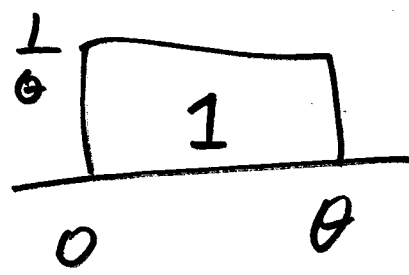


THT 2
#4

(2)



PDF of \mathcal{I}_i

$$f_{\mathcal{I}_i}(y_i | \theta) =$$

$$\frac{1}{\theta} I(0 \leq y_i < \theta) = \begin{cases} \frac{1}{\theta} & \text{for } 0 < y_i < \theta \\ 0 & \text{else} \end{cases}$$

$(0 < y_i < \theta \text{ for all } i=1, \dots, n)$

$$= (0 < \underbrace{\max(y_i)}_m < \theta)$$

$\mathcal{Y} = (y_1, \dots, y_n)$
 $\mathcal{I} = (\mathcal{I}_1, \dots, \mathcal{I}_n)$

$$f_{\mathcal{I}}(\mathcal{Y} | \theta)$$

prob. beh. of \mathcal{I}_1 and \mathcal{I}_2 and \dots and $\mathcal{I}_n | \theta$

vector (bold)

indep. \downarrow IID
 $(\mathcal{I}_i | \theta) \sim \text{Uniform}(\theta)$
 $(i=1, \dots, n)$

$$(*) = \frac{1}{\theta} I(0 < y_1 < \theta) \frac{1}{\theta} I(0 < y_2 < \theta) \dots \frac{1}{\theta} I(0 < y_n < \theta)$$

$$\otimes = \frac{1}{\theta^n} I(0 < \gamma_1 < \theta) \cdot I(0 < \gamma_2 < \theta) \cdot \dots \cdot I(0 < \gamma_n < \theta) \quad \textcircled{3}$$

$$= \frac{1}{\theta^n} I(0 \leq \gamma_1 \leq \theta \text{ and } 0 \leq \gamma_2 \leq \theta \text{ and } \dots \text{ and } 0 \leq \gamma_n \leq \theta)$$

$$= \frac{1}{\theta^n} I(\underbrace{\max(\gamma_1, \dots, \gamma_n)}_{\downarrow} \leq \theta) = \frac{f}{F}(z | \theta)$$

This ~~is~~ looks like a function of z

for fixed θ , but it's really just a function of both z and θ ,

and if we want we're free to also think of it as a f of θ ^{Laplace (1774), Fisher (1922)} for fixed z

under IID sampling

④

$$\underline{f_{\Sigma}(z|\theta)} = \prod_{i=1}^n f_{\Sigma_i}(y_i|\theta)$$

$$\underset{\uparrow}{\mathcal{L}(\theta|z)} = c \underset{\uparrow}{f_{\Sigma}(z|\theta)}$$

likelihood

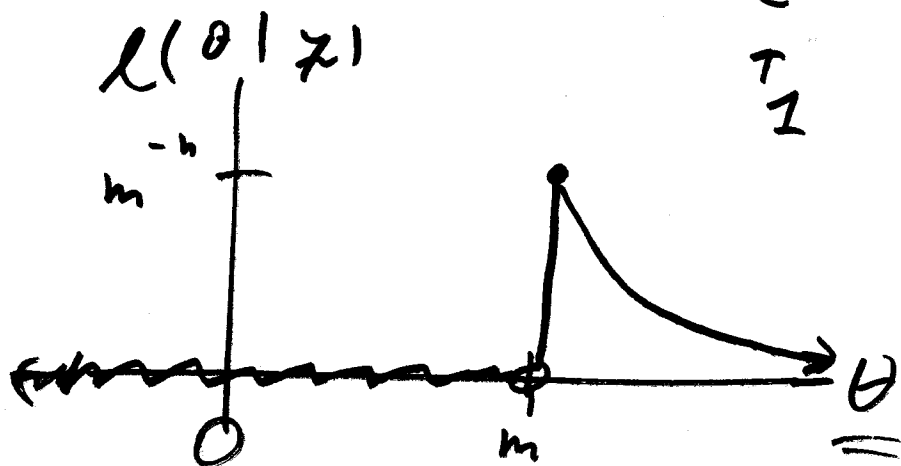
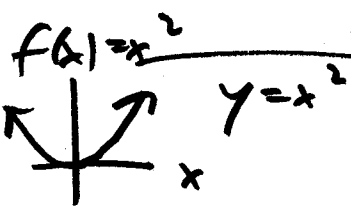
function

