

$$\text{Ex. } X_1, \dots, X_n \text{ i.i.d. } \sim f(x; \theta, \sigma) = \frac{1}{2\sigma} e^{-\frac{|x-\theta|}{\sigma}}$$

$$l_n(\theta, \sigma) = \log \left( \prod_{i=1}^n \frac{1}{2\sigma} e^{-\frac{|X_i-\theta|}{\sigma}} \right) =$$

$$= -n \log \sigma - \sum_{i=1}^n \frac{|X_i-\theta|}{\sigma} + c$$

$$\nabla_{\sigma > 0} \underset{\theta}{\operatorname{argmin}} \sum_{i=1}^n \frac{|X_i-\theta|}{\sigma} = \tilde{m}_n$$

↑ MEDIAN

$$\rightarrow l_n(\tilde{m}_n, \sigma) = -n \log \sigma - \sum_{i=1}^n \frac{|X_i-\tilde{m}_n|}{\sigma}$$

$$\frac{\partial l_n(\tilde{m}_n, \sigma)}{\partial \sigma} = -\frac{n}{\sigma} + \frac{1}{\sigma^2} \sum_{i=1}^n |X_i - \tilde{m}_n|$$

$$\rightarrow \hat{\sigma}_n = \frac{1}{n} \sum_{i=1}^n |X_i - \tilde{m}_n|$$

Ex 40)  $X_1, \dots, X_n$  i.i.d

$$\hat{\theta}_n^{(u)} = \underset{\theta \in \mathbb{R}}{\operatorname{argmax}} \frac{1}{n} \sum_{i=1}^n \rho_H(x_i - \theta),$$

where  $\rho_H(x) \begin{cases} x^2, & |x| \leq k \\ 2(|x| - \frac{k}{2}), & |x| > k \end{cases}$

$$\rho_H(x) \text{ CONVEX} \rightarrow \psi_H(x) \begin{cases} x, & |x| \leq k \\ k \operatorname{sign}(x), & |x| > k \end{cases}$$

$$\boxed{\text{TH 10}} \quad \sqrt{n} (\hat{\theta}_n^{(u)} - \theta_H) \xrightarrow[n \rightarrow \infty]{d} N\left(0, \frac{\sigma_\psi^2}{k^2}\right),$$

$$\text{where } \theta_H = \underset{\theta \in \mathbb{R}}{\operatorname{argmin}} E \rho_H(x_i - \theta),$$

$$E \psi(x_i - \theta_H) = 0$$

Further:

$$\begin{aligned} \sigma_\psi^2 &= \operatorname{var}(\psi(x_i - \theta_H)) = E[\psi(x_i - \theta_H)]^2 \\ &= \int_{-\infty}^{\infty} \psi^2(x - \theta_H) dF(x) \\ &= \int_{-\infty}^{\infty} [(x - \theta_H)^2 \mathbf{1}_{\{|x - \theta_H| \leq k\}} \\ &\quad + k^2 \operatorname{sign}^2(x - \theta_H) \mathbf{1}_{\{|x - \theta_H| > k\}}] dF(x) \end{aligned}$$

$$= \int_{\theta_H - k}^{\theta_H + k} (x - \theta_H)^2 dF(x) + k^2 P(|X_i - \theta_H| > k)$$

$$k^2 (F(\theta_H - k) + 1 - F(\theta_H + k))$$

$$\boxed{\text{TH. 10}} \quad g = \frac{\partial^2 M(\theta)}{\partial \theta^2} \Big|_{\theta=\theta_m}, \quad M(\theta) = \mathbb{E} \rho_H(X_1 - \theta)$$

$$\frac{\partial M(\theta)}{\partial \theta} = - \mathbb{E} \psi_H(X_1 - \theta)$$

$\uparrow$   
 $X_1$  HAS A DENSITY WRT TO LEB. MEASURE

$$\begin{aligned} &= - \mathbb{E} \left[ (X_1 - \theta) \mathbb{1}_{\{|X_1 - \theta| \leq \lambda\}} + \lambda \text{sign}(X_1 - \theta) \mathbb{1}_{\{|X_1 - \theta| > \lambda\}} \right] \\ &= - \int_{\theta - \lambda}^{\theta + \lambda} (x - \theta) dF(x) + \lambda \underbrace{P(X_1 < \theta - \lambda)}_{= F(\theta - \lambda)} - \lambda \underbrace{P(X_1 > \theta + \lambda)}_{= 1 - F(\theta + \lambda)} \end{aligned}$$

$$\begin{aligned} \frac{\partial^2 M(\theta)}{\partial \theta^2} &= - (\theta + \lambda - \theta) f(\theta + \lambda) + (\theta - \lambda - \theta) f(\theta - \lambda) \\ &\quad + \int_{\theta - \lambda}^{\theta + \lambda} 1 dF(x) + \lambda f(\theta - \lambda) + \lambda f(\theta + \lambda) \end{aligned}$$

$$= F(\theta + \lambda) - F(\theta - \lambda)$$

$$\leadsto g = F(\theta_m + \lambda) - F(\theta_m - \lambda)$$

LET  $X$  HAVE A DENSITY (WRT TO LEB, MEAS.)

