Some ideas

Oleg V. Lepski

Institut de Mathématiques de Marseille Aix-Marseille Université

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▶ $(\mathcal{X}^{(n)}, \mathfrak{T}^{(n)}, \mathbb{P}_{f}^{(n)}, f \in \mathbb{F})$ is the statistical experiment generated by the observation $X^{(n)}$.

▶ $A : \mathbb{F} \to \mathfrak{S}$ and $B : \mathbb{F} \to \mathfrak{S}$ are two mappings to be estimated and \mathfrak{S} is a set endowed with semi-metrics ℓ and ρ .

► For any $X^{(n)}$ -measurable \mathfrak{S} -valued map \widetilde{Q} , $f \in \mathbb{F}$, $q \ge 1$ $\mathcal{R}^{q}_{A}[\widetilde{Q}, f] = \mathbb{E}^{(n)}_{f} \Big[\ell(\widetilde{Q}, A(f)) \Big]^{q}$ $\mathcal{R}^{q}_{B}[\widetilde{Q}, f] = \mathbb{E}^{(n)}_{f} \Big[\rho(\widetilde{Q}, B(f)) \Big]^{q}$

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Problem formulation.

▶ $(\mathcal{X}^{(n)}, \mathfrak{T}^{(n)}, \mathbb{P}_{f}^{(n)}, f \in \mathbb{F})$ is the statistical experiment generated by the observation $X^{(n)}$.

▶ $A : \mathbb{F} \to \mathfrak{S}$ and $B : \mathbb{F} \to \mathfrak{S}$ are two mappings to be estimated and \mathfrak{S} is a set endowed with semi-metrics ℓ and ρ

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angle For any $X^{(n)}$ -measurable ${\mathfrak S}$ -valued map $\widetilde{{m Q}}$, ${m f}\in {\mathbb F}$, ${m q}\geq 1$

$$\mathcal{R}^{q}_{A}[\widetilde{Q}, f] = \mathbb{E}^{(n)}_{f} \Big[\ell(\widetilde{Q}, A(f)) \Big]^{q}, \ \mathcal{R}^{q}_{B}[\widetilde{Q}, f] = \mathbb{E}^{(n)}_{f} \Big[\rho(\widetilde{Q}, B(f)) \Big]^{q}$$

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Important! We will assume that $X^{(n)} = (X_1^{(n)}, X_2^{(n)})$, where $X_1^{(n)}, X_2^{(n)}$ are independent random elements.

▶
$$\mathbb{P}_{1,f}^{(n)}$$
 and $\mathbb{P}_{2,f}^{(n)}$ denote marginal laws of $X_1^{(n)}$ and $X_2^{(n)}$;

▶ $\mathbb{E}_{i,f}^{(n)}$, i = 1, 2, – mathematical expectation w.r.t. $\mathbb{P}_{i,f}^{(n)}$.

Estimation of A. Hypotheses.

- ▶ \mathfrak{H} is a set, $\mathfrak{H}_n \subseteq \mathfrak{H}, n \in \mathbb{N}^*$, are countable of subsets.
- ▶ $\{\widehat{A}_h, \mathfrak{h} \in \mathfrak{H}\}$, $\{\widehat{A}_{\mathfrak{h},\eta}, \mathfrak{h}, \eta \in \mathfrak{H}\}$ $X_1^{(n)}$ -measurable \mathfrak{S} -valued;

▶
$$\varepsilon_n \rightarrow 0, n \rightarrow \infty$$
 be a given sequence.

