

Lecture 10 : 10/10/17

(31)

$$X \sim \text{Exp}(1), Y = -\ln(X) \sim \text{Gumbel}(0,1) = e^{-(y+\bar{e}^y)}$$

$$Y \sim \text{Gumbel}(0,1), X = \bar{e}^Y \sim \text{Exp}(1) = \bar{e}^Y \bar{e}^{-e^Y}$$

$$\begin{aligned} F_Y(y) &= P(Y \leq y) = P(-Y \geq -y) = P(\bar{e}^{-Y} \geq \bar{e}^{-y}) \\ &= P(X \geq \bar{e}^y) = 1 - F_X(\bar{e}^y) = e^{-\bar{e}^y} \end{aligned}$$

$$\begin{aligned} X \sim \text{Gumbel}(0,1), Y = \mu + \beta X &\sim \text{Gumbel}(\mu, \beta) \\ &= \frac{1}{\beta} \bar{e}^{\left(\frac{y-\mu}{\beta} + \bar{e}^{\left(\frac{y-\mu}{\beta}\right)}\right)} \end{aligned}$$

$$\begin{aligned} F_Y(y) &= P(Y \leq y) = P\left(\frac{Y-\mu}{\beta} \leq \frac{y-\mu}{\beta}\right) = P\left(X \leq \frac{y-\mu}{\beta}\right) \\ &= F_X\left(\frac{y-\mu}{\beta}\right) = e^{-\bar{e}^{\left(\frac{y-\mu}{\beta}\right)}} \end{aligned}$$

Valid for any linear transform

$$X \sim \text{Gumbel}(0,1), Y = \bar{e}^X \sim \text{Exp}(1)$$

$$\text{support}[X] = \mathbb{R}$$

$$X \sim \text{Gumbel}(\mu, \beta), Y = \bar{e}^X \sim ?$$

$$g(x) = \bar{e}^{-x} \Rightarrow X = -\ln(g(x)) = \bar{g}'(y) \quad \text{support}[Y] = (0, \infty)$$

$$f_Y(y) = f_X(\bar{g}'(y)) \frac{d}{dy} [\bar{g}'(y)]$$

$$\left| \frac{d}{dy} [-\ln(y)] \right| = \bar{y}'$$

$$= f_X(-\ln(y)) \bar{y}' = \frac{1}{\beta} e^{-\left(\frac{-\ln(y) - \mu}{\beta}\right)} e^{-\left(\frac{-\ln(y) - \mu}{\beta}\right)} \bar{y}'$$

Note: $-\left(\frac{-\ln(y) - \mu}{\beta}\right) = \frac{k}{\beta} (\ln(y) + \mu) = k (\ln(y) + \ln(d))$

$k = \frac{1}{\beta}$ let $\mu = \ln(d)$

$$e^{-\left(\frac{-\ln(y) - \mu}{\beta}\right)} = e^{\ln(dy)^k} = (dy)^k \quad \left. \begin{array}{l} \beta \in (0, \infty) \Rightarrow k \in (0, \infty) \\ \mu \in \mathbb{R} \Rightarrow d \in (0, \infty) \end{array} \right\}$$

$$f_Y(y) = k(dy)^k e^{-(dy)^k} \frac{1}{y}$$

$$= \underbrace{(kd)}_{\frac{d^k}{d^{k-1}} y^k} (dy)^{k-1} e^{-(dy)^k} = \text{Weibull}(k, d)$$

CAF: $F_Y(y) = P(Y \leq y) = P(\ln(Y) \leq \ln(y)) =$

$$P(-\ln(Y) \geq -\ln(y)) = P(X \geq -\ln(y)) =$$

$$1 - F_X(-\ln(y)) = 1 - e^{-\left(\frac{-\ln(y) - \mu}{\beta}\right)}$$

$$= 1 - e^{-(dy)^k}$$

If $\beta = 1, \Rightarrow k = 1$ Weibull $(1, d) = d e^{-dy}$
 $= \text{Exp}(d)$

\Rightarrow Weibull $(1, 1) = \text{Exp}(1)$ "memoryless"

Case 1 $k > 1$ eg $k = 2$

$$X \sim \text{Weibull}(2, d) \Rightarrow F_X(x) = 1 - e^{-(dx)^2}$$

$$\Rightarrow 1 - F_X(x) = e^{-(dx)^2}$$

WTS: $P(X \geq b) > P(X \geq a+b | X \geq a)$

$$\begin{aligned} e^{-(db)^2} &= 1 - F_X(b) > \frac{P(X \geq a+b)}{P(X \geq a)} = \frac{1 - F_X(a+b)}{1 - F_X(a)} \\ &= \frac{e^{-(d(a+b))^2}}{e^{-(da)^2}} = \frac{e^{-(da)^2 - 2dab - (db)^2}}{e^{-(da)^2}} \end{aligned}$$



Case 2

$k < 1$ eg $k = \frac{1}{2}$

WTS: $P(X \geq b) < P(X \geq a+b | X \geq a)$

$$\begin{aligned} e^{-(db)^{1/2}} &< \frac{e^{-(d(a+b))^{1/2}}}{e^{-(da)^{1/2}}} = e^{\frac{-(d(a+b))^{1/2} + (da)^{1/2}}{-d^{1/2}((a+b)^{1/2} - a^{1/2})}} \\ &= e \end{aligned}$$