(c>0)
constant

$$= c \frac{1}{\theta^n} I(m \leq \theta)$$

$$= c \theta^{-n} I(\theta \geq m)$$

$$= c \theta^{-n} I(\theta \geq \max(y_1, \dots, y_n))$$

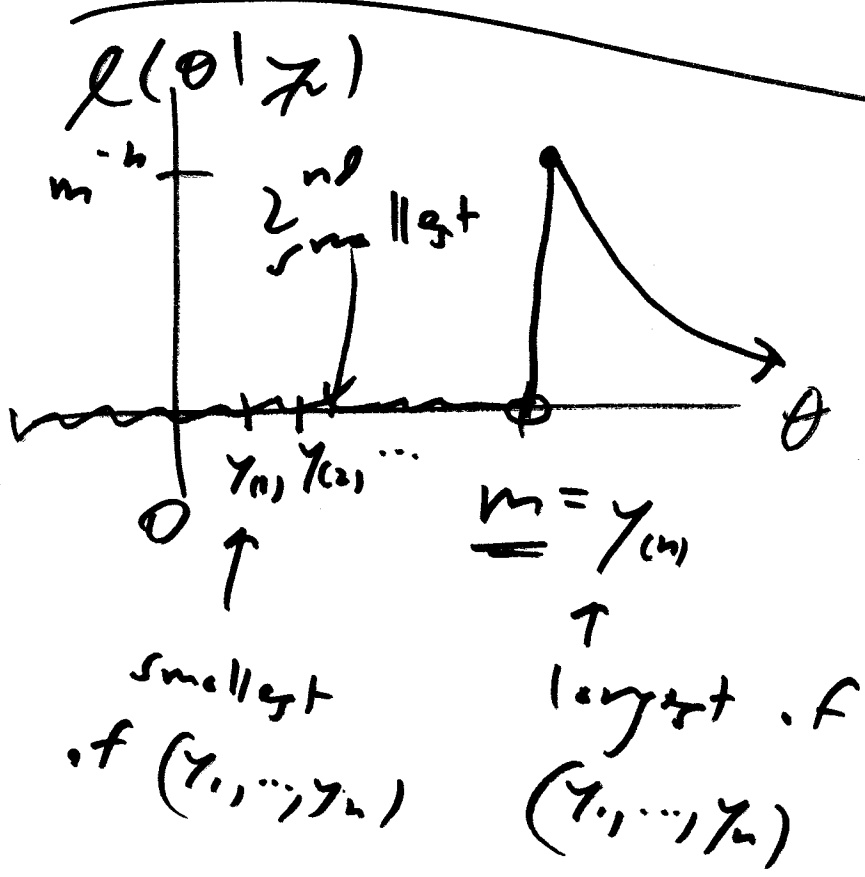


$$\hat{\theta}_{MLE} = m$$

Fisher: trust me, define

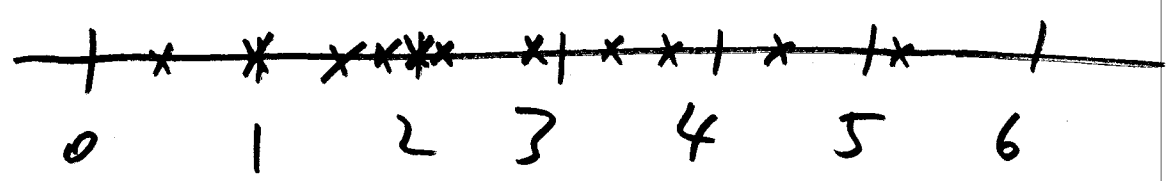
$\hat{\theta}_{MLE}$
 = the θ that maximizes
 $l(\theta | Z)$
 maximum likelihood
 estimate (or)

