Maxiset point of view for signal detection in inverse problems

F. Autin, M. Clausel, J.-M. Freyermuth et C. Marteau

Aix-Marseille Université

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Physical domain :

$$Y = \mathbf{A}f + \varepsilon \xi.$$

A : $H \rightarrow K$ compact operator, ξ Gaussian White Noise.

Sequential domain :

$$y_k = \mathbf{b}_{\mathbf{k}} \theta_k + \varepsilon \xi_k, \quad k \in \mathbb{N}^*,$$

where $\mathbf{b}^2 := (\mathbf{b_k}^2)_k$ is the sequence of eigenvalues values of the operator $\mathbf{A}^*\mathbf{A}$ and ξ_k are i.i.d $\mathcal{N}(0,1)$. Here the noise level $\varepsilon > 0$ is known.

<u>Goal</u>: we aim at detecting whether the signal f is the null function (hypothesis H_0) or not (alternative hypothesis), using the observations $y = (y_k)_k$.

Definition (Hypotheses testing problems)

Indirect testing problem

 $\mathbf{H}_{\mathbf{0}}: \theta = \mathbf{0}_{l_{2}(\mathbb{N}^{*})} \quad \text{against} \quad \mathbf{H}_{\mathbf{1}}: \theta \in \Theta, \ \|\theta\|^{2} \geq r_{\varepsilon}^{2}.$

Direct testing problem

$$\mathbf{H_0}: \theta = \mathbf{0}_{l_2(\mathbb{N}^*)} \quad \text{against} \quad \mathbf{\tilde{H}_1}: \mathbf{b}. \theta \in \tilde{\Theta}, \ \|\mathbf{b}.\theta\|^2 \geq \mu_{\varepsilon}^2$$

Above :

r = (r_ε)_{ε>0} and μ = (μ_ε)_{ε>0} are decreasing and non negative sequences, called the chosen rates of detection,

•
$$\Theta$$
 and $\tilde{\Theta}$ are subset of $l_2(\mathbb{N}^*)$.

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Definition (α -testing procedure)

Fix $0 < \alpha < 1$. An α -testing procedure $\Delta_{\alpha,\varepsilon} = \Delta_{\alpha,\varepsilon}(y)$ is a measurable function of $y = (y_k)_{k \in \mathbb{N}^*}$, such that $\Delta_{\alpha,\varepsilon} \in \{0,1\}$ and

$$\mathbb{P}_{\mathbf{0}_{l_2(\mathbb{N}^*)}}(\Delta_{\alpha,\varepsilon}=1) \leq \alpha.$$

<u>Convention</u> :

- $\Delta_{\alpha,\varepsilon} = 1$ means H_0 is rejected
- $\Delta_{\alpha,\varepsilon} = 0$ means H_0 is not rejected

For a given truncation that is an increasing sequence of non negative integers $(D_{\varepsilon})_{\varepsilon>0}$.

Definition

 $\frac{\text{Indirect testing Procedure}}{\Delta_{\alpha,\varepsilon}^{IP} = \mathbf{1}_{\{T_{D_{\varepsilon}} > t_{\alpha,\varepsilon}\}}, \text{ where } T_{D_{\varepsilon}} = \sum_{k=1}^{D_{\varepsilon}} \mathbf{b}_{\mathbf{k}}^{-2} y_{k}^{2}$

Direct testing Procedure : $\mathbf{b} = (\mathbf{b}_k)_{k \in \mathbb{N}^*}$ is unknown.

$$\Delta^{DP}_{lpha,arepsilon} = \mathbf{1}_{\{S_{D_arepsilon} > s_{lpha,arepsilon}\}} \quad ext{where} \quad S_{D_arepsilon} = \sum_{k=1}^{D_arepsilon} y_k^2,$$

where $t_{\alpha,\varepsilon}$ and $s_{\alpha,\varepsilon}$ denote appropriate thresholds.

