

## lecture 9

In this lecture we will try to understand some ideas from "rate adaptive" estimation of quadratic functionals of a density.

Recall: We proved the following,  $(X(\eta) = \int \eta^2 d\mu)$

$$\inf_{T_n} \sup_{\eta \in \mathcal{P}(\alpha, M, B)} \mathbb{E}_\eta (T_n - X(\eta))^2 \sim \begin{cases} n^{-8\alpha/4\alpha+1} & \text{if } \alpha \leq 1/4 \\ n^{-1} & \text{if } \alpha > 1/4 \end{cases}$$

Our estimator  $X(\eta)$  was

$$\hat{X}_n = \frac{1}{n(n-1)} \sum_{i \neq j} \sum_{\ell=1}^k e_\ell(x_i) e_\ell(x_j) \quad \text{for an o.n.b. } \{e_\ell\} \text{ of } L_2[0,1]$$

We showed that  $\mathbb{E}_\eta (\hat{X}_n - X(\eta))^2 \leq (\text{Bias}_\eta(\hat{X}_n))^2 + \text{Var}_\eta(\hat{X}_n)$

$$\leq \text{c(M)} k^{-4\alpha} + \text{c(B)} \left( \frac{1}{n} + \frac{k}{n^2} \right)$$

The match between  $(\text{bias})^2$  and variance was then obtained by choosing  $k \sim n^{2/4\alpha+1}$  for  $\alpha \leq 1/4$  and  $k \sim n$  for  $\alpha > 1/4$ .

Therefore it was crucial that we knew  $\alpha$ !

Question: Can we find an estimator  $\hat{X}_n$  which does not depend on  $\alpha$  s.t. for any  $\alpha$ ,

$$\sup_{\eta \in \mathcal{P}(\alpha, M, B)} \mathbb{E}_\eta (\hat{X}_n - X(\eta))^2 \sim \inf_{T_n} \sup_{\eta \in \mathcal{P}(\alpha, M, B)} \mathbb{E}_\eta (T_n - X(\eta))^2 ?$$

(1)

"Answer": YES if  $\alpha \geq 1/4$   
 NO if  $\alpha < 1/4$

We shall prove the following result.

Theorem: Let  $0 < \alpha < 1$ . (i) Then there exists an estimator  $\hat{\chi}_n$  (free of  $\alpha$ ) such that

$$\sup_{\eta \in \mathcal{P}(\alpha, M, B)} \mathbb{E}_{\eta} (\hat{\chi}_n - x(\eta))^2 \sim \begin{cases} \left( \frac{n}{\sqrt{\log n}} \right)^{-\frac{8\alpha}{4\alpha+1}} & \text{if } \alpha < 1/4 \\ n^{-1} & \text{if } \alpha \geq 1/4 \end{cases}$$

(ii) Further, if for some estimator  $T_n$ , one has for some  $\alpha < 1/4$

$$\sup_{\eta \in \mathcal{P}(\alpha, M, B)} \mathbb{E}_{\eta} (T_n - x(\eta))^2 \lesssim \left( \frac{n}{\sqrt{\log n}} \right)^{-\frac{8\alpha}{4\alpha+1}}$$

Then  $\exists \alpha' < \alpha$  s.t.

$$\sup_{\eta \in \mathcal{P}(\alpha', M, B)} \mathbb{E}_{\eta} (T_n - x(\eta))^2 \gtrsim \left( \frac{n}{\sqrt{\log n}} \right)^{-\frac{8\alpha'}{4\alpha'+1}}$$

Proof: The proof of (i) (Upper Bound) is based on an idea, often referred to as Lepski's Method.

The proof of (ii) (Lower Bound) is based on constrained Risk Inequalities.

