+y^2}{2}} dx dy ($$
 极坐标变换)

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

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