

Exercise2

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See in the last 4 pages

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(a*) Cauchy

$$F_X(x) = \int f_X(x)dx = \int \frac{1}{\pi(1+x^2)}dx$$

Let $x = \tan\theta$, then:

$$\begin{aligned} F(\theta) &= \int \frac{1}{\pi(1+\frac{\sin^2\theta}{\cos^2\theta})}d\tan\theta \\ &= \frac{1}{\pi} \int \frac{1}{1+\frac{\sin^2\theta}{\cos^2\theta}} \frac{1}{\cos^2\theta} d\theta \\ &= \frac{1}{\pi} \int 1 d\theta \\ &= \frac{1}{\pi}(\theta+C) \end{aligned}$$

As $\theta = \arctan(x)$, then:

$$F_X(x) = \frac{1}{\pi}(\arctan(x)+C)$$

According to the property of CDF, $\lim_{x \rightarrow \infty} F(x) = 1$.

As $\lim_{x \rightarrow \infty} \arctan(x) = \frac{\pi}{2}$, then $C = \frac{\pi}{2}$.

$$F_X(x) = \frac{\arctan(x)}{\pi} + \frac{1}{2}$$

(b*) Logistic

$$F_X(x) = \int f_X(x)dx = \int \frac{e^{-x}}{(1+e^{-x})^2} dx$$

$$= \frac{1}{1+e^{-x}} + C$$

$$\text{As } \lim_{x \rightarrow \infty} \frac{1}{1+e^{-x}} = 1, \text{ then } C = 0.$$

$$F_X(x) = \frac{1}{1+e^{-x}}$$

(c*) Pareto

$$F_X(x) = \int f_X(x)dx = \int \frac{a-1}{(1+x)^a} dx$$

$$= -(1+x)^{1-a} + C$$

$$\text{As } \lim_{x \rightarrow \infty} -(1+x)^{1-a} = 0, \text{ then } C = 1.$$

$$F_X(x) = -(1+x)^{1-a} + 1 \quad (x > 0)$$

$$F_X(x) = 0 \quad (x \leq 0)$$

(d*) Weibull

$$F_X(x) = \int f_X(x)dx = \int c^{\tau-1} e^{-cx^\tau} dx$$

$$= -e^{-cx^\tau} + C$$

$$\text{As } \lim_{x \rightarrow \infty} -e^{-cx^\tau} = 0, \text{ then } C = 1.$$

$$F_X(x) = -e^{-cx^\tau} + 1 \quad (x = 1, 2, \dots)$$

$$F_X(x) = 0 \quad (x \leq 0)$$

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(a*) Gamma Distribution

Xs from Gamma Distribution are continuous. Therefore, $E(X) = \int x f_X(x) dx$.

$$\int_{-\infty}^{\infty} x f_X(x) dx = \int_0^{\infty} x \frac{e^{-kx} x^{r-1} k^r}{(r-1)!} dx + \int_{-\infty}^0 0 dx = \int_0^{\infty} \frac{e^{-kx} x^{r-1} k^r}{(r-1)!} dx$$

$$= \int_0^{\infty} x \frac{e^{-kx} x^{r-1} k^r}{(r-1)!} dx = \int_0^{\infty} \frac{e^{-kx} x^r k^r}{(r-1)!} dx = \frac{r}{k} \int_0^{\infty} \frac{e^{-kx} x^{r-1} k^r}{(r-1)!} dx = \frac{r}{k} E(X) = \frac{r}{k}$$

$$\text{Var}(X) = E(x^2) - E(x)^2$$

$$E(X^2) = \int_{-\infty}^{\infty} x^2 f_X(x) dx$$

$$\text{Likewise, } E(X^2) = \frac{r^2 + r}{k^2}. \text{ Var}(X) = \frac{r}{k^2}$$

$$E(X) = \frac{r}{k}, \text{ Var}(X) = \frac{r}{k^2}$$

(b*) Poisson Distribution

$$E(X) = \sum_{x=0}^{\infty} \frac{e^{-\lambda} \lambda^x}{(x-1)!} = \lambda \sum_{x=1}^{\infty} \frac{e^{-\lambda} \lambda^{x-1}}{(x-1)!} + 0 = \lambda$$

$$E(X^2) = \sum_{x=0}^{\infty} \frac{(x-1)e^{-\lambda} \lambda^x + e^{-\lambda} \lambda^x}{(x-1)!} = \lambda^2 + \lambda$$

$$\text{Var}(X) = \lambda$$

(c*) Pareto Distribution

$$E(X) = \int_0^{\infty} \frac{x(a-1)}{(1+x)^a} dx = \int_0^{\infty} \frac{x(a-1) + (a-1) - (a-1)}{(1+x)^a} dx =$$