We will take this opportunity learn a little bit about both of these ideas

(i) Upper Bound & Lepski's Method

Crucial to our construction is noting that proof of a non-adaptive estimator  $\hat{\chi}_n$  for known  $\alpha$  depends on a bias variance tradeoff.

$$\text{let } \hat{\chi}_n(j) = \frac{1}{n(n-1)} \sum_{i_1 \neq i_2} K_{V_j}(x_{i_1}, x_{i_2}) \quad K_{V_j}(x_1, x_2) = \sum_{k=1}^K \psi_{ek}(x_1) \psi_{ek}(x_2)$$

then  $\mathbb{E}_\eta (\hat{\chi}_n(j) - \chi(\eta))^2$

$$= \{\text{Bias}_\eta(\hat{\chi}_n)\}^2 + \text{var}_\eta(\hat{\chi}_n) \quad \text{--- } 2j\alpha$$

$$= \|\Pi_{V_j}^\perp(\eta)\|_2^4 + \text{var}_\eta(\hat{\chi}_n)$$

$$\leq \|\Pi_{V_j}^\perp(\eta)\|_2^2 + \frac{4}{n} \mathbb{E}_\eta [\mathbb{E}_\eta^2(K_{V_j}(x_1, x_2) | x_1)] + \frac{2}{n(n-1)} \mathbb{E}_\eta(K_{V_j}^2(x_1, x_2))$$

$$\leq \|\Pi_{V_j}^\perp(\eta)\|_2^4 + \frac{4\|\eta\|_\alpha^3}{n} + \frac{2\|\eta\|_\alpha^2 \cdot 2^j}{n(n-1)}$$

$$\leq \|f\|_\alpha \cdot 2^{-2j\alpha} + \frac{4\|\eta\|_\alpha^3}{n} + \frac{2\|\eta\|_\alpha^2 \cdot 2^j}{n(n-1)}$$

$$\leq \|f\|_\alpha \cdot 2^{-2j\alpha} + \frac{4\|\eta\|_\alpha^3}{n} + \frac{3\|\eta\|_\alpha^2 \cdot 2^j}{n^2} \text{ if } n \geq 3$$

where  $\|f\|_\alpha = \sup_{x, y \in [0, 1]} \frac{|f(x) - f(y)|}{|x - y|^\alpha}$  for  $0 < \alpha < 1$ .

Now when  $\alpha$  is known, ~~the~~ we choose from the collection of  $\{\hat{\chi}_n(j) : j \geq \log_2 n\}$  the estimator which minimizes the mean squared error.

The choice is given by  $2^j \sim n^{\frac{2}{4\alpha+1}}$  if  $0 < \alpha < 1/4$ .

Now suppose we do not know  $\alpha$ , but our guess of  $\alpha$  is  $\alpha'$  with  $|\alpha - \alpha'| \leq \frac{c}{\log n}$  for some constant  $c > 0$ . We then will want  $2^j \sim n^{\frac{2}{4\alpha'+1}}$

How much do we lose in MSE with this choice?  $\rightarrow$   
We lose by a constant! This implies the following idea.

Idea (consider adapting over  $0 < \alpha < 1/4$ )

(i) Discretize  $(0, 1/4)$  into a grid  $\alpha_0 > \alpha_1 > \dots > \alpha_N$  s.t.  
 $|\alpha_i - \alpha_{i+1}| \leq \frac{c}{\log n}$

(ii) ~~Test between~~ Perform a multiple hypothesis testing to choose  $\hat{\alpha} \in \{\alpha_0, \alpha_1, \dots, \alpha_N\}$

(iii) Take candidate estimator as  $\hat{\chi}_n(\hat{j})$  with  
 $2^{\hat{j}} \sim n^{\frac{2}{4\hat{\alpha}+1}}$

Caution: Note that we are ~~doing~~ same data do perform the test and construction of the estimator. ~~the~~ Also the price to be paid for adaptation also comes from this multiple hypothesis testing.

~~the~~ the I try to understand this strategy is the following. Begin with a two point adaptation problem i.e you are given the knowledge that  $\alpha \in \{\alpha_0, \alpha_1\}$  with  $\alpha_0 > \alpha_1$ . We want to construct an estimator  $\hat{\chi}_n$  which does not depend on  $\alpha$  and attains the "right rate" over both  $\alpha_0$  and  $\alpha_1$ .

