

~~log~~

$$f_{\Theta|x_1, \dots, x_n}(\theta|x_1, \dots, x_n) = \exp[\log\{f_{\Theta|x_1, \dots, x_n}(\theta|x_1, \dots, x_n)\}]$$
$$= \exp\left[\log\left\{c \cdot f_{\Theta}(\theta) \cdot \prod_{i=1}^n f_{x_i|\Theta}(x_i|\theta)\right\}\right] \quad (1)$$

Let's find a 2nd-order Taylor approximation to  $(\text{at } \hat{\Theta}^{MLE})$

$$\log\left\{f_{\Theta}(\theta) \cdot \prod_{i=1}^n f_{x_i|\Theta}(x_i|\theta)\right\}$$
$$= \log(c) + \log\{f_{\Theta}(\theta)\} + \sum_{i=1}^n \log\{f_{x_i|\Theta}(x_i|\theta)\}$$

By our argument in pictures,  $\log\{f_{\Theta}(\theta)\}$  will be nearly constant in comparison to  $\sum_{i=1}^n \log\{f_{x_i|\Theta}(x_i|\theta)\}$  as a function to  $\Theta$  for large  $n$

$$P_2(\theta) \approx \underbrace{\log(c)}_0 + l'(\hat{\Theta}^{MLE})(\theta - \hat{\Theta}^{MLE}) + \frac{1}{2} l''(\hat{\Theta}^{MLE})(\theta - \hat{\Theta}^{MLE})^2 \quad (2)$$

Plugging (2) into (1),

$$f_{\Theta|x_1, \dots, x_n}(\theta|x_1, \dots, x_n) \approx \exp\left[\log(c) + l(\hat{\Theta}^{MLE}) + \frac{-1}{2 \left(\frac{d^2}{d\theta^2} l(\theta)\big|_{\theta=\hat{\Theta}^{MLE}}\right)} (\theta - \hat{\Theta}^{MLE})^2\right]$$
$$\propto \exp\left[\frac{-1}{2 \left(\frac{d^2}{d\theta^2} l(\theta)\big|_{\theta=\hat{\Theta}^{MLE}}\right)} (\theta - \hat{\Theta}^{MLE})^2\right]$$

This is proportional to the pdf of a Normal  $(\hat{\Theta}^{MLE}, -\left[\frac{d^2}{d\theta^2} l(\theta)\big|_{\theta=\hat{\Theta}^{MLE}}\right]^{-1})$  distribution