

# **Asymptotic Statistics : Asymptotic Normality of Z Estimators**

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# Setup

Context: 2-estimator  $\hat{\theta}_n$  s.t.

$$2_n(\hat{\theta}_n) = \frac{1}{n} \sum_{i=1}^n 2(X_i, \hat{\theta}_n) = 0$$

with  $X_1, \dots$  i.i.d

$$2: \mathbb{R}^p \times \Theta \rightarrow \mathbb{R}$$

$$\exists \theta_0 \in \Theta \text{ s.t. } E(2(X_1, \theta_0)) = 0$$

$$\hat{\theta}_n \xrightarrow[n \rightarrow \infty]{P} \theta_0 \quad (\text{cf lectures 4 and 5}).$$

# Intuition

Taylor around  $\theta_0$ : (which makes sense since  $\hat{\theta}_n \xrightarrow{\mathbb{P}} \theta_0$ )

$$O_n(\hat{\theta}_n) \approx 2_n(\theta_0) + (J2_n)(\theta_0)(\hat{\theta}_n - \theta_0).$$

" => "  $\sqrt{n}(\hat{\theta}_n - \theta_0) = - (J2_n)(\theta_0)^{-1}(\sqrt{n}2_n(\theta_0))$

# Intuition

Taylor around  $\theta_0$ : (which makes sense since  $\hat{\theta}_n \xrightarrow{P} \theta_0$ )

$$0_n(\hat{\theta}_n) \approx 0_n(\theta_0) + (J_0)(\theta_0)(\hat{\theta}_n - \theta_0).$$

$$\Rightarrow \sqrt{n}(\hat{\theta}_n - \theta_0) = - (J_0)^{-1}(\sqrt{n}0_n(\theta_0))$$

L.L.N  $(J_0)^{-1}(\theta_0) \xrightarrow{P} \mathbb{E}(J_0(\theta_0, \theta_0)) =: J$

and if  $\det J \neq 0$ , C.N  $\Rightarrow (J_0)^{-1} \xrightarrow{P} J^{-1}$

C.L.T.  $\sqrt{n} \left[ 0_n(\theta_0) - \underbrace{\mathbb{E}(0_n(\theta_0))}_{= 0} \right] \xrightarrow{\mathcal{L}} \mathcal{N}(0, \text{cov}(0_n(\theta_0)))$

# Intuition

Taylor around  $\theta_0$ : (which makes sense since  $\hat{\theta}_n \xrightarrow{P} \theta_0$ )

$$\hat{\theta}_n \approx \theta_0 + (\nabla \hat{\theta}_n)(\theta_0) (\hat{\theta}_n - \theta_0).$$

$$\Rightarrow \sqrt{n} (\hat{\theta}_n - \theta_0) = - (\nabla \hat{\theta}_n)(\theta_0)^{-1} (\sqrt{n} \hat{\theta}_n)$$

L.L.N  $(\nabla \hat{\theta}_n)(\theta_0) \xrightarrow{P} \mathbb{E}(\nabla \hat{\theta}_n(\theta_0)) =: J$

and if  $\det J \neq 0$ , C.N  $\Rightarrow (\nabla \hat{\theta}_n)(\theta_0) \xrightarrow{P} J^{-1}$

C.L.T.  $\sqrt{n} \left[ \hat{\theta}_n - \mathbb{E}(\hat{\theta}_n) \right] \xrightarrow{D} \mathcal{N}(0, \text{cov}(\hat{\theta}_n))$

Spatsky

$$\sqrt{n} (\hat{\theta}_n - \theta_0) \xrightarrow{D} \mathcal{N}(0, J^{-1} \text{cov}(\hat{\theta}_n) J^{-T})$$

Goal of this Lecture: Make this rigorous.