For  $\alpha_0$  we want to use  $\hat{\chi}_n(j_0)$  for some  $j_0$  depending on  $\alpha_0$   
 For  $\alpha_1$  " " " "  $\hat{\chi}_n(j_1)$  " "  $j_1$  " "  $\alpha_1$

We will need to have  $j_1 > j_0$  to kill the bias at  $\alpha_1$ .

Note  $\hat{\chi}_n(j) = \frac{1}{n(n-1)} \sum_{i_1 \neq i_2} K_{V_j}(X_{i_1}, X_{i_2})$  where  $K_{V_j}(x_1, x_2) = \sum_{l=-1}^j \sum_{k=0}^{2-l} \psi_{lk}(x_1) \psi_{lk}(x_2)$

Assume for now  $2^j \ll n^2$  but  $2^j \gg n$ . Therefore

$$\text{Var}(\hat{\chi}_n(j)) \leq c(M, B) 2^j / n^2.$$

Now indeed  $\frac{\hat{\chi}_n(j) - \mathbb{E}(\hat{\chi}_n(j))}{\sqrt{\text{Var}(\hat{\chi}_n(j))}}$  is a tight sequence of

random variables by Chebychev's inequality. Assume for now

$$\frac{\hat{\chi}_n(j) - \mathbb{E}(\hat{\chi}_n(j))}{\sqrt{\text{Var}(\hat{\chi}_n(j))}} \xrightarrow{d} N(0,1) \text{ as } n \rightarrow \infty. \quad (*)$$

Let  $\hat{j} \in \{j_0, j_1\}$  be a data dependent choice of truncation level.

How does one analyze the resulting estimator  $\hat{\chi}_n(\hat{j})$ ?

First consider the truth to be  $\alpha = \alpha_0$  i.e.  $\eta \in \mathcal{P}(\alpha_0, M, B)$

$$\begin{aligned} \Rightarrow \mathbb{E}_\eta \left( (\hat{\chi}_n(\hat{j}) - x(\eta))^2 \right) &= \mathbb{E}_\eta \left( (\hat{\chi}_n(j_0) - x(\eta))^2 \mathbb{I}(\hat{j} = j_0) \right) \\ &\quad + \mathbb{E}_\eta \left( (\hat{\chi}_n(j_1) - x(\eta))^2 \mathbb{I}(\hat{j} = j_1) \right) \\ &= T_0 + T_1 \end{aligned}$$

Now,  $T_0$  is under control since the truth is  $\alpha_0$  and we chose  $j_0$ .

The crucial part therefore is control of  $T_1$ . Here the truth is  $\alpha_0$  but your choice guides you to lower smoothness truncation i.e.  $j_1$ .

$$\begin{aligned} \text{Now, } (\hat{\chi}_n(j_1) - x(\eta))^2 &= O_p \left( \cancel{2^{-j_1 \alpha_0}} 2^{-j_1 \alpha_0} + 2^{j_1/n^2} \right) \\ &\sim O_p \left( 2^{-j_1 \alpha_0} + 2^{-j_1 \alpha_1} \right) \sim O_p \left( 2^{-j_1 \alpha_1} \right) \text{ as } \alpha_1 < \alpha_0. \end{aligned}$$

$\therefore (\hat{\chi}_n(j_1) - x(\eta))^2$  can be at most like  $O_p \left( n^{-8\alpha_1/4\alpha_1+1} \right)$ .

But for  $T_1$  to behave like  $O_p \left( n^{-8\alpha_0/4\alpha_1+1} \right)$ , the event  $\{\hat{j} = j_1\}$  must have very low ~~low~~ probability under  $\alpha_0$ .

This probability therefore intuitively needs to be  $O(1/n)$  since for any  $\alpha_1 < \alpha_0 < 1/4$  we need to get  $n^{-8\alpha_1/4\alpha_1+1}$  down to  $n^{-8\alpha_0/4\alpha_1+1}$  by multiplying with this probability.

