

①

1) It is non-negative, and we can check that

$$\int_{-\infty}^{+\infty} f(x; \gamma) dx = \int_{-\infty}^{+\infty} \frac{1}{M} \gamma e^{-\gamma^4 x^4} dx$$

$$= \int_{-\infty}^{+\infty} \frac{1}{M} e^{-u^4} du = \frac{M}{M} = 1, \text{ so } f(\cdot; \gamma) \text{ is a pdf.}$$

2) Likelihood function

$$L_n(\gamma) = \prod_{i=1}^n \frac{1}{M} \gamma e^{-x_i \gamma^4}$$

Log-likelihood

$$\log L_n(\gamma) = -n \log M + n \log \gamma - \sum_{i=1}^n x_i \gamma^4$$

Derivative = 0?

$$\frac{n}{\gamma} - 4 \sum_{i=1}^n \gamma^3 x_i = 0 \Leftrightarrow \gamma^4 = \frac{n}{4 \sum_{i=1}^n x_i}$$

So MLE  $\hat{\gamma}_n = \left( \frac{1}{\frac{4}{n} \sum_{i=1}^n x_i} \right)^{\frac{1}{4}}$

3) Fisher information

$$I_1(\gamma) = - \int_{-\infty}^{+\infty} \frac{\partial^2 \log f(x; \gamma)}{\partial \gamma^2} f(x; \gamma) dx$$

Compute first:  $\log f(x; \gamma) = -\log M + \log \gamma - \gamma^4 x^4$

$$\frac{\partial}{\partial \gamma} \text{ --- } = \frac{1}{\gamma} - 4\gamma^3 x^4$$

$$\frac{\partial^2}{\partial \gamma^2} \text{ --- } = -\frac{1}{\gamma^2} - 12\gamma^2 x^4$$

$$\text{So } I_1(\gamma) = \int_{-\infty}^{+\infty} \left( \frac{1}{\gamma^2} + 12\gamma^2 x^4 \right) \frac{\gamma}{M} e^{-\gamma^4 x^4} dx$$

( $U = \gamma x$ )

change of variables

$$= \int_{-\infty}^{+\infty} \left( \frac{1}{\gamma^2} + \frac{12 U^4}{\gamma^2} \right) \frac{1}{M} e^{-U^4} dU$$

$$= \frac{1}{\gamma^2} \left( \int_{-\infty}^{+\infty} \frac{12 U^4 e^{-U^4}}{M} dU \right) \leftarrow \begin{array}{l} \text{Some constant} \\ A \end{array}$$

4] Likelihood  $L_n(\mu) = \frac{1}{M^n} \gamma^n e^{-\gamma^4 \sum_{i=1}^n (X_i - \mu)^4}$

log-likelihood  $\log L_n(\mu) = -n \log M + n \log \gamma - \gamma^4 \sum_{i=1}^n (X_i - \mu)^4$

Derivative = 0?

$$-\gamma^4 \cdot 4 \sum_{i=1}^n (X_i - \mu)^3 = 0$$

So  $\sum_{i=1}^n (X_i - \mu)^3 = 0$

is the "MLE equation", but not easy to solve analytically.

5] Same as above

$$I_2(\mu) = - \int_{-\infty}^{+\infty} \frac{\partial^2 \log g(x; \mu)}{\partial \mu^2} g(x; \mu) dx$$

$$\log g(x; \mu) = -\log M + \log \gamma - \gamma^4 (x - \mu)^4$$

$$\frac{\partial}{\partial \mu} = + 4 \gamma^4 (x - \mu)^3$$

$$\frac{\partial^2}{\partial \mu^2} = - 12 \gamma^4 (x - \mu)^2$$

$$\text{So } I_2(\mu) = \int_{-\infty}^{+\infty} 12 \gamma^4 (x - \mu)^2 \frac{\gamma e^{-(x - \mu)^4 \gamma^4}}{M} dx$$