$f(x;\theta) = f(x-\theta)$ , WHERE  $f$  IS SYMMETRIC

$$\rightarrow \theta_H = \theta$$

$$\begin{aligned}\sigma^2_F &= \int_{\theta_H - \lambda}^{\theta_H + \lambda} (x - \theta_H)^2 f(x - \theta_H) dx + \\ &\quad \lambda^2 (F(\theta_H - \lambda) + 1 - F(\theta_H + \lambda)) \\ &= \int_{-\lambda}^{\lambda} x^2 f(x) dx + \underbrace{\lambda^2 (F(-\lambda) + 1 - F(\lambda))}_{2\lambda^2 (1 - F(\lambda))}\end{aligned}$$

$$\begin{aligned}\gamma &= F(\theta_H + \lambda) - F(\theta_H - \lambda) = F(\lambda) - F(-\lambda) = \\ &= 2F(\lambda) - 1\end{aligned}$$

# NUMERICAL ILLUSTRATIONS IN R

## 1. ROBUST ESTIMATION OF LOCATION

(A) CONTAMINATED NORMAL, DISTRIB.:

$$0.9 \cdot N(0, 1)'' + 0.1 \cdot N(0, 25)''$$

huber(...,  $k=1.5$ )



$$\sum_{i=1}^n \psi\left(\frac{x_i - \hat{\theta}_n^{(k)}}{s_n}\right) = 0,$$

$$\text{where } s_n = \frac{\max_{1 \leq i \leq n} \{|x_i - \tilde{m}_n|\}}{\tilde{\mathbb{E}}[0.75]}$$

$$\psi(x) = x \mathbf{1}\{|x| \leq k\} + k \text{sign}(x) \mathbf{1}\{|x| > k\}$$

(B)  $X_1, \dots, X_{51} \sim \text{i.i.d } N(0, 1)$ ,  $X_{52} = \dots = X_{100} = 10^{12}$

(C)  $X_1, \dots, X_m \sim \text{i.i.d } 0.9 \cdot N(0, 1)'' + 0.1 \cdot N(0, 25)''$   
 $m = 100$

(D)  $X_1, \dots, X_n \sim \text{i.i.d } LN(\mu, \sigma^2)$ ,

$$\text{SO THAT } \mathbb{E} X_1 = e^{\mu + \frac{\sigma^2}{2}} = 38525$$

$$\text{med } X_1 = e^{\mu} = 32870$$

## 2. COMPARISON OF DIFF. ESTIM IN LINEAR MODEL

(A)  $Y_i = \beta_0 + \beta_1 X_i + \varepsilon_i, X_i \sim U(0, 1), \varepsilon_i \sim Exp(1)$

$$(\hat{\beta}_0, \hat{\beta}_1)^T = \underset{b_0, b_1}{\text{argmin}} \sum_{i=1}^n \rho(Y_i, X_i; b_0, b_1)$$

LS:  $\rho(Y_i, X_i; b_0, b_1) = (Y_i - b_0 - b_1 X_i)^2$

LAD:  $\rho(Y_i, X_i; b_0, b_1) = |Y_i - b_0 - b_1 X_i|$

HUBER:  $\text{Huber} \dots \text{LATER}$

(B)  $Y_i | X_i \sim Exp\left(\frac{1}{2(1+X_i)}\right), X_i \sim U(0, 2)$   $n = 10000$

$$\mathbb{E}[Y_i | X_i] = 2(1+X_i) = 2 + 2X_i$$

$$\text{med}(Y_i | X_i) = 2(1+X_i) \log(2) = \\ \approx \underbrace{1.39}_{\beta_0^{\text{LAD}}} + \underbrace{1.39 X_i}_{\beta_1^{\text{LAD}}} \quad \overset{\beta_0^{\text{LS}}}{\swarrow} \quad \overset{\beta_1^{\text{LS}}}{\swarrow}$$

HUBER?

$$\hat{\beta}_0 \doteq 2, \hat{\beta}_1 \doteq 1.35, S_n \doteq 3.01$$

$$\frac{1}{n} \sum_{i=1}^n \psi\left(\frac{Y_i - \hat{\beta}_0 - \hat{\beta}_1 X_i}{S_n}\right) = \begin{pmatrix} 0 \\ 0 \end{pmatrix}$$

$X_i = \begin{pmatrix} 1 \\ X_i \end{pmatrix}$

$\text{RIM}(\dots, k=1, 345)$

$$\hat{\beta}^{(0)} = \hat{\beta}^{(LS)}, \quad \hat{\varepsilon}_i^{(0)} = Y_i - \hat{X}_i^T \hat{\beta}^{(0)}, \quad i=1, \dots, n$$

$$\hat{\sigma}_n^{(0)} = \frac{\text{med}_{1 \leq i \leq n} \{ |\hat{\varepsilon}_i^{(0)}| \}}{\Phi^{-1}(0.75)}$$


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ITER STEP:

$$W^{(k+1)} = \text{diag} \{ w_1^{(k+1)}, \dots, w_n^{(k+1)} \}$$

( $n, n$ )

$$w_i^{(k+1)} = \underbrace{\psi \left( \frac{\hat{\varepsilon}_i^{(k)}}{\hat{\sigma}_n^{(k)}} \right)}_{\hat{\varepsilon}_i^{(k)}}$$

$$\hat{\beta}^{(k+1)} = (\hat{X}^T W^{(k)} \hat{X})^{-1} \hat{X}^T W^{(k)} \hat{Y}$$

$$\hat{\varepsilon}_i^{(k+1)} = Y_i - \hat{X}_i^T \hat{\beta}^{(k+1)}, \quad i=1, \dots, n$$

$$\hat{\sigma}_n^{(k+1)} = \text{med}_{1 \leq i \leq n} \{ |\hat{\varepsilon}_i^{(k+1)}| \}$$