Consider the test between  $\alpha_0$  and  $\alpha_1$  given by:

Choose  $j_0$  if  $(\hat{\chi}_n(j_0) - \hat{\chi}_n(j_1))^2 \leq a_n 2^{j_1/n^2}$

choose  $j_1$  if  $(\hat{\chi}_n(j_0) - \hat{\chi}_n(j_1))^2 > a_n 2^{j_1/n^2}$

~~This~~ This choice is guided by the philosophy that as  $j$  increases, the bias decreases but variance increases.

But what should be the choice of  $a_n$ ?

Indeed by the above heuristics, we want that under the smoothness  $\alpha$ ,  $P\left(\left(\hat{\chi}_n(j_0) - \hat{\chi}_n(j_1)\right)^2 > an \frac{2^{j_1}}{n^2}\right) = O(1/n)$

Guided by the fact that  $\hat{\chi}_n(j_0), \hat{\chi}_n(j_1)$  are asymptotically normal under right centering & scaling,  $j_1 > j_0$ , we have  $an \sim \log n$ . This is because we know that  $P(|N(0,1)| > \sqrt{2 \log n})$

$$= O(1/n).$$

But then this choice of ~~an~~ <sup>the list</sup> might not guarantee that when the truth is  $\alpha$ , we will choose something  $\hat{j} = j_1$  with high probability. This can be heuristically understood by the calculations below.

If  $\alpha$  is the truth, then

$$\begin{aligned} \left(\hat{\chi}_n(j_0) - \hat{\chi}_n(j_1)\right)^2 &\sim \left(\hat{\chi}_n(j_0) - \chi(\eta)\right)^2 + \left(\hat{\chi}_n(j_1) - \chi(\eta)\right)^2 \\ &\sim 2^{-4j_0\alpha} + \frac{2^{j_0}}{n^2} + 2^{-4j_1\alpha} + \frac{2^{j_1}}{n^2} \quad (**) \end{aligned}$$

We have already decided to choose  $j_0$  to be the right truncation corresponding to  $\alpha$  i.e.  $2^{j_0} \sim n^{2/4\alpha+1}$ . If we also choose  $2^{j_1} \sim n^{2/4\alpha+1}$  then ~~(\*\*)~~ ~~we get suboptimal result~~ ~~so this leads to that  $\log n \frac{2^{j_1}}{n^2} \sim \log n n^{-2/4\alpha+1}$  which cannot happen~~

The idea is to change the choice of  $2^{j_1} \sim \left(\frac{n^2}{\log n}\right)^{1/4\alpha+1}$ . Then ~~(\*\*)~~ can be of the order of  $\log n \frac{2^{j_1}}{n^2}$ . But this means that we pay a price at the mean squared error for  $\alpha$  due to oversmoothing.

Let's do the calculations in detail now to make things concrete.

let  $j_0$  and  $j_1$  be such that  $2^{j_0} \sim n^{2/4\alpha_1+1}$  and  $2^{j_1} \sim (n^2/\log n)^{1/4\alpha_1+1}$

let  $\hat{j} = j_0$  if  $(\hat{\chi}_n(j_0) - \hat{\chi}_n(j_1))^2 \leq c^* \log n \cdot 2^{j_1}/n^2$   
 $\hat{j} = j_1$  otherwise. ( $c^*$  will be chosen later)

Consider the estimator  $\hat{\chi}_n = \hat{\chi}_n(\hat{j})$ . We now study the mean squared error properties of this estimator over  $\mathcal{P}(\alpha_0, M, B)$  and  $\mathcal{P}(\alpha_1, M, B)$ .

First let  $\eta \in \mathcal{P}(\alpha_1, M, B)$ . Then

$$\begin{aligned} \mathbb{E}_\eta \left( \hat{\chi}_n(\hat{j}) - x(\eta) \right)^2 &= \mathbb{E}_\eta \left( \left( \hat{\chi}_n(\hat{j}) - x(\eta) \right)^2 \mathbb{I}(\hat{j} = j_0) \right) \\ &\quad + \mathbb{E}_\eta \left( \left( \hat{\chi}_n(\hat{j}) - x(\eta) \right)^2 \mathbb{I}(\hat{j} = j_1) \right) \\ &= T_0 + T_1 \end{aligned}$$

