

Chapter 3.3: Z-Estimators

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1 Recap of M-estimators

2 Z-estimators

- What are they?
- Limiting distribution
- The i.i.d. case
- Example

M-Estimators Recap

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We have seen results that ensure:

- Consistency: $\hat{\theta}_n \xrightarrow{P^*} \theta_0$
- Rate of convergence: $r_n d(\hat{\theta}_n, \theta_0) = O_P^*(1)$
- Limiting distribution

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We hope that $\hat{\theta}_n$ tends to a value θ_0 satisfying

$$\Psi(\theta_0) = 0.$$

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- What is the rate of convergence?
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Results from last week allow us to derive similar results for Z-estimators very easily! Therefore, we will only be looking at the limiting distribution.

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$$\|\Psi(\theta) - \Psi(\theta_0) - \dot{\Psi}_{\theta_0}(\theta - \theta_0)\| = o(\|\theta - \theta_0\|) \quad \text{as } \theta \rightarrow \theta_0,$$

where $\dot{\Psi}_{\theta_0} : \text{lin } \Theta \rightarrow \mathbb{L}$ is a continuous, linear, and one-to-one map.

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In the following theorem we will make the assumption that $\dot{\Psi}_{\theta_0}^{-1}$ exists and is continuous on the range of $\dot{\Psi}_{\theta_0}$.

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In the following theorem we will make the assumption that $\dot{\Psi}_{\theta_0}^{-1}$ exists and is continuous on the range of $\dot{\Psi}_{\theta_0}$.

Remark: this assumption is easy to verify if Θ were finite-dimensional.

Theorem (3.3.1)

Assume that

$$\sqrt{n}(\Psi_n - \Psi)(\hat{\theta}_n) - \sqrt{n}(\Psi_n - \Psi)(\theta_0) = o_P^*(1 + \sqrt{n}\|\hat{\theta}_n - \theta_0\|),$$

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and that the sequence $\sqrt{n}(\Psi_n - \Psi)(\theta_0)$ converges in distribution to a tight random element Z . If $\Psi(\theta_0) = 0$ and $\Psi_n(\hat{\theta}_n) = o_P^*(n^{-1/2})$, and $\hat{\theta}_n \xrightarrow{P^*} \theta_0$, then

$$\sqrt{n}\dot{\Psi}_{\theta_0}(\hat{\theta}_n - \theta_0) = -\sqrt{n}(\Psi_n - \Psi)(\theta_0) + o_P^*(1).$$

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$$\sqrt{n}\dot{\Psi}_{\theta_0}(\hat{\theta}_n - \theta_0) = -\sqrt{n}(\Psi_n - \Psi)(\theta_0) + o_P^*(1).$$

Consequently, $\sqrt{n}(\hat{\theta}_n - \theta_0) \rightsquigarrow -\dot{\Psi}_{\theta_0}^{-1}Z$.

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Since $\dot{\Psi}_{\theta_0}$ is continuously invertible, there exists $c > 0$ such that

$$\begin{aligned}\|\theta - \theta_0\| &= \|\dot{\Psi}_{\theta_0}^{-1} \dot{\Psi}_{\theta_0}(\theta - \theta_0)\| \leq \frac{1}{c} \|\dot{\Psi}_{\theta_0}(\theta - \theta_0)\| \\ &\implies \|\dot{\Psi}_{\theta_0}(\theta - \theta_0)\| \geq c \|\theta - \theta_0\|.\end{aligned}$$

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and we conclude that $\hat{\theta}_n$ is \sqrt{n} -consistent for θ_0 in norm.

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Using continuity of $\dot{\Psi}_{\theta_0}^{-1}$, the continuous mapping theorem gives

$$\sqrt{n}(\hat{\theta}_n - \theta_0) \rightsquigarrow -\dot{\Psi}_{\theta_0}^{-1}Z.$$

Remark: if $\sqrt{n}\|\hat{\theta}_n - \theta_0\|$ were asymptotically tight, the first conclusion is valid without requiring continuous invertibility of $\dot{\Psi}_{\theta_0}$.