$$= \int_0^{\infty} \left(\frac{(a-1)}{(1+x)^{a-1}} - \frac{a-1}{(1+x)^a} \right) dx$$

$$= \frac{a-1}{2-a} (1+x)^{2-a} \Big|_0^{\infty} + (1+x)^{1-a} \Big|_0^{\infty} = \frac{1}{a-2}$$

$$E(X^2) = \int_0^{\infty} \left(\frac{a-1}{(1+x)^{a-2}} - \frac{2(a-1)}{(1+x)^{a-1}} + \frac{a-1}{(1+x)^a} \right) dx$$

$$= \left[\frac{a-1}{3-a} (1+x)^{3-a} - \frac{2(a-1)}{2-a} (1+x)^{2-a} - (1+x)^{1-a} \right] \Big|_0^{\infty} = \frac{2}{(3-a)(2-a)}$$

$$\text{Var}(X) = \frac{1-a}{(3-a)(2-a)^2}$$

(d) Negative Binomial

$$P(X = x) = \frac{(a+x-1)!}{x!(a-1)!} \left[\frac{b}{1+b} \right]^a \left[\frac{1}{1+b} \right]^x$$

For convenience, I substitute $\frac{b}{1+b}$ with p, then the equation above can be expressed as:

$$P(X = x) = C_{a+x-1}^x p^a (1-p)^x$$

$$E(X) = \sum_0^{\infty} x P(x) = \sum_1^{\infty} \frac{(a+x-1)!}{(x-1)!(a-1)!} p^a (1-p)^x$$

(As $0 * P(0) = 0$, summation starting from is equivalent to the original one)

$$\sum_{x=1}^{\infty} \frac{(a+x-1)!}{(x-1)!(a-1)!} p^a (1-p)^x = \sum_{x=1}^{\infty} a C_{a+x-1}^{x-1} p^a (1-p)^x$$

Let $t=x-1$, then

$$\begin{aligned} \sum_{x=1}^{\infty} a C_{a+x-1}^{x-1} p^a (1-p)^x &= \sum_{t=0}^{\infty} a C_{a+t}^t p^a (1-p)^{t+1} \\ &= \frac{a(1-p)}{p} \sum_{t=0}^{\infty} C_{a+t}^t p^{a+1} (1-p)^t \end{aligned}$$

$C_{a+t}^t p^{a+1} (1-p)^t$ is a density function of negative binomial. Hence, $\sum_{t=0}^{\infty} C_{a+t}^t p^{a+1} (1-p)^t = 1$.

$$\text{Finally, } E(X) = \frac{a(1-p)}{p} = \frac{a}{b}$$

$$\text{Var}(X) = E(X^2) - E(X)^2$$

$$\begin{aligned} E(X^2) &= \sum_{x=0}^{\infty} x^2 \frac{(a+x-1)!}{x!(a-1)!} p^a (1-p)^x \\ &= \sum_{x=1}^{\infty} \frac{x(a+x-1)!}{(x-1)!(a-1)!} p^a (1-p)^x \\ &= \sum_{x=1}^{\infty} a x C_{a+x-1}^{x-1} p^a (1-p)^x \end{aligned}$$

Let $t=x-1$, then

$$\begin{aligned} \sum_{x=1}^{\infty} a x C_{a+x-1}^{x-1} p^a (1-p)^x &= \sum_{t=0}^{\infty} a(t+1) C_{a+t}^t p^a (1-p)^{t+1} \\ &= \sum_{t=0}^{\infty} \frac{a(t+1)(1-p)}{p} C_{a+t}^t p^{a+1} (1-p)^t \\ &= \frac{a(1-p)}{p} \sum_{t=0}^{\infty} (t+1) C_{a+t}^t p^{a+1} (1-p)^t \\ &= \sum_{t=0}^{\infty} (t+1) C_{a+t}^t p^{a+1} (1-p)^t = \sum_{t=0}^{\infty} C_{a+t}^t p^{a+1} (1-p)^t + \sum_{t=0}^{\infty} t C_{a+t}^t p^{a+1} (1-p)^t \\ &= \sum_{t=0}^{\infty} C_{a+t}^t p^{a+1} (1-p)^t = 1 \\ &= \sum_{t=0}^{\infty} t C_{a+t}^t p^{a+1} (1-p)^t = \frac{(1+p)(a+1)}{p} \end{aligned}$$

(The calculating process is slightly omitted here, as the procedure is almost the same as that in calculating $E(X)$)

Just combine the two parts of $\sum_{t=0}^{\infty} (t+1) C_{a+t}^t p^{a+1} (1-p)^t$,

$$\begin{aligned} E(X^2) &= \frac{a(1-p)}{p} \sum_{t=0}^{\infty} (t+1) C_{a+t}^t p^{a+1} (1-p)^t = \frac{a(1-p)}{p} \left(\frac{(1-p)(a+1)}{p} + 1 \right) \\ \text{Var}(X) &= E(X^2) - E(X)^2 = \frac{a(1-p)}{p} \left(\frac{(1-p)(a+1)}{p} + 1 \right) - \left[\frac{a(1-p)}{p} \right]^2 = \frac{a(1-p)}{p^2} \end{aligned}$$