$$T_1 \leq \mathbb{E}_\eta \left( \left( \hat{\chi}_n(j_1) - x(\eta) \right)^2 \right) \leq c(M, B) \left[ 2^{-4j_1\alpha_1} + 2^{j_1}/n^2 \right] \quad \text{as } 2^{j_1} \gg n$$

$$\leq 2c(M, B) \left( \frac{n}{\sqrt{\log n}} \right)^{-\frac{8\alpha_1}{4\alpha_1+1}}$$

$$T_0 = \mathbb{E}_\eta \left( \left( \hat{\chi}_n(\hat{j}) - x(\eta) \right)^2 \mathbb{I}(\hat{j} \neq j_0) \right)$$

matches the claimed adaptive bound.

$$\leq 2 \mathbb{E}_\eta \left( \left( \hat{\chi}_n(j_0) - \hat{\chi}_n(j_1) \right)^2 \mathbb{I}(\hat{j} = j_0) \right) + 2 \mathbb{E} \left( \left( \hat{\chi}_n(j_1) - x(\eta) \right)^2 \right)$$

$$\leq 2c^* \log n \frac{2^{j_1}}{n^2} + 2c(M, B) \left( \frac{n}{\sqrt{\log n}} \right)^{-\frac{8\alpha_1}{4\alpha_1+1}}$$

$$\leq \left( 2c^* + 2c(M, B) \right) \left( \frac{n}{\sqrt{\log n}} \right)^{-\frac{8\alpha_1}{4\alpha_1+1}} \Rightarrow T_0 + T_1 \text{ is under desired control.}$$



Now let  $\eta \in \mathcal{P}(d_0, M, B)$ . Then

$$\begin{aligned} \mathbb{E}_\eta \left( (\hat{\chi}_n(\hat{j}) - \chi(\eta))^2 \right) &= \mathbb{E}_\eta \left( (\hat{\chi}_n(\hat{j}) - \chi(\eta))^2 \mathbb{I}(\hat{j} = j_0) \right) \\ &\quad + \mathbb{E}_\eta \left( (\hat{\chi}_n(\hat{j}) - \chi(\eta))^2 \mathbb{I}(\hat{j} = j_1) \right) \\ &= T_0 + T_1 \end{aligned}$$

this time,  $T_0 \leq \mathbb{E}_\eta \left( (\hat{\chi}_n(j_0) - \chi(\eta))^2 \right) \leq c(M, B) n^{-8d_0/4d_0+1}$   
 the crucial term is  $T_1$ , because this corresponds to choosing a lower smoothness when the bandwidth is higher.

$$T_1 = \mathbb{E}_\eta \left( (\hat{\chi}_n(\hat{j}) - \chi(\eta))^2 \mathbb{I}(\hat{j} = j_1) \right)$$

$$\leq \left\{ \mathbb{E}_\eta \left( (\hat{\chi}_n(j_1) - \chi(\eta))^2 \right) \right\}^{1/p} \left\{ \mathbb{P}_\eta(\hat{j} = j_1) \right\}^{1/q} = T_{11} \times T_{12} \quad \left( \frac{1}{p} + \frac{1}{q} = 1 \right)$$

We show that  $T_{11}$  is appropriately bounded and  $\mathbb{P}_\eta(\hat{j} = j_1)$  is small.

Analysis of  $T_{12}$

$$\begin{aligned} \mathbb{P}_\eta(\hat{j} = j_1) &= \mathbb{P}_\eta \left( |\hat{\chi}_n(j_0) - \hat{\chi}_n(j_1)| > \sqrt{c^* \log n} \sqrt{2^{j_1}/n^2} \right) \\ &\leq \mathbb{P}_\eta \left( |\hat{\chi}_n(j_0) - \mathbb{E}_\eta(\hat{\chi}_n(j_0))| + |\hat{\chi}_n(j_1) - \mathbb{E}_\eta(\hat{\chi}_n(j_1))| \right. \\ &\quad \left. > \sqrt{c^* \log n} \sqrt{2^{j_1}/n^2} - |\mathbb{E}_\eta(\hat{\chi}_n(j_1)) - \mathbb{E}_\eta(\hat{\chi}_n(j_0))| \right) \end{aligned}$$