(take ln both side)

$$\Rightarrow \frac{-d^{1/2} b^{1/2}}{-d^{1/2}} < \frac{-d^{1/2}}{-d^{1/2}} (\dots) \Rightarrow b^{1/2} > (a+b)^{1/2} - a^{1/2}$$

$$a^{1/2} + b^{1/2} > (a+b)^{1/2} \Rightarrow (a^{1/2} + b^{1/2})^2 > a+b$$

$$\Rightarrow a+b + 2a^{1/2}b^{1/2} > a+b$$

$$\Rightarrow 2a^{1/2}b^{1/2} > 0 \checkmark$$

let $X \sim \text{Weibull}(k, d)$, $Y = \frac{1}{X} \sim ?$ support $[Y] = (0, \infty)$

$$\bar{g}'(y) = \frac{1}{y}, \quad \left| \frac{d}{dy} [\bar{g}'(y)] \right| = \frac{1}{y^2}$$

$$f_Y(y) = f_X\left(\frac{1}{y}\right) \frac{1}{y^2} = (kd) \left(\frac{d}{y}\right)^{k-1} e^{-\left(\frac{d}{y}\right)^k} \frac{1}{y^2}$$

$$f_Y(y) = (kd) \left(\frac{d}{y}\right)^{k-1} e^{-\left(\frac{d}{y}\right)^k} \frac{1}{y^2}$$

$$= kd^k \frac{1}{y^{k-1}} \frac{1}{y^2} e^{-\left(\frac{d}{y}\right)^k} = \frac{k}{d} d^{k+1} \frac{1}{y^{k+1}} e^{-\left(\frac{y}{d}\right)^k}$$

$$= \frac{k}{d} \left(\frac{y}{d}\right)^{-(k+1)} e^{-\left(\frac{y}{d}\right)^k}$$

$$= \frac{k}{d} \left(\frac{y}{d}\right)^{-(k+1)} e^{-\left(\frac{y}{d}\right)^k} \quad \text{Frechet}(k, d, 0)$$

Centered

$\{\text{Gumbell, Weibull, Frechet}\}$ belong to a special family called the Generalized extreme value distribution

$$X \sim \text{Erlang}(k, d) := \frac{\overset{\text{Gamma}(k, d)}{d^k x^{k-1} e^{-dx}}}{(k-1)!} = \frac{d^k x^{k-1} e^{-dx}}{\Gamma(k)}$$

$$X \sim \text{Negbin}(k, p) := \binom{x+k-1}{k-1} p^k (1-p)^x \quad \begin{matrix} k \in \mathbb{N} \\ d \in (0, \infty) \end{matrix}$$

$$\text{what if } k \in (0, \infty)? = \frac{\Gamma(x+k)}{\Gamma(x+1)\Gamma(k)} p^k (1-p)^x \quad p \in (0, 1)$$

$$X \sim \text{Negbin}(k, p) = \frac{\Gamma(x+k)}{\Gamma(x+1)\Gamma(k)} p^k (1-p)^x$$

Extended negative binomial

Recall $X \sim \text{Erlang}(k_1, d)$ independent $Y \sim \text{Erlang}(k_2, d)$
 $\Rightarrow X + Y \sim \text{Erlang}(k_1 + k_2, d)$

WTS if $X \sim \text{Gamma}(k_1, d)$ independent of
 $Y \sim \text{Gamma}(k_2, d) \Rightarrow X + Y \sim \text{Gamma}(k_1 + k_2, d)$

$$\begin{aligned} X + Y &\sim \int_0^t f_X(x) f_Y(t-x) dx = \int_0^t \frac{d^{k_1} x^{k_1-1} e^{-dx}}{\Gamma(k_1)} \frac{d^{k_2} (t-x)^{k_2-1} e^{-d(t-x)}}{\Gamma(k_2)} dx \\ &\quad \text{Gamma}(k_1 + k_2, d) \end{aligned}$$

$$= \frac{\sqrt{k_1+k_2} e^{-\lambda t}}{\Gamma(k_1)\Gamma(k_2)} \int_0^t x^{k_1-1} (t-x)^{k_2-1} dx$$

$$\text{let } u = \frac{x}{t} \Rightarrow \frac{du}{dx} = \frac{1}{t} \Rightarrow dx = t du$$

$$\begin{aligned} x_e = 0 &\Rightarrow u_e = 0 & (x_e \text{ } x_{\text{lower}}) \\ x_u = t &\Rightarrow u_u = 1 & (x_u \text{ } x_{\text{upper}}) \end{aligned}$$

$$= \frac{\sqrt{k_1+k_2} e^{-\lambda t}}{\Gamma(k_1)\Gamma(k_2)} \int_0^1 (ut)^{k_1-1} (t-ut)^{k_2-1} t du$$

$$= \frac{\sqrt{k_1+k_2} e^{-\lambda t}}{\Gamma(k_1)\Gamma(k_2)} \int_0^1 t^{k_1-1} t^{k_2-1} u^{k_1-1} (1-u)^{k_2-1} t du$$

$$= \frac{\sqrt{k_1+k_2} e^{-\lambda t}}{\Gamma(k_1)\Gamma(k_2)} t^{k_1+k_2-1} \int_0^1 u^{k_1-1} (1-u)^{k_2-1} du$$