# Maximal Inequality

Theorem (Maximal Inequality)

- $(X_i)_{i \geq 1}$  iid with distribution  $\mathcal{L}(\mathbb{R}^d)$
- $\mathcal{F}$ : set of functions from  $\mathbb{R}^d$  to  $\mathbb{R}$ .
- $\exists F: \mathbb{R}^d \rightarrow \mathbb{R}$  s.t.  $\forall f \in \mathcal{F}, |f(\omega)| \leq F(\omega)$   $\mathcal{L}$ -a.e.,  
 $C_F := \mathbb{E}(F(X_1)) < \infty$ .

Then  $\mathbb{E}^* \sup_{f \in \mathcal{F}} \frac{1}{\sqrt{n}} \left| \sum_{i=1}^n f(X_i) - \mathbb{E}(f(X_1)) \right| \leq C_{MI} \int_0^{C_F} \sqrt{\log(N_{\mathcal{F}}(F, L^2(\mathcal{L}), \varepsilon))} d\varepsilon$

# Maximal Inequality

Exercise If  $X_1, \dots, X_n$   $\stackrel{i.i.d.}{\sim} \text{Unif}([0,1])$ ,  $\mathcal{F} = \left\{ \mathbb{1}_{(-\infty, t]} ; t \in [0,1] \right\}$ ,

Find an upper-bound on

$$\mathbb{E}^* \sup_{f \in \mathcal{F}} \frac{1}{\sqrt{n}} \left| \sum_{i=1}^n f(X_i) - \mathbb{E}(f(X_i)) \right|.$$

# Application to Z Estimators

Theorem (Asymptotic Normality of Z-estimators). If,

$$\bullet \frac{1}{n} \sum_{i=1}^n z(x_i, \hat{\theta}_n) = o_p(1) \text{ with } z: \mathbb{R}^k \times \Theta \rightarrow \mathbb{R}^p \text{ s.t. } \mathbb{E}(\|z(x_i, \theta)\|^2) < \infty \ \forall \theta,$$

And  $\exists \theta_0 \in \Theta$  s.t.  $\mathbb{E}(z(x_i, \theta_0)) = 0$ ,

$$\hat{\theta}_n \xrightarrow{P} \theta_0.$$

$$\bullet \exists \mathcal{N} \text{ neighbourhood of } \theta_0 \text{ s.t. } \theta \mapsto \mathbb{E}(z(x_i, \theta)) \in C^1(\mathcal{N}).$$

$J\mathbb{E}(x_i, \theta_0)$  is invertible.

$$\bullet \mathcal{F}_j := \left\{ x \mapsto z(x, \theta) ; \theta \in A \right\}.$$

$$\forall j, \forall \delta > 0, \int_0^{\delta} \int_{\mathbb{R}^k} \text{by}_{\mathcal{F}_j}(F_j, L^2(\mathcal{L}), \varepsilon) d\varepsilon < \infty$$

$$\bullet \mathbb{E} \sup_{\substack{\theta \in \mathcal{N} \\ \|\theta - \theta_0\| \leq \delta}} \|z(x_i, \theta) - z(x_i, \theta_0)\|^2 \xrightarrow{\delta \rightarrow 0} 0.$$

# Application to Z Estimators

Theorem (Asymptotic Normality of Z-estimators). IF

- $\frac{1}{n} \sum_{i=1}^n z(x_i, \hat{\theta}_n) = o_p(1)$  with  $z: \mathbb{R}^k \times \Theta \rightarrow \mathbb{R}^p$  st  $\mathbb{E}(\|z(x_i, \theta)\|^2) < \infty \forall \theta$ ,  
And  $\exists \theta_0 \in \Theta$  st  $\mathbb{E}(z(x_i, \theta_0)) = 0$ ,

- $\exists \mathcal{X}$  neighborhood of  $\theta_0$  st.  $\theta \mapsto \mathbb{E}(z(x_i, \theta)) \in C^1(\mathcal{X})$ .