$$\begin{aligned} \text{Now, } |\mathbb{E}_\eta(\hat{\chi}_n(j_1)) - \mathbb{E}_\eta(\hat{\chi}_n(j_0))| &\leq |\text{Bias}_\eta(\hat{\chi}_n(j_1))| + |\text{Bias}_\eta(\hat{\chi}_n(j_0))| \\ &\leq M \left( 2^{-2j_1 d_0} + 2^{-2j_0 d_0} \right) \\ &\leq 2M 2^{-2j_0 d_0} \quad \text{as } j_1 \geq j_0 \\ &\leq 2M \sqrt{2^{j_1}/n^2} \quad \neq n \end{aligned}$$

$$\Rightarrow \mathbb{P}_\eta (\hat{j} = j_\perp) \leq \mathbb{P}_\eta \left[ \left| \hat{\chi}_n(j_0) - \mathbb{E}_\eta(\hat{\chi}_n(j_0)) \right| + \left| \hat{\chi}_n(j_\perp) - \mathbb{E}_\eta(\hat{\chi}_n(j_\perp)) \right| \right. \\ \left. > \sqrt{\frac{C^* \log n}{2}} \sqrt{\frac{2^{j_0}}{n^2}} \right]$$

$$\leq \mathbb{P}_\eta \left[ \left| \hat{\chi}_n(j_0) - \mathbb{E}_\eta(\hat{\chi}_n(j_0)) \right| > \sqrt{\frac{C^* \log n}{4}} \sqrt{\frac{2^{j_0}}{n^2}} \right] + \\ \mathbb{P}_\eta \left[ \left| \hat{\chi}_n(j_\perp) - \mathbb{E}_\eta(\hat{\chi}_n(j_\perp)) \right| > \sqrt{\frac{C^* \log n}{4}} \sqrt{\frac{2^{j_\perp}}{n^2}} \right]$$

$$\leq \mathbb{P}_\eta \left[ \left| \hat{\chi}_n(j_0) - \mathbb{E}_\eta(\hat{\chi}_n(j_0)) \right| > \sqrt{\frac{C^* \log n}{4}} \sqrt{\frac{2^{j_0}}{n^2}} \right] + \mathbb{P}_\eta \left[ \left| \hat{\chi}_n(j_\perp) - \mathbb{E}_\eta(\hat{\chi}_n(j_\perp)) \right| > \sqrt{\frac{C^* \log n}{4}} \sqrt{\frac{2^{j_\perp}}{n^2}} \right]$$

Therefore the analysis depends on

$$\mathbb{P}_\eta \left[ \left| \hat{\chi}_n(j) - \mathbb{E}_\eta(\hat{\chi}_n(j)) \right| > \sqrt{C^{**} \log n} \sqrt{\frac{2^j}{n^2}} \right] \text{ for } 2^j \gg n \\ \text{ \& } 2^j \ll n^2.$$

$$\mathbb{E} \hat{\chi}_n(j) - \mathbb{E}_\eta(\hat{\chi}_n(j)) = \frac{1}{n(n-1)} \sum_{i_1 \neq i_2} K_{V_j}(x_{i_1}, x_{i_2}) - \mathbb{E}_\eta(K_{V_j}(x_{i_1}, x_{i_2}))$$

$$= \frac{2}{n} \sum_{i=1}^n \sum_{l=-1}^j \sum_{k=0}^{j-l} (\Psi_{ek}(x_i) - \langle \Psi_{ek}, \eta \rangle) \langle \Psi_{ek}, \eta \rangle$$

$$+ \frac{1}{n(n-1)} \sum_{i_1 \neq i_2} \sum_{l, k} (\Psi_{ek}(x_{i_1}) - \langle \Psi_{ek}, \eta \rangle) (\Psi_{ek}(x_{i_2}) - \langle \Psi_{ek}, \eta \rangle)$$