& use $\hat{\theta}_{MLE}$
 as a good estimate
 of θ



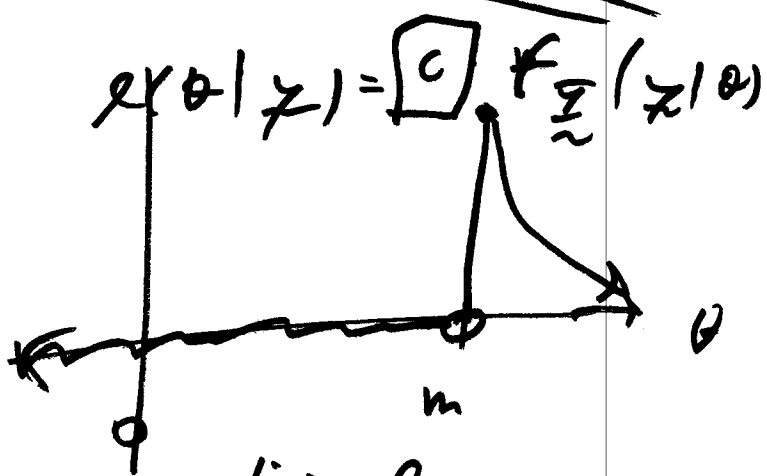
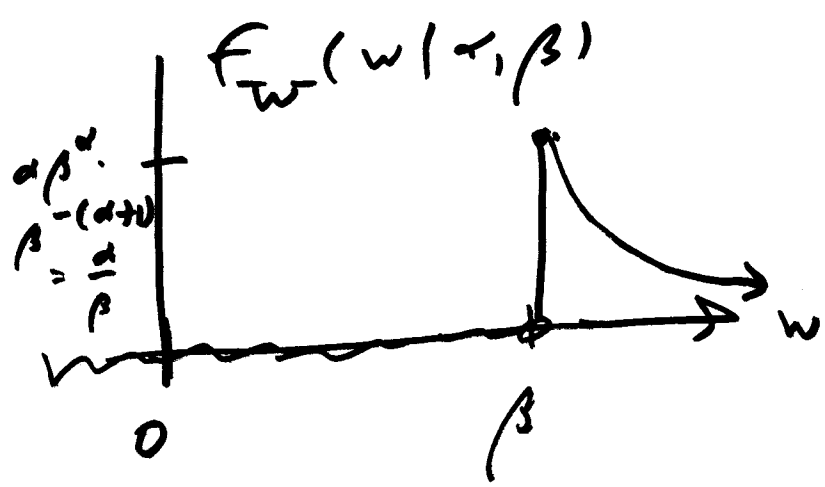
$\hat{\theta}_{MLE} = (0, \theta)$

$(\sum_i | \theta) \sim \text{Uniform}(\theta)$
 IID



$W \sim \text{Pareto}(\alpha, \beta) \rightarrow f_W(w | \alpha, \beta) = \begin{cases} c w^{-(\alpha+1)} & \text{for } w \geq \beta \\ 0 & \text{else} \end{cases}$

PDF (6)
 $(\alpha, \beta > 0)$



un-normalized

$l(\theta | z)$ is an Pareto distribution

in θ

$$\int_m^{\infty} \theta^{-n} d\theta = \frac{m^{1-n}}{n-1}$$

$$l(\theta | z) = \theta^{-n} I(\theta \geq m)$$

$$l_{\text{normalized}}(\theta | z) = \frac{n-1}{m^{1-n}} \theta^{-n} I(\theta \geq m)$$