$$\begin{array}{l} \underline{A}^{\text{permute.}} & \widehat{A}_{\mathfrak{h},\eta} \equiv \widehat{A}_{\eta,\mathfrak{h}}, \text{ for any } \eta, \mathfrak{h} \in \mathfrak{H}. \\ \underline{A}^{\text{upper.}} & \text{For any } n \geq 1 \\ \sup_{f \in \mathbb{F}} \mathbb{E}_{1,f}^{(n)} \bigg(\sup_{\mathfrak{h} \in \mathfrak{H}_n} \Big[\ell(\widehat{A}_{\mathfrak{h}}, \Lambda_{\mathfrak{h}}(f)) - \Delta_n(\mathfrak{h}) \Big]_+^q \bigg) \leq \varepsilon_n^q; \end{array}$$

$$\sup_{f\in\mathbb{F}}\mathbb{E}_{1,f}^{(n)}\bigg(\sup_{\mathfrak{h},\eta\in\mathfrak{H}_n}\Big[\ell(\widehat{A}_{\mathfrak{h},\eta},\Lambda_{\mathfrak{h},\eta}(f))-\big\{\Delta_n(\mathfrak{h})\wedge\Delta_n(\eta)\big\}\Big]_+^q\bigg)\leq\varepsilon_n^q.$$

- ▶ $\{\Lambda_{\mathfrak{h}}(f), \mathfrak{h} \in \mathfrak{H}\}$, $\{\Lambda_{\mathfrak{h},\eta}(f), \mathfrak{h}, \eta \in \mathfrak{H}\}$ \mathfrak{S} -valued;
- ► $\Delta_n = {\Delta_n(\mathfrak{h}), \mathfrak{h} \in \mathfrak{H} } X_1^{(n)}$ -measurable positive variables.

(Ψ_n, ℓ) -selection rule for estimating A.

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(Ψ_n, ℓ) -selection rule for A. Oracle inequality

$$\widehat{R}_{n}(\mathfrak{h}) = \sup_{\eta \in \mathfrak{H}_{n}} \left[\ell(\widehat{A}_{\mathfrak{h},\eta}, \widehat{A}_{\eta}) - 2\Psi_{n}(\eta) \right]_{+}$$
$$\widehat{R}(\widehat{\mathfrak{h}}^{(n)}) + 2\Psi_{n}(\widehat{\mathfrak{h}}^{(n)}) \leq \inf_{\mathfrak{h} \in \mathfrak{H}_{n}} \left\{ \widehat{R}(\mathfrak{h}) + 2\Psi_{n}(\mathfrak{h}) \right\} + \varepsilon_{n}$$

Theorem 1. Let A^{permute} and A^{upper} be fulfilled.

Then, for any $f \in \mathbb{F}$, $n \geq 1$ and $\Psi_n \in \mathfrak{M}_n$

$$\mathcal{R}_{\mathcal{A}}[\widehat{A}_{\widehat{\mathfrak{h}}^{(n)}}, f] \leq \inf_{\mathfrak{h} \in \mathfrak{H}_n} \left\{ \mathcal{B}_{\mathcal{A}}^{(n)}(f, \mathfrak{h}) + 5\psi_n(f, \mathfrak{h}) \right\} + 6\varepsilon_n v$$

$$\mathcal{B}_{A}^{(n)}(f,\mathfrak{h}) = \ell(\Lambda_{\mathfrak{h}}(f), A(f)) + 2 \sup_{\eta \in \mathfrak{H}_{n}} \ell(\Lambda_{\mathfrak{h},\eta}(f), \Lambda_{\eta}(f))$$
$$\mathcal{W}_{n}(f,\mathfrak{h}) = \left[\mathbb{E}_{1,f}^{(n)} \{\Psi_{n}^{q}(\mathfrak{h})\}\right]^{\frac{1}{q}}$$

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Estimation of B. Hypotheses.

▶ $\{\widehat{B}_{\mathfrak{h}}, \mathfrak{h} \in \mathfrak{H}\}$ – family of $X_2^{(n)}$ -measurable \mathfrak{S} -valued mappings;

Objective: To bound from above the risk of the "*plug-in*" estimator $\hat{B}_{\hat{\mathfrak{h}}^{(n)}}$.

