

# **M and Z Estimators**

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# M Estimators

Setup  $\Theta \subset \mathbb{M}^p$ ,  $\{\mathcal{L}_\theta; \theta \in \Theta\}$  is a statistical model.

$(M_n)_{n \in \mathbb{N}}$  a sequence of random functions from  $\Theta$  to  $\mathbb{M}^d$ :  
 $\forall n, \forall \theta, M_n(\theta)$  is a random vector in  $\mathbb{M}^d$ .  
and  $\{M_n(\theta); \theta \in \Theta\}$  are defined on the same space.

Definition A M-Estimator is a sequence of random  $(\hat{\theta}_n)$  taking values in  $\Theta$  such that  
 $\forall n$ , almost surely,  $\hat{\theta}_n \in \arg \max_{\theta \in \Theta} M_n(\theta)$

$M$  = "maximizer".

Exercise: Given random vectors  $X_1, \dots, X_n \in \mathbb{R}^d$ , express the empirical mean  $\bar{X}_n = \frac{1}{n} \sum_i X_i$  as a M-estimator.

# Maximum Likelihood

Assumption:  $\forall \theta, \mathcal{L}_\theta$  has a density  $f_\theta$  w.r.t. a reference measure  $\mu$ .

$$L_n(\theta) \equiv \prod_{i=1}^n f_\theta(X_i) \quad (\text{Likelihood}).$$

$$l_n(\theta) \equiv \log(L_n(\theta)) \equiv \sum_{i=1}^n \log(f_\theta(X_i)) \quad (\text{log-Likelihood}).$$

Log-Likelihood estimator:

$$\hat{\theta}_n \in \arg\max_{\theta \in \Theta} l_n(\theta) \quad \text{with } l_n(\theta) = \log(L_n(\theta)).$$

Idea: Choose the model that maximizes the "probability" of observing the samples.

Exercise: What is the maximum likelihood estimator in the Gaussian model?

# Consistency of M Estimators

Theorem: Consider a sequence  $(\Pi_n)$  of random functions from  $\Theta \in \mathbb{R}^d$  to  $\mathbb{R}$ . Consider a deterministic function  $M: \Theta \rightarrow \mathbb{R}$ .

$$\text{If } \sup_{\theta \in \Theta} |\Pi_n(\theta) - M(\theta)| \xrightarrow{\mathbb{P}} 0$$

$$\text{and } \exists \theta_0 \in \Theta \text{ s.t. } \forall \varepsilon > 0, \sup_{\substack{\theta \in \Theta \\ \|\theta - \theta_0\| \geq \varepsilon}} \Pi(\theta) < \Pi(\theta_0),$$

$$\text{and } (\hat{\theta}_n) \text{ is a sequence s.t. } \Pi_n(\hat{\theta}_n) \geq \left( \sup_{\theta \in \Theta} \Pi_n(\theta) \right) + o_{\mathbb{P}}(1)$$

$$\text{Then } \hat{\theta}_n \xrightarrow{\mathbb{P}} \theta_0.$$

# Z Estimators

Setup  $\Theta \subset \mathbb{M}^p$ ,  $\{\mathcal{L}_\theta; \theta \in \Theta\}$  is a statistical model.

$(Z_n)_{n \in \mathbb{N}}$  a sequence of random functions from  $\Theta$  to  $\mathbb{M}^d$ :  
 $\forall n, \forall \theta, M_n(\theta)$  is a random vector in  $\mathbb{M}^d$   
and  $\{M_n(\theta); \theta \in \Theta\}$  are defined on the same space.

Definition A M-Estimator is a sequence of random  $(\hat{\theta}_n)$  taking values in  $\Theta$  such that

$$\forall n, \text{ a.s. }, Z_n(\hat{\theta}_n) = 0.$$

Remark Often, M-estimators are defined by  $\nabla M_n(\hat{\theta}_n) = 0$ , in which case they are also Z-estimators.

Remark The method of moments is a Z-estimator.



# Consistency of Z Estimators

Theorem  $(Z_n)$  sequence of random functions from  $(H) \subset \mathbb{R}^p$  to  $\mathbb{R}^q$  and  
 $Z : (H) \rightarrow \mathbb{R}^q$  a deterministic function.

$$\text{If } \sup_{\theta \in (H)} \|Z_n(\theta) - Z(\theta)\| \xrightarrow{\mathbb{P}} 0$$

$$\text{and } \inf_{\substack{\theta \in (H) \\ \|\theta - \theta_0\| \geq \varepsilon}} \|Z(\theta)\| > 0 = \|Z(\theta_0)\|$$

and  $(\hat{\theta}_n)$  is a sequence such that  $Z_n(\hat{\theta}_n) = o_{\mathbb{P}}(1)$

$$\text{Then } \hat{\theta}_n \xrightarrow{\mathbb{P}} \theta_0.$$

# Easy Case : Monotone in 1D

Theorem If  $\Theta = \mathbb{R}$ ,  $(Z_n)$  is a sequence of random functions from  $\Theta$  to  $\mathbb{R}$  and  $Z: \mathbb{R} \rightarrow \mathbb{R}$  is a deterministic function such that

•  $\forall \theta$  fixed  $Z_n(\theta) \xrightarrow{\mathbb{P}} Z(\theta)$  (not uniform)

•  $\forall n$ ,  $Z_n$  is non-decreasing a.s.

•  $\exists \theta_0$  s.t.  $\forall \varepsilon > 0$ ,  $Z(\theta_0 - \varepsilon) < 0 < Z(\theta_0 + \varepsilon)$ .

Then, if  $(\hat{\theta}_n)$  is such that  $Z_n(\hat{\theta}_n) = o_p(1)$ ,

$$\underline{\hat{\theta}_n} \xrightarrow{\mathbb{P}} \theta.$$

Exercise  $X_1, \dots, X_n \stackrel{i.i.d.}{\sim} X$ . By considering the empirical median  $\hat{\theta}_n$  defined  
as 
$$\sum_{i=1}^n \text{sign}(\hat{\theta}_n - X_i) = 0,$$

show its consistency. ( $X$  has a continuous density w.r.t. Lebesgue bounded > 0 by below).