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Let $(\alpha, \beta) \in (0, 1)^2$ be respectively the Type-I and the Type-II errors. Fix a set $\Theta \subset l_2(\mathbb{N}^*)$. Let $\bullet \in \{IP, DP\}$.

Definition (β -separation rate for $\Delta^{\bullet}_{\alpha,\varepsilon}$)

The β -separation rates over Θ for $\Delta^{\bullet}_{\alpha,\varepsilon}$ is defined as :

$$egin{aligned} &R_arepsilon(\Delta^{IP}_{lpha,arepsilon},\Theta,eta) = \inf\left\{r_arepsilon>0,\ \sup_{ heta\in\Theta,\ \|eta\|^2\geq r_arepsilon^2}\mathbb{P}_ heta(\Delta^{IP}_{lpha,arepsilon}=0)\leqeta
ight\}.\ &R_arepsilon(\Delta^{DP}_{lpha,arepsilon},eta) = \inf\left\{\mu_arepsilon>0,\ \sup_{ heta\in\Theta,\ \|f b, heta\|^2\geq \mu_arepsilon^2}\mathbb{P}_ heta(\Delta^{DP}_{lpha,arepsilon}=0)\leqeta
ight\}. \end{aligned}$$

The (α, β) -minimax separation rates associated to the testing problems are then defined as $r^* = (r_{\varepsilon}^*)_{\varepsilon>0}$ and $\mu^* = (\mu_{\varepsilon}^*)_{\varepsilon>0}$ where : $r_{\varepsilon}^* := \inf_{\Delta_{\alpha,\varepsilon}} R_{\varepsilon}(\Delta_{\alpha,\varepsilon}, \Theta, \beta)$ and $\mu_{\varepsilon}^* := \inf_{\Delta_{\alpha,\varepsilon}} R_{\varepsilon}(\Delta_{\alpha,\varepsilon}, \tilde{\Theta}, \beta)$

Theorem (B. Laurent, J.-M. Loubes and C. Marteau (2010))

Consider mildly or severely ill-posed model. Then, with a good choice of $(D_{\varepsilon})_{\varepsilon}$:

- in the Indirect testing problem (IP), $\Delta_{\alpha,\varepsilon}^{IP}$ is (α,β) -minimax optimal over of Besov balls,
- (2) in the Direct testing problem (DP), $\Delta_{\alpha,\varepsilon}^{DP}$ is (α,β) -minimax optimal over Besov ellipsoids.
- Any (α, β)-minimax optimal testing procedure over ellipsoids balls for (DP) is (α, β)-minimax optimal procedure over ellipsoids balls for (IP). The converse are wrong.

Corollary (B. Laurent, J.-M. Loubes and C. Marteau (2010))

According to the <u>minimax sense</u>, $\Delta^{DP}_{\alpha,\varepsilon}$ outperforms $\Delta^{IP}_{\alpha,\varepsilon}$ for the problem of signal detection.

Questions on the minimax point of view :

- Can other signals be detected by our testing procedures at the chosen (α, β) -minimax separation rates ?
- What about the performance of our testing procedures for other rates of detection ?
- \Longrightarrow Could maxiset approach tackle this problem ?

Definition (Maxiset of $\Delta^{\bullet}_{\alpha}$ for a chosen rate of detection)

Indirect testing problem

$$MS(\Delta^{I\!P}_{lpha},r,eta) = \left\{ heta: orall arepsilon\in (0,1), \left[\| heta\|^2\geq r_arepsilon^2\Rightarrow \mathbb{P}_{ heta}\left[\Delta^{I\!P}_{lpha,arepsilon}=0
ight]\leq eta
ight]
ight\}.$$

Direct testing problem

$$\textit{MS}(\Delta^{\textit{DP}}_{\alpha}, \mu, \beta) = \left\{ \theta : \forall \varepsilon \in (0, 1), \left[\left\| \mathbf{b}. \theta \right\|^2 \geq \mu_{\varepsilon}^2 \Rightarrow \mathbb{P}_{\theta} \left[\Delta^{\textit{DP}}_{\alpha, \varepsilon} = 0 \right] \leq \beta \right] \right\}$$

<u>Remark</u>: The faster the chosen rates of detection $r = (r_{\varepsilon})_{\varepsilon}$ and $\mu = (\mu_{\varepsilon})_{\varepsilon}$ the thinner the maxisets.