▶ $\{\Upsilon_{\mathfrak{h}}, \mathfrak{h} \in \mathfrak{H}\}$ – a collection of \mathfrak{S} -valued functionals.

 $\begin{array}{ll} \underline{\mathsf{B}}^{\mathrm{main}.} & \exists \textit{C}_{\ell} \text{ such that for any } f \in \mathbb{F}, \ n \geq 1 \ \mathrm{and} \ \mathfrak{h} \in \mathfrak{H}_n \\ & \rho(\Upsilon_{\mathfrak{h}}(f),\textit{B}(f)) \leq \textit{C}_{\ell} \ \ell(\Lambda_{\mathfrak{h}}(f),\textit{A}(f)) \end{array}$

<u>Bupper</u>. $\Phi_n \in \mathfrak{M}_n$ and for any $n \geq 1$

$$\sup_{f \in \mathbb{F}} \mathbb{E}_{1,f}^{(n)} \left(\sup_{\mathfrak{h} \in \mathfrak{H}_n} \left[\mathcal{E}_n(\mathfrak{h}, f) - \Phi_n(\mathfrak{h}) \right]_+^q \right) \le \varepsilon_n^q;$$

$$\mathcal{E}_n(\mathfrak{h}, f) = \left(\mathbb{E}_{2,f}^{(n)} \left\{ \rho^q(\widehat{B}_{\mathfrak{h}}, \Upsilon_{\mathfrak{h}}(f)) \right\} \right)^{\frac{1}{q}};$$

$$\Phi_n = \left\{ \Phi_n(\mathfrak{h}), \ \mathfrak{h} \in \mathfrak{H} \right\} - X_1^{(n)} \text{-measurable positive variables.}$$

B^{main}. $\exists C_{\ell}$ such that for any $f \in \mathbb{F}$, n > 1 and $\mathfrak{h} \in \mathfrak{H}_n$ $\rho(\Upsilon_{\mathfrak{h}}(f), B(f)) < C_{\ell} \ell(\Lambda_{\mathfrak{h}}(f), A(f))$ $\mathsf{B}^{\mathsf{upper}}$. $\Phi_n \in \mathfrak{M}_n$ and for any n > 1 $\sup_{f \in \mathbb{R}} \mathbb{E}_{1,f}^{(n)} \left(\sup_{\mathfrak{h} \in \mathfrak{S}} \left[\mathcal{E}_n(\mathfrak{h}, f) - \Phi_n(\mathfrak{h}) \right]_{\perp}^q \right) \leq \varepsilon_n^q;$ $\triangleright \ \mathcal{E}_n(\mathfrak{h},f) = \left(\mathbb{E}_{2,f}^{(n)} \{ \rho^q(\widehat{B}_{\mathfrak{h}},\Upsilon_{\mathfrak{h}}(f)) \} \right)^{\frac{1}{q}};$ • $\Phi_n = {\Phi_n(\mathfrak{h}), \mathfrak{h} \in \mathfrak{H}} - X_1^{(n)}$ -measurable positive variables. **Remark.** Set $\mathcal{E}_n(\mathfrak{h}) = \sup_{f \in \mathbb{F}} \mathcal{E}_n(\mathfrak{h}, f)$ and note that if $\mathcal{E}_n \in \mathfrak{M}_n$ the hypothesis $\mathsf{B}^{\text{upper}}$ is obviously fulfilled with $\Phi_n = \mathcal{E}_n$. This choice of Φ_n is reasonable for the statistical models in which $\mathcal{E}_n(\mathfrak{h}, f)$ is independent or depends "weakly" on f.

First procedure and oracle inequality.

