

## The Gamma Distribution $\text{gamma}(\alpha, \beta)$

$$f_X(x) = \frac{1}{\Gamma(\alpha) \beta^\alpha} x^{\alpha-1} e^{-x/\beta} \quad I(x, \alpha, \beta > 0)$$

①  $X \sim \text{gamma}(\alpha, \beta) \longrightarrow 2X/\beta \sim \chi^2_{(2\alpha)}$

$$Y = g(x) = \frac{2}{\beta} x$$

$$Y' = g'(x) = \frac{2}{\beta}$$

$$\frac{d}{dy} g^{-1}(y) = \frac{\beta}{2}$$

$$f_Y(y) = f_X\left(\frac{\beta}{2}y\right) \left|\frac{\beta}{2}\right| = \frac{1}{\Gamma(\alpha) \beta^\alpha} \left(\frac{\beta}{2}y\right)^{\alpha-1} e^{-\frac{\beta}{2}y/\beta} \left|\frac{\beta}{2}\right|$$

$$= \frac{1}{\Gamma(\alpha) 2^\alpha} y^{\alpha-1} e^{-y/2} \longrightarrow \text{gamma}(\alpha, 2) \equiv \chi^2_{(2\alpha)}$$

②  $X_1, X_2, \dots, X_n \stackrel{iid}{\sim} \text{gamma}(\alpha_i, \beta) \longrightarrow \sum X_i \sim \text{gamma}(\sum \alpha_i, \beta)$

③  $\text{gamma}(1, \beta) \equiv \text{exponential}(\beta)$

④  $X_1, X_2, \dots, X_n \stackrel{iid}{\sim} \text{gamma}\left(\frac{v_i}{2}, 2\right) \equiv \chi^2_{(v_i)} \longrightarrow \sum X_i \sim (\sum v_i)$

## MGF

$$\begin{aligned}M_x(t) = E(e^{tx}) &= \int_0^{\infty} e^{tx} \left[ \frac{1}{\Gamma(\alpha) \beta^\alpha} x^{\alpha-1} e^{-x/\beta} \right] dx \\&= \frac{1}{\Gamma(\alpha) \beta^\alpha} \int_0^{\infty} x^{\alpha-1} e^{-x(\frac{1}{\beta} - t)} dx \\&= \frac{1}{\Gamma(\alpha) \beta^\alpha} \int_0^{\infty} x^{\alpha-1} e^{-x/(\beta/(1-\beta t))} dx \\&= \frac{\Gamma(\alpha) (\beta/(1-\beta t))^\alpha}{\Gamma(\alpha) \beta^\alpha} \underbrace{\int_0^{\infty} \frac{1}{\Gamma(\alpha) (\beta/(1-\beta t))^\alpha} x^{\alpha-1} e^{-x/(\beta/(1-\beta t))} dx}_{\text{gamma}(\alpha, (\beta/(1-\beta t)))} \\&= \frac{1}{\beta^\alpha} \left( \frac{\beta}{1-\beta t} \right)^\alpha \\&= \left( \frac{1}{1-\beta t} \right)^\alpha\end{aligned}$$

## Sufficient Statistic

$$f(x|\alpha, \beta) = f(x|\theta) = \prod f(x_i|\theta) = \left(\frac{1}{\Gamma(\alpha)\beta^\alpha}\right)^n \prod x_i^{\alpha-1} e^{-\frac{1}{\beta}x_i}$$

$$= \left(\frac{1}{\Gamma(\alpha)\beta^\alpha}\right)^n e^{-\frac{1}{\beta}\sum x_i} \prod x_i^{\alpha-1}$$

$$= \left(\frac{1}{\Gamma(\alpha)\beta^\alpha}\right)^n e^{-\frac{1}{\beta}\sum x_i + (\alpha-1)\sum \ln(x_i)} \quad (1)$$

$h(x)$

$\therefore T(x) = \begin{bmatrix} \sum x_i \\ \sum \ln(x_i) \end{bmatrix}$  is a sufficient statistic

## Minimally Sufficient

$\forall$  2 sample points  $x, y$

$$\frac{f(x|\theta)}{f(y|\theta)} = \frac{\left(\frac{1}{\Gamma(\alpha)\beta^\alpha}\right)^n e^{-\frac{1}{\beta}\sum x_i + (\alpha-1)\sum \ln(x_i)}}{\left(\frac{1}{\Gamma(\alpha)\beta^\alpha}\right)^n e^{-\frac{1}{\beta}\sum y_i + (\alpha-1)\sum \ln(y_i)}} = e^{-\frac{1}{\beta}(\sum x_i - \sum y_i) + (\alpha-1)(\sum \ln(x_i) - \sum \ln(y_i))}$$

\* This will be a constant of  $\alpha, \beta$  iff  $\sum x_i = \sum y_i$  and  $\sum \ln(x_i) = \sum \ln(y_i)$

$\therefore \begin{bmatrix} \sum x_i \\ \sum \ln(x_i) \end{bmatrix}$  is a minimally sufficient statistic for  $\alpha, \beta$

## Ancillary Statistic

$X_1, X_2, \dots, X_n \sim \text{gamma}(\alpha_0, \beta)$

$$f_x(x) = \frac{1}{\Gamma(\alpha_0) \beta^{\alpha_0}} x^{\alpha_0-1} e^{-x/\beta} \equiv \frac{1}{\beta} f_z\left(\frac{x}{\beta}\right) \text{ where } f_z(z) = \frac{1}{\Gamma(\alpha_0)} z^{\alpha_0-1} e^{-z}$$

Thus we have shown gamma to be a scale-family so any statistic that is a function of a ratio of the form  $\frac{X_i}{X_j}$  will be ancillary.