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Lemma (Indirect testing problem)

There exist $C_{\max}(\alpha,\beta)$ and $C_{\min}(\alpha,\beta)$ such that, for all $\varepsilon \in (0,1)$:

$$\begin{array}{ll} (i) & \sum_{k=1}^{D_{\varepsilon}} \theta_{k}^{2} > C_{\max}(\alpha,\beta) \varepsilon^{2} \sqrt{\sum_{k=1}^{D_{\varepsilon}} b_{k}^{-4}} & \Rightarrow \mathbb{P}_{\theta}(\Delta_{\alpha,\varepsilon}^{IP}=0) \leq \beta, \\ (ii) & \sum_{k=1}^{D_{\varepsilon}} \theta_{k}^{2} \leq C_{\min}(\alpha,\beta) \varepsilon^{2} \sqrt{\sum_{k=1}^{D_{\varepsilon}} b_{k}^{-4}} & \Rightarrow \mathbb{P}_{\theta}(\Delta_{\alpha,\varepsilon}^{IP}=0) > \beta. \end{array}$$

<u>Remark</u> : A consequence of (*ii*) is :

$$\|\theta\|^2 = C_{\min}(\alpha,\beta)\varepsilon_o^2 \sqrt{\sum_{k=1}^{D_{\varepsilon_o}} b_k^{-4}} \text{ for some } 0 < \varepsilon_o < 1 \Longrightarrow \mathbb{P}_{\theta}(\Delta_{\alpha,\varepsilon_o}^{IP} = 0) > \beta.$$

Lemma (Direct testing problem)

There exist
$$C'_{\min}(\alpha, \beta)$$
 and $C'_{\max}(\alpha, \beta)$ such that, for all $\varepsilon \in (0, 1)$:
(i) $\sum_{k=1}^{D_{\varepsilon}} b_k^2 \theta_k^2 > C'_{\max}(\alpha, \beta) \varepsilon^2 \sqrt{D_{\varepsilon}} \Rightarrow \mathbb{P}_{\theta}(\Delta_{\alpha, \varepsilon}^{DP} = 0) \le \beta,$
(ii) $\sum_{k=1}^{D_{\varepsilon}} b_k^2 \theta_k^2 \le C'_{\min}(\alpha, \beta) \varepsilon^2 \sqrt{D_{\varepsilon}} \Rightarrow \mathbb{P}_{\theta}(\Delta_{\alpha, \varepsilon}^{DP} = 0) > \beta.$

<u>Remark</u> : A consequence of (*ii*) is :

$$\|\mathbf{b}.\theta\|^2 = C_{\min}'(\alpha,\beta)\varepsilon_o^2\sqrt{D_{\varepsilon_o}} \text{ for some } 0 < \varepsilon_o < 1 \Longrightarrow \mathbb{P}_{\theta}(\Delta_{\alpha,\varepsilon_o}^{DP} = 0) > \beta.$$

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<u>Comment</u> :

• Poorly informative setting \Rightarrow Robust version of Maxisets.

Definition (Robustness)

A set $\mathcal{H} \subset I_2(\mathbb{N}^*)$ is said to be robust if for any filter $h \in I_{\infty}(\mathbb{N}^*)$ with I_{∞} -norm smaller than 1 :

$$\theta \in \mathcal{H} \Rightarrow h.\theta \in \mathcal{H}.$$

<u>Heuristic idea</u> : focusing on detected signal θ or **b**. θ with the smallest information.