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In case of i.i.d. observations, we may use $\Psi_n(\theta)h = \mathbb{P}_n \psi_{\theta,h}$ and $\Psi(\theta)h = \mathbb{P} \psi_{\theta,h}$ for given measurable functions $\psi_{\theta,h}$.

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The stochastic condition reduces to

$$\|\mathbb{G}_n(\psi_{\hat{\theta}_n,h} - \psi_{\theta_0,h})\|_{\mathcal{H}} = o_P^*(1 + \sqrt{n}\|\hat{\theta}_n - \theta\|).$$

The stochastic condition revisited

Lemma (3.3.5)

Suppose the class of functions

$$\{\psi_{\theta,h} - \psi_{\theta_0,h} : \|\theta - \theta_0\| < \delta, h \in \mathcal{H}\}$$

is P -Donsker for some $\delta > 0$ and that

$$\sup_{h \in \mathcal{H}} P(\psi_{\theta,h} - \psi_{\theta_0,h})^2 \rightarrow 0, \quad \theta \rightarrow \theta_0.$$

If $\hat{\theta}_n \xrightarrow{P^} \theta_0$, then the stochastic condition in Theorem 3.3.1 is satisfied.*

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Define $f : \ell^\infty(\Theta_\delta \times \mathcal{H}) \times \Theta_\delta \rightarrow \ell^\infty(\mathcal{H})$ by $f(z, \theta)h = z(\theta, h)$. This function is continuous at (z, θ_0) such that

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Define a stochastic process Z_n indexed by $\Theta_\delta \times \mathcal{H}$ by

$$Z_n(\theta, h) = \mathbb{G}_n(\psi_{\theta, h} - \psi_{\theta_0, h}).$$

This sequence converges in $\ell^\infty(\Theta_\delta \times \mathcal{H})$ to a tight Gaussian process Z .

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This sequence converges in $\ell^\infty(\Theta_\delta \times \mathcal{H})$ to a tight Gaussian process Z . Moreover, it has continuous sample paths with respect to the semimetric ρ given by

$$\rho^2((\theta_1, h_1), (\theta_2, h_2)) = P(\psi_{\theta_1, h_1} - \psi_{\theta_0, h_1} - \psi_{\theta_2, h_2} + \psi_{\theta_0, h_2})^2.$$

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By assumption

$$\sup_h \rho^2((\theta, h), (\theta_0, h)) = \sup_h P(\psi_{\theta, h} - \psi_{\theta_0, h})^2 \rightarrow 0 \quad \text{as } \theta \rightarrow \theta_0.$$

It follows that f is continuous at almost all sample paths of Z .

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The continuous mapping theorem then gives

$$Z_n(\hat{\theta}_n) = f(Z_n, \hat{\theta}_n) \rightsquigarrow f(Z, \theta_0) = 0 \text{ in } \ell^\infty(\mathcal{H}).$$

Examples

In case of Euclidean Θ and i.i.d. random variables, the following examples satisfy the stochastic condition:

Example 3.3.7 (Lipschitz): For every θ_1, θ_2 in a neighbourhood of θ_0 ,

$$\|\psi_{\theta_1}(x) - \psi_{\theta_2}(x)\| \leq \dot{\psi}(x) \|\theta_1 - \theta_2\|,$$

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Example 3.3.8 (Classical smoothness): Assume $\theta \mapsto \psi_{\theta}(x)$ is twice continuously differentiable for each x , with derivatives satisfying

$$P\|\dot{\psi}_{\theta_0}\|^2 < \infty; \quad P^* \sup_{\|\theta - \theta_0\| < \delta} \|\ddot{\psi}_{\theta}\| < \infty.$$

Idea: Taylor $\mathbb{G}_n(\psi_{\theta} - \psi_{\theta_0})$ to show that

$$\|\mathbb{G}_n(\psi_{\hat{\theta}_n} - \psi_{\theta_0})\| \leq o_P(1) + o_P(1)\sqrt{n}\|\hat{\theta}_n - \theta_0\|.$$