$$\text{JF}_j := \left\{ x \mapsto z(x, \theta) ; \theta \in A \right\}.$$

$\forall j, \forall \delta > 0, \int_0^{\delta} \int_{\mathcal{X}} \text{JF}_j(x_j, L^2(\omega), \varepsilon) d\varepsilon < \infty$

$$\mathbb{E} \sup_{\substack{\theta \in \mathcal{X} \\ \|\theta - \theta_0\| \leq \delta}} \|z(x_i, \theta) - z(x_i, \theta_0)\|^2 \xrightarrow[\delta \rightarrow 0]{} 0$$

Then

$$\sqrt{n} (\hat{\theta}_n - \theta_0) = - \left( \text{JF}(z(x_i, \theta_0)) \right)^{-1} \frac{1}{\sqrt{n}} \sum_{i=1}^n z(x_i, \theta_0) + o_p(1)$$

and thus

$$\sqrt{n} (\hat{\theta}_n - \theta_0) \xrightarrow[n \rightarrow +\infty]{\mathcal{D}} \mathcal{N} \left( 0, \text{JF}(z(x_i, \theta_0))^{-1} \text{cov} \left( z(x_i, \theta_0) \right) \text{JF}(z(x_i, \theta_0))^{-T} \right).$$

# Asymptotic Normality of the Median

$(x_i)_{i \in \mathbb{N}}$  iid with  $f_{X_i}$  and with density  $f$

Assumption 1:  $f(x) > 0 \quad \forall x \in \mathbb{R}$  almost surely.

Population median  $\theta_0$  the only real number such that  $f_{X_i}(\theta_0) = \frac{1}{2}$

Empirical median  $\hat{\theta}_n$  s.t.  $\sum_{i=1}^n \text{sgn}(\hat{\theta}_n - x_i) = 0$

Remark: We might restrict  $n$  to even numbers and that all the  $X$ 's are different (it happens almost surely).

$\Rightarrow$  By lecture 4,  $\hat{\theta}_n \xrightarrow{P} \theta_0$  (The first point of the theorem is satisfied)

# Asymptotic Normality of the Median

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Remark: We might restrict  $n$  to even numbers and that all the  $x$ 's are different (it happens almost surely).

$\Rightarrow$  By lecture 4,  $\theta_n \xrightarrow{P} \theta_0$  (The first point of the theorem is satisfied)

Assumption 2:  $f$  is continuous on a neighborhood of  $\theta_0$ .

$\Rightarrow \mathbb{E}(\text{sgn}(\theta - x_i)) = 2F_{x_i}(\theta) - 1$  is  $C^1$  on a neighborhood of  $\theta_0$ .

with derivatives  $2f(\theta)$  at  $\theta_0$ .

(The second point of the theorem is satisfied).

Next Step:  $\mathcal{F} := \{x \mapsto \text{sgn}(\theta - x); \theta \in \mathbb{R}\}$

Control  $\mathcal{M}_{C_2}(\mathcal{F}, L^2(\mathcal{L}), \mathcal{E})$

# Asymptotic Normality of the Median

Exercise:

1) Show that  $\forall N$  st  $N+1 \geq \frac{1}{\varepsilon^2}$ ,  $\exists t_1, \dots, t_N$  st

$$\forall j = 0, \dots, N, \mathcal{L}((t_j, t_{j+1})) \leq \varepsilon^2$$

with  $t_0 = -\infty$  and  $t_{N+1} = +\infty$ .

2) By considering functions of the form  $x \mapsto \mathbb{1}_{\{t_j \leq x\}}$   
and  $x \mapsto \mathbb{1}_{\{t_j^0 < x\}}$ ,

Build brackets of  $\mathcal{F}_- = \{x \mapsto \mathbb{1}_{\{\theta < x\}}; \theta \in \mathbb{R}\}$ .

Do the same thing for  $\mathcal{F}_+ = \{x \mapsto \mathbb{1}_{\{x < \theta\}}; \theta \in \mathbb{R}\}$

3) After noticing that  $\text{sgn}(\theta - x) = \mathbb{1}_{\{x < \theta\}} - \frac{1}{2} \mathbb{1}_{\{\theta < x\}}$ ,  
conclude.