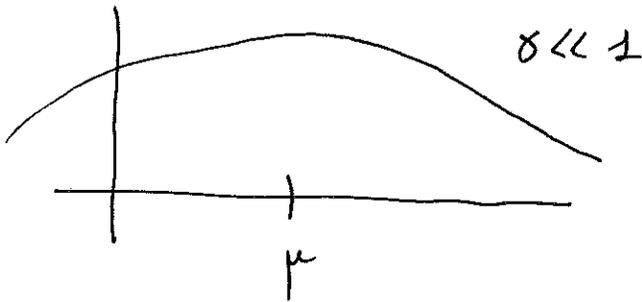
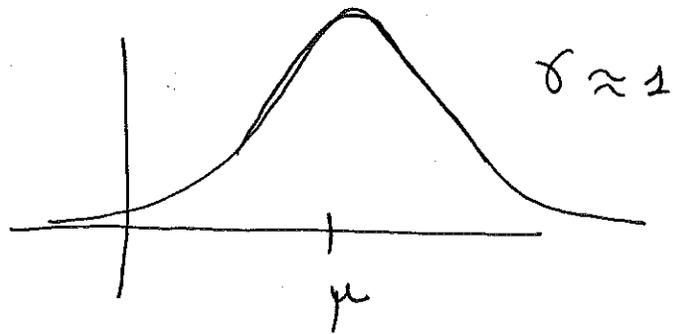
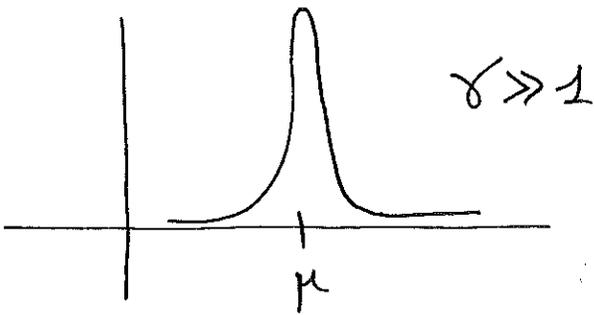
$$\begin{aligned} (U = \gamma(x - \mu)) \\ = \int_{-\infty}^{+\infty} \frac{12 \gamma^2 U^2 e^{-U^4}}{M} dU \end{aligned}$$

$$= \gamma^2 \cdot B$$

where  $B = \frac{12}{M} \int_{-\infty}^{+\infty} e^{-U^4} U^2 dU$   
some constant.

6) b) is the clearest one.

(2)



When  $\delta$  is large, the pdf is sharply peaked around  $\mu$ ,  
 when  $\delta$  is small, the pdf is "flatter".  
 So  $\delta$  large  $\rightarrow$  more "personality"  
 $\rightarrow$  more information.

a) is simply the fact that the pdf for various  $\mu$  are obtained by translating the graph, but they have all the same shape, hence the same amount of "personality".

7) Likelihood

$$L_n(\sigma) = \frac{1}{M^n} \frac{1}{\sigma^n} e^{-\frac{\sum_{i=1}^n X_i^4}{\sigma^4}}$$

$$\log L_n(\sigma) = -n \log M - n \log \sigma - \frac{1}{\sigma^4} \sum_{i=1}^n X_i^4$$

$$\text{Derivative} = 0? \quad -\frac{n}{\sigma} + \frac{4}{\sigma^5} \sum_{i=1}^n X_i^4 = 0$$

$$\text{So } \sigma = \left( \frac{4}{n} \sum_{i=1}^n X_i^4 \right)^{1/4}$$

8) "Equivariance"

Write

$$\begin{aligned} \hat{\sigma}_n - \sigma_* &\approx \sqrt{n} N(0, 1/\mathcal{I}_*^{\sigma_*}(\sigma_*)) \\ \hat{\delta}_n - \delta_* &\approx \sqrt{n} N(0, 1/\mathcal{I}_*^{\delta_*}(\delta_*)) \end{aligned}$$

9) Same computation as before, essentially

10) The Fisher information is indeed not equivariant  
 Assume

$\sigma = \varphi(\delta)$   
 is a transformation of the parameters.

$\hat{\sigma}_n = \varphi(\hat{\delta}_n)$   
 for MLE, because MLE is equivariant.