 $\begin{array}{ll} \underline{\mathsf{B}}^{\mathrm{main}.} & \exists \textit{C}_{\ell} \text{ such that for any } f \in \mathbb{F}, \ n \geq 1 \ \mathrm{and} \ \mathfrak{h} \in \mathfrak{H}_n\\ & \rho(\Upsilon_\mathfrak{h}(f),\textit{B}(f)) \leq \textit{C}_{\ell} \ \ell(\Lambda_\mathfrak{h}(f),\textit{A}(f)) \end{array}$

<u>**B**</u>^{upper}. $\Phi_n \in \mathfrak{M}_n$ and for any $n \geq 1$

$$\sup_{f\in\mathbb{F}}\mathbb{E}_{1,f}^{(n)}\left(\sup_{\mathfrak{h}\in\mathfrak{H}_n}\left[\mathcal{E}_n(\mathfrak{h},f)-\Phi_n(\mathfrak{h})\right]_+^q\right)\leq\varepsilon_n^q;$$

Theorem 2. Let A^{permute} , A^{upper} , B^{main} and B^{upper} be fulfilled. Let $\hat{\mathfrak{h}}^{(n)}$ is obtained by (Φ_n, ℓ) -selection rule. Then, for any $f \in \mathbb{F}$ and $n \geq 1$

$$\mathcal{R}_{B}[\widehat{B}_{\widehat{\mathfrak{h}}^{(n)}},f] \leq C_{1} \inf_{\mathfrak{h}\in\mathfrak{H}_{n}} \left\{ \mathcal{B}_{A}^{(n)}(f,\mathfrak{h}) + \phi_{n}(f,\mathfrak{h}) \right\} + C_{2}\varepsilon_{n}.$$

$$\blacktriangleright \phi_n(f,\mathfrak{h}) = \left[\mathbb{E}_{1,f}^{(n)}\{\Phi_n^q(\mathfrak{h})\}\right]^{\frac{1}{q}}, C_1 = 7C_\ell + 2, C_2 = 10C_\ell + 4.$$

Second procedure and oracle inequality.

Problem. We note that the use (Φ_n, ℓ) -selection rule if $\Phi_n \neq \Psi_n$ does not allow to solve the problems of estimating $A(\cdot)$ and $B(\cdot)$ simultaneously, i.e. by use of the same (Ψ_n, ℓ) -selection rule in both problems.

Objective. To prove an analog of Theorem 2 when $\hat{\mathfrak{h}}^{(n)}$ is obtained by (Ψ_n, ℓ) -selection rule with $\Psi_n \in \mathfrak{M}_n(\delta_n)$.

•
$$\delta_{\textit{n}}
ightarrow \textit{0}, \textit{n}
ightarrow \infty$$
 - given sequence and

$$\mathfrak{M}_{n}(\delta_{n}) := \left\{ \Psi_{n} \in \mathfrak{M}_{n} : \inf_{\mathfrak{h} \in \mathfrak{H}_{n}} \Psi_{n}(\mathfrak{h}) \geq \delta_{n} \right\}$$
Remark.
$$\mathfrak{M}_{n}(\delta_{n}) \supset \left\{ \Psi_{n}^{*} : \Psi_{n}^{*} \equiv \Psi_{n} + \delta_{n}, \Psi_{n} \in \mathfrak{M}_{n} \right\}.$$
Notations.
$$\tau_{n}(f) = \left[\mathbb{E}_{1,f}^{(n)} \left\{ \sup_{\mathfrak{h} \in \mathfrak{H}_{n}} (\mathfrak{h}) \right\} \right]^{\frac{1}{q}} + \mathfrak{r}_{n}(f)$$

$$\mathfrak{H}_{n}(f) = \left\{ \mathfrak{h} \in \mathfrak{H}_{n} : \Psi_{n}(\mathfrak{h}) < 2 \inf_{\mathfrak{h} \in \mathfrak{H}_{n}} \left[\mathcal{B}_{A}^{(n)}(f, \mathfrak{h}) + 2 \Psi_{n}(\mathfrak{h}) \right] \right\}$$
•
$$\mathfrak{r}_{n}(f) = \left[\mathbb{E}_{1,f}^{(n)} \left\{ \sup_{\mathfrak{h} \in \mathfrak{H}_{n}} \Phi_{n}^{2q}(\mathfrak{h}) \right\} \right]^{\frac{1}{2q}} \left(8\varepsilon_{n}/\delta_{n} \right)^{\frac{1}{2}}$$

Second procedure and oracle inequality.