## Complete Statistic

$$f_x(x) = \frac{1}{\Gamma(\alpha_0) \beta^{\alpha_0}} x^{\alpha_0-1} e^{-x/\beta} = \frac{1}{\underbrace{\Gamma(\alpha_0) \beta^{\alpha_0}}_{c(\alpha, \beta)}} e^{(\alpha_0-1)\ln(x) - x/\beta} \quad (1)$$

$w_1(a, b) = \alpha_0 - 1 \quad w_2 = -\frac{1}{\beta} \quad h(x)$   
 $t_1(x) = \ln(x) \quad t_2(x) = x$

∴ The gamma function is an exponential family so a complete statistic for  $\alpha, \beta$  is  $\begin{bmatrix} \sum \ln(x_i) \\ \sum x \end{bmatrix}$

## Method of Moments

$$m_1 = \frac{1}{n} \sum x_i \quad \mu_1 = E(x) = \alpha\beta$$

$$m_2 = \frac{1}{n} \sum x_i^2 \quad \mu_2 = E(x^2) = \text{var}(x) + E(x)^2 = \alpha\beta^2 + \alpha^2\beta^2$$

$$\text{Solve } \bar{x} = \alpha\beta \Rightarrow \beta = \alpha\bar{x} \Rightarrow \frac{1}{n} \sum x^2 = \alpha^2 \bar{x}^2 (1 - \alpha)$$

$$\frac{1}{n} \sum x^2 = \alpha\beta^2(1 - \alpha)$$

$$\Rightarrow n\bar{x}^2 = \alpha^2 \bar{x}^2 (1 - \alpha) \Rightarrow n = \alpha^2 - \alpha^3$$

∴ This gets too nasty (non linear)

- Let's say  $\alpha$  is known, let's find the Method of Moments estimator for  $\beta$

$$m_1 = \frac{1}{n} \sum x_i \quad \mu_1 = E(x) = \alpha_0 \beta$$

$$\hat{\beta} = \bar{x} / \alpha_0$$

- Let's say  $\beta$  is known, let's find the Method of Moments estimator for  $\alpha$

$$m_1 = \frac{1}{n} \sum x_i \quad \mu_1 = E(x) = \alpha \beta_0$$

$$\hat{\alpha} = \bar{x} / \beta_0$$

## Maximum Likelihood Estimator

$$L(\alpha, \beta | X) = \prod \frac{1}{\Gamma(\alpha)\beta^\alpha} x^{\alpha-1} e^{-x/\beta} = \left(\frac{1}{\Gamma(\alpha)\beta^\alpha}\right)^n \prod x^{\alpha-1} e^{-\frac{1}{\beta} \sum x_i}$$

$$\ln(L(\alpha, \beta | X)) = -n \ln(\Gamma(\alpha)\beta^\alpha) + (\alpha-1) \sum \ln(x_i) - \frac{1}{\beta} \sum x_i = -n \ln(\Gamma(\alpha)) - \alpha n \ln(\beta) + (\alpha-1) \sum \ln(x_i) - \frac{1}{\beta} \sum x_i$$

$$\frac{\partial}{\partial \alpha} \ln(L(\alpha, \beta | X)) = \frac{-n \Gamma'(\alpha)}{\Gamma(\alpha)} - n \ln(\beta) + \sum \ln(x_i) \stackrel{\text{set}}{=} 0$$

$$\frac{\partial}{\partial \beta} \ln(L(\alpha, \beta | X)) = \frac{-\alpha n}{\beta} + \frac{\sum x_i}{\beta^2} \stackrel{\text{set}}{=} 0 \Rightarrow \frac{\alpha n}{\beta} = \frac{\sum x_i}{\beta^2} \Rightarrow \hat{\beta} = \bar{x} / \alpha$$

← Plug this in and solve numerically

$$\frac{\partial^2}{\partial \alpha^2} \ln(L(\alpha, \beta | X)) = \text{really ugly}$$

$$\frac{\partial^2}{\partial \beta^2} \ln(L(\alpha, \beta | X)) = \frac{\alpha n}{\beta^2} - \frac{2 \sum x_i}{\beta^3} \Big|_{\bar{x}/\alpha} = \frac{\alpha n}{(\bar{x}/\alpha)^2} - \frac{2 \sum x_i}{(\bar{x}/\alpha)^3} \Rightarrow \frac{\alpha^3 n}{(\sum x_i)^2} - \frac{2 \alpha^3 n^3}{(\sum x_i)^2} < 0$$

$$\hat{\beta} = \bar{x} / \alpha$$

$\alpha$  needs to be solved numerically