Definition

For any C > 0 we introduce the following subset of $l_2(\mathbb{N}^*)$:

$$egin{aligned} \mathcal{F}_{r,D}(\mathcal{C}) &= \left\{ heta \in l_2(\mathbb{N}^*), \ orall arepsilon \in (0,1); \sum_{k > D_arepsilon} heta_k^2 < r_arepsilon^2 - \mathcal{C}arepsilon^2 \sqrt{\sum_{k=1}^D b_k^{-4}}
ight\}, \ \mathcal{G}_{\mu,D}(\mathcal{C}) &= \left\{ heta \in l_2(\mathbb{N}^*), \ orall arepsilon \in (0,1); \sum_{k > D_arepsilon} b_k^2 heta_k^2 < \mu_arepsilon^2 - \mathcal{C}arepsilon^2 \sqrt{D_arepsilon}
ight\}. \end{aligned}$$

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• Maxisets are empty for fast rates of detection.

Corollary (Indirect testing problem)

$$MS(\Delta^{IP}_{\alpha},r,eta)
eq \emptyset \iff r_{arepsilon}^2 \succeq arepsilon^2 \sqrt{\sum_{k=1}^{D_{arepsilon}} b_k^{-4}}, \quad orall arepsilon \in (0,1).$$

Corollary (Direct testing problem)

$$MS(\Delta^{DP}_{\alpha}, \mu, \beta) \neq \emptyset \iff \mu_{\varepsilon}^2 \succeq \varepsilon^2 \sqrt{D_{\varepsilon}}, \quad \forall \varepsilon \in (0, 1).$$

<u>Remarks</u> :

- Direct testing Procedure can detect signals with small information while Indirect procedure can not.
- For the Indirect testing Procedure, the worse the operator, the further the horizon of detection.

Theorem

Consider the two testing procedures Δ_{α}^{IP} and Δ_{α}^{DP} as defined previously. Denote as $MS^{filt}(\Delta_{\alpha}^{IP}, r, \beta)$ and $MS^{filt}(\Delta_{\alpha}^{DP}, r, \beta)$ the respective **robust maxisets** associated with chosen rates $r = (r_{\varepsilon})_{\varepsilon>0}$ and $\mu = (\mu_{\varepsilon})_{\varepsilon>0}$ that are beyond the horizon of detection. Then :

•
$$MS^{filt}(\Delta_{\alpha}^{IP}, r, \beta) = \mathcal{F}_{r,D}$$
. More precisely,

$$\mathcal{F}_{r,D}(\mathcal{C}_{\max}(\alpha,\beta)) \subset MS^{filt}(\Delta_{\alpha}^{IP},r,\beta) \subset \mathcal{F}_{\sqrt{2}r,D}(\mathcal{C}_{\min}(\alpha,\beta)),$$

• $MS^{filt}(\Delta_{\alpha}^{DP}, \mu, \beta) = \mathcal{G}_{\mu,D}$. More precisely,

$$\mathcal{G}_{\mu,D}(\mathcal{C}_{\mathsf{max}}(\alpha,\beta)) \subset MS^{\mathit{filt}}(\Delta_{\alpha}^{DP},\mu,\beta) \subset \mathcal{G}_{\sqrt{2}\mu,D}(\mathcal{C}_{\mathsf{min}}(\alpha,\beta)).$$

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Corollary

Choose $r = (r_{\varepsilon})_{\varepsilon>0}$, and $\mu = (\mu_{\varepsilon})_{\varepsilon>0}$ such that, for any $\varepsilon \in (0, 1)$, $\mu_{\varepsilon} \succeq \mathbf{b}_{\mathbf{D}_{\varepsilon}} r_{\varepsilon}$. Then,

$$MS(\Delta^{IP}_{\alpha},r) \subset MS(\Delta^{DP}_{\alpha},\mu).$$

According to the <u>maxiset sense</u>, $\Delta_{\alpha,\varepsilon}^{DP}$ outperforms $\Delta_{\alpha,\varepsilon}^{IP}$ for the problem of signal detection.

We presented many reasons to prefer the Direct testing Procedure (DP) for signal detection in inverse problem :

- looking at minimax performance (optimality),
- looking at maxiset performance (horizon of detection, embedding).

Bibliography :

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Merci de votre attention

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