Notations.
$$\tau_n(f) = \left[\mathbb{E}_{1,f}^{(n)} \left\{ \sup_{\mathfrak{h} \in \mathfrak{H}_n(f)} \Phi_n^q(\mathfrak{h}) \right\} \right]^{\frac{1}{q}} + \mathfrak{r}_n(f)$$

 $\mathfrak{H}_n(f) = \left\{ \mathfrak{h} \in \mathfrak{H}_n : \Psi_n(\mathfrak{h}) < 2 \inf_{\mathfrak{h} \in \mathfrak{H}_n} \left[\mathcal{B}_A^{(n)}(f,\mathfrak{h}) + 2 \Psi_n(\mathfrak{h}) \right] \right\}$
• $\mathfrak{r}_n(f) = \left[\mathbb{E}_{1,f}^{(n)} \left\{ \sup_{\mathfrak{h} \in \mathfrak{H}_n} \Phi_n^{2q}(\mathfrak{h}) \right\} \right]^{\frac{1}{2q}} (8\varepsilon_n/\delta_n)^{\frac{1}{2}}$

Theorem 3. Let A^{permute} , A^{upper} , B^{main} and B^{upper} be fulfilled. Let $\hat{\mathfrak{h}}^{(n)}$ is obtained by (Ψ_n, ℓ) -selection rule. Then, for any $f \in \mathbb{F}, n \geq 1$ and $\Psi_n \in \mathfrak{M}_n(\delta_n)$

 $\mathcal{R}_{B}[\widehat{B}_{\widehat{\mathfrak{h}}^{(n)}},f] \leq C_{3}\inf_{\mathfrak{h}\in\mathfrak{H}_{n}}\left\{\mathcal{B}_{A}^{(n)}(f,\mathfrak{h})+\psi_{n}(f,\mathfrak{h})\right\}+\tau_{n}(f)+C_{4}\varepsilon_{n}$

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•
$$C_3 = 7C_{\ell} + 1$$
, $C_4 = 10C_{\ell} + 1$.

Problem. We would like to emphasize that the hypothesis B^{main} is quite restrictive since it can be checked for any $f \in \mathbb{F}$.

Objective. To weaken **B**^{main} in the case of adaptive estimation.

▶ Let $\{\mathbb{F}_{\alpha}, \alpha \in \mathfrak{A}\}$ be a given collection of subsets of \mathbb{F} .

<u>Badap.</u> $\forall \alpha \in \mathfrak{A} \exists \pi_{\alpha} : \mathbb{R}_{+} \to \mathbb{R}_{+}$, nondecreasing, concave and such that for any $f \in \mathbb{F}_{\alpha}$, $n \geq 1$ and $\mathfrak{h} \in \mathfrak{H}_{n}$

 $ho^{q}(\Upsilon_{\mathfrak{h}}(f), B(f)) \leq \pi_{lpha}\Big(\ell^{q}(\Lambda_{\mathfrak{h}}(f), A(f))\Big)$

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Adaptive estimation of *B*.

▶ Let $\{\mathbb{F}_{\alpha}, \alpha \in \mathfrak{A}\}$ be a given collection of subsets of \mathbb{F} .