Replace p with the original expression $\frac{b}{1+b}$,

$$Var(X) = \frac{a(b+1)}{b^2}$$

$$E(X) = \frac{a}{b}, Var(X) = \frac{a(b+1)}{b^2}.$$

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Exponential Distribution

As both of x and y are greater than 0, then $P(x + y > X, X > x) = P(x + y > X)$.

$$P(x + y > X | x > X) = \frac{P(x+y>X)}{P(x>X)}.$$

$$\begin{aligned} P(x > X) &= 1 - \int_0^x \frac{1}{\lambda} e^{-\frac{x}{\lambda}} dx = \int_x^\infty \frac{1}{\lambda} e^{-\frac{x}{\lambda}} dx \\ &= -e^{-\frac{x}{\lambda}} \Big|_x^\infty = e^{-\frac{x}{\lambda}} \end{aligned}$$

$$\text{Likewise, } P(y > X) = e^{-\frac{y}{\lambda}}, \text{ and } P(x + y > X) = e^{-\frac{(x+y)}{\lambda}}$$

$$P(x + y > X | x > X) = \frac{P(x+y>X)}{P(x>X)} = P(y > X) = e^{-\frac{y}{\lambda}}$$

Geometric Distribution

$$P(x > X) = 1 - \sum_1^x q^{x-1} p$$

$$\sum_1^x q^{x-1} p \text{ is a geometric sequence whose sum equals to } \frac{(q^x - 1)p}{q - 1}.$$

$$P(x > X) = 1 - \frac{(q^x - 1)p}{q - 1}$$

$$\text{Likewise, } P(y > X) = 1 - \frac{(q^y - 1)p}{q - 1}, \text{ and } P(x + y > X) = 1 - \frac{(q^{x+y} - 1)p}{q - 1}$$

Substitute p with $1-q$, then we can get:

$$P(x > X) = q^x, P(y > X) = q^y, \text{ and } P(x + y > X) = q^{x+y}.$$

$$\text{It is obvious that } P(x + y > X | x > X) = \frac{P(x+y>X)}{P(x>X)} = P(y > X) = q^y$$

So far, I have shown that if X has either the exponential distribution, or a geometric distribution, then X has no memory.

"No memory" means what happens in the process will not affect the probability of the next event. To draw an economics analogy, sunk cost should not

affect the future decision, as it does not matter after happening.

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(a)

As $Y = e^X$, then $X = \ln Y$.

$$F_X(x) = F_X(\ln y)$$

$$f(y) = \frac{\partial F(\ln y)}{\partial y} = \frac{f_X(\ln y)}{y} = \frac{1}{y\sqrt{2\pi}\sigma} \exp\left(-\frac{(\ln y - \mu)^2}{2\sigma^2}\right)$$

$$E(Y^n) = E(e^{nx}) = \int e^{nx} f(x) dx$$

$$= \int e^{nx} \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{(x-\mu)^2}{2\sigma^2}} dx$$

$$= \int \frac{1}{\sqrt{2\pi}\sigma} e^{\frac{2\sigma^2 nx - x^2 - \mu^2 + 2\mu x}{2\sigma^2}} dx$$

$$= \int \frac{1}{\sqrt{2\pi}\sigma} e^{\frac{(\sigma^2 n + \mu)^2 - (x - \sigma^2 n - \mu)^2 - \mu^2}{2\sigma^2}} dx$$

$$= \frac{(\sigma^2 n + \mu)^2 - \mu^2}{e^{2\sigma^2}} \int \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{(x - \sigma^2 n - \mu)^2}{2\sigma^2}} dx$$

$$\int \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{(x - \sigma^2 n - \mu)^2}{2\sigma^2}} dx = 1$$

$$\text{Therefore, } E(Y^n) = e^{\frac{\sigma^4 n^2 + 2\sigma^2 n\mu}{2\sigma^2}}$$

$$E(Y) = e^{\frac{\sigma^2}{2} + \mu}, \quad E(Y^2) = e^{2\sigma^2 + 2\mu}$$

$$\text{Var}(Y) = E(X^2) - E(Y)^2 = e^{\sigma^2 + 2\mu}(e^{\sigma^2} - 1).$$

$$\text{Finally, } E(Y) = e^{\frac{\sigma^2}{2} + \mu}, \quad \text{Var}(Y) = e^{\sigma^2 + 2\mu}(e^{\sigma^2} - 1).$$

(b) See in the last 4 pages