 $\begin{array}{l} \underline{\mathsf{B}^{\mathsf{adap}}}_{} \quad \forall \alpha \in \mathfrak{A} \ \exists \pi_{\alpha} : \mathbb{R}_{+} \to \mathbb{R}_{+}, \ \mathsf{nondecreasing, \ concave} \\ \text{ and such that for any } f \in \mathbb{F}_{\alpha}, \ n \geq 1 \ \mathsf{and} \ \mathfrak{h} \in \mathfrak{H}_{n} \\ \rho^{q}(\Upsilon_{\mathfrak{h}}(f), B(f)) \leq \pi_{\alpha} \Big(\ell^{q} \big(\Lambda_{\mathfrak{h}}(f), A(f) \big) \Big) \end{array}$

Theorem 4. Let A^{permute}, A^{upper}, B^{adap} and B^{upper} be fulfilled. Let $\hat{\mathfrak{h}}^{(n)}$ is obtained by (Ψ_n, ℓ) -selection rule. Then, for any $\alpha \in \mathfrak{A}, n \geq 1$ and $\Psi_n \in \mathfrak{M}_n(\delta_n)$ $\sup_{f \in \mathbb{F}_{\alpha}} \mathcal{R}_B[\widehat{B}_{\hat{\mathfrak{h}}^{(n)}}, f] \leq \pi_{\alpha}^{1/q} ([\varphi_n(\mathbb{F}_{\alpha}) + 10\varepsilon_n]^q) + \varphi_n^*(\mathbb{F}_{\alpha}) + \varepsilon_n$

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$$\blacktriangleright \varphi_n(\mathbb{F}_{\alpha}) = \sup_{f \in \mathbb{F}_{\alpha}} [\inf_{\mathfrak{h} \in \mathfrak{H}_n} \{ \mathcal{B}_A^{(n)}(f, \mathfrak{h}) + \psi_n(f, \mathfrak{h}) \}].$$

$$\varphi_{\mathbf{n}}^*(\mathbb{F}_{\alpha}) = \sup_{f \in \mathbb{F}_{\alpha}} \tau_{\mathbf{n}}(f).$$

Examples $\rho = \ell$. Generalized deconvolution model.

• Observation
$$Z^{(n)} = (Z_1, \ldots, Z_n)$$

$$Z_i = X_i + \varepsilon_i Y_i, \quad i = 1, \ldots, n$$

▶ $X_i \in \mathbb{R}^d$, i = 1, ..., n are i.i.d. random vectors with common density f to be estimated;

▶ The noise variables $Y_i \in \mathbb{R}^d$, i = 1, ..., n, are i.i.d. random vectors with known common density g;

▶ $\varepsilon_i \in \{0, 1\}, i = 1, ..., n$, are i.i.d. Bernoulli random variables with $\mathbb{P}(\varepsilon_1 = 1) = \alpha$, $\alpha \in [0, 1]$ is supposed to be known;

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▶ The sequences $\{X_i, i = 1, ..., n\}, \{Y_i, i = 1, ..., n\}$ and $\{\varepsilon_i, i = 1, ..., n\}$ are supposed to be mutually independent.

<u>Goal</u>: estimation of B(f) = f under \mathbb{L}_p -loss, i.e

$$\ell(\cdot) = \|\cdot\|_{p}, 1 \leq p \leq \infty.$$

Examples. Generalized deconvolution model.

 \blacktriangleright For any $ec{m{h}}\in\mathcal{H}^d$ let $m{M}(\cdot,ec{m{h}})$ satisfy the operator equation

$$K_{\vec{h}}(\cdot) = (1 - lpha) M(\cdot, \vec{h}) + lpha \int_{\mathbb{R}^d} g(t - \cdot) M(t, \vec{h}) dt$$

•
$$\mathcal{H}^d$$
 is the diadic grid in $(0,\infty)^d$;

•
$$K_{\vec{h}}(y) = \left[\prod_{j=1}^{d} h_{j}^{-1}\right] K(y_{1}/h_{1}, \dots, y_{d}/h_{d}), \ y \in \mathbb{R}^{d}$$

• Estimator for B(f) = f

$$\widehat{B}_{\vec{h}}(x) = n^{-1} \sum_{i=1}^{n} M(Z_i - x, \vec{h})$$

Objective: to propose a data-driven selection rule from the family

$$\mathcal{F}(\mathcal{H}^d) = \{\widehat{B}_{\vec{h}}(\cdot), \ \vec{h} \in \mathcal{H}^d\}$$

Examples. Generalized deconvolution model.

Idea: to estimate first $A(f) = g \star f$ which is the density of Z_1 using the selection rule from the family of usual kernel estimators

$$\widehat{A}_{\vec{h}}(x) = n^{-1} \sum_{i=1}^{n} K_{\vec{h}}(Z_i - x), \ \vec{h} \in \mathcal{H}^d$$

and then to use the estimator $\hat{B}_{\vec{\mathfrak{h}}}$, where $\vec{\mathfrak{h}}$ is the selected multi-bandwidth.

▶ If p = 2 the hypothesis B^{main} is verified for any $\alpha \in (0, 1)$ with $C_{\ell} = \nu^{-1}$ under the following assumption

There exists $\nu > 0$: $|1 - \alpha + \alpha \check{g}(t)| \ge \nu, \ \forall t \in \mathbb{R}^d$

▶ If $p \neq 2$ the hypothesis \mathbb{B}^{main} is verified for all $\alpha \in (1/2, 1)$ with $C_{\ell} = (2\alpha - 1)^{-1}$ without any assumption imposed on g.

Examples. Adaptive estimation of derivatives.

▶ $X_i \in \mathbb{R}, i = 1, ..., n$ are i.i.d. random variables with common density f to be estimated;

Goal: estimation of $B(f) = f^{(m)}, m \in \mathbb{N}^*$ under \mathbb{L}_p -loss, i.e $\ell(\cdot) = \|\cdot\|_p, 1 \le p \le \infty.$ • $\mathbb{F}_{\alpha} = W_s^k(L), \alpha = (k, L), k > m, L > 0$, where $W_s^k(L) = \left\{ w : \mathbb{R} \to \mathbb{R} : \|w\|_s + \|w^{(k)}\|_s \le L \right\}$

<u>Idea</u>: to estimate first A(f) = f using the selection rule from the family of usual kernel estimators

$$\widehat{A}_h(x) = n^{-1} \sum_{i=1}^n K_h(X_i - x), \ h \in \mathcal{H}$$

and then to use the estimator $\widehat{B}_{\mathfrak{h}} = \widehat{A}_{\mathfrak{h}}^{(m)}$, where \mathfrak{h} is the selected bandwidth.

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Examples. Adaptive estimation of derivatives.

<u>Goal</u>: estimation of $B(f) = f^{(m)}, m \in \mathbb{N}^*$ under \mathbb{L}_p -loss.

$$\mathbb{F}_{\alpha} = W_{s}^{k}(L), \alpha = (k, L), k > m, L > 0, \text{ where}$$
$$W_{s}^{k}(L) = \left\{ w : \mathbb{R} \to \mathbb{R} : \|w\|_{s} + \|w^{(k)}\|_{s} \leq L \right\}$$

<u>Idea</u>: to estimate first A(f) = f using the selection rule from the family of usual kernel estimators

$$\widehat{A}_h(x) = n^{-1} \sum_{i=1}^n \kappa_h(X_i - x), \ h \in \mathcal{H}$$

and then to use the estimator $\widehat{B}_{\mathfrak{h}} = \widehat{A}_{\mathfrak{h}}^{(m)}$, where \mathfrak{h} is the selected bandwidth.

► Hypothesis **B**^{adap} is verified if
$$s \le p$$
 with
 $\pi_{\alpha}(z) = \kappa L^{\frac{m}{k-1/s+1/p}} z^{\frac{k-m-1/s+1/p}{k-1/s+1/p}}, \quad \alpha = (k, L)$

• κ is the universal constant appeared in Kolmogorov inequality.

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