$$= I_1 + I_2$$

$$\Rightarrow \mathbb{P}_\eta \left[ \left| \hat{\chi}_n(j) - \mathbb{E}_\eta(\hat{\chi}_n(j)) \right| > \sqrt{C^{**} \log n} \sqrt{\frac{2^j}{n^2}} \right]$$

$$\leq \mathbb{P}_\eta \left[ |I_1| > \sqrt{\frac{C^{**} \log n}{2}} \sqrt{\frac{2^j}{n^2}} \right] + \mathbb{P}_\eta \left[ |I_2| > \sqrt{\frac{C^{**} \log n}{2}} \sqrt{\frac{2^j}{n^2}} \right]$$

$$\Rightarrow \text{Now } I_1 = \frac{2}{n} \sum_{i=1}^n R(x_i) \quad \text{where } R(x) = \sum_{l=-1}^j \sum_{k=0}^{j-l} (\Psi_{ek}(x) - \langle \Psi_{ek}, \eta \rangle) \langle \Psi_{ek}, \eta \rangle$$

To control tail of  $I_1$  we will use standard Hoeffding's inequality.

For that we need to bound  $\|R\|_\infty$ . Fix  $x \in [0, 1]$ .

First note that  $|\langle \psi_{ek}, \eta \rangle| = \left| \int \psi_{ek}(x) \eta(x) dx \right| \leq 2^{l/2} \|\eta\|_\infty \cdot 1/2^l$   
 $\leq B/2^{l/2}$

Also, for any  $l$ ,  $\exists$  a fixed  $k_x$  s.t.  $x \in \text{support}(\psi_{k_x})$ .

By disjointness of the supports of  $\psi_{ek}$ 's as  $k=0, 1, \dots, 2^l-1$ , we have

for each  $l=0, 1, \dots, j$ ,  $\left| \sum_{k=0}^{2^l-1} (\psi_{ek}(x) - \langle \psi_{ek}, \eta \rangle) \langle \psi_{ek}, \eta \rangle \right|$

$$\leq 2^{l/2} \cdot 2B/2^{l/2} \leq 2B$$

$$\Rightarrow |R(x)| \leq 2(j+1)B \leq 4jB \text{ for all } x.$$

$\Rightarrow$  By Hoeffding's inequality,

$$\mathbb{P}_\eta \left[ |I_1| > \sqrt{\frac{C^{**} \log n}{2}} \sqrt{\frac{2^j}{n^2}} \right] \leq \exp \left[ -2n \frac{C^{**} \log n}{2} \cdot \frac{2^j}{n^2} \cdot \frac{1}{4jB} \right]$$

$$= \exp \left[ -\frac{C^{**} \log n \times 2^j}{4B j n} \right]$$

Now  $2^j \leq n^2$

$$\Rightarrow j \leq \log n / 2$$

$$\leq \exp \left[ -\frac{C^{**}}{2B} \times \frac{2^j}{n} \right]$$

Now we need to control the tail of  $I_2$ . Now symmetric &

$$I_2 = \frac{1}{n(n-1)} \sum_{i_1 \neq i_2} H(x_{i_1}, x_{i_2}) \text{ where } H \text{ is degenerate under } \mathbb{P}_\eta.$$

We shall use the following very important tail bound for second order degenerate U-statistics.

Lemma (Giné, Latała, Zinn (2000), Houdré, Renaud-Bourret (2003))

If  $R(x_1, x_2)$  is degenerate under  $\mathbb{P}$  and symmetric, then

$$\mathbb{P}\left[\left|\sum_{i \neq j} R(x_i, x_j)\right| \geq C_0 (\lambda_1 \sqrt{n} + \lambda_2 n + \lambda_3 n^{3/2} + \lambda_4 n^2)\right] \leq 6 \exp(-n)$$

where  $\lambda_1 = \frac{n(n-1)}{2} \mathbb{E}(R^2(X_1, X_2))$

$$\lambda_2 = n \sup \left\{ \mathbb{E}(R(X_1, X_2) \phi(X_1) \xi(X_2)) : \mathbb{E}(\phi^2(X_1)) \leq 1, \mathbb{E}(\xi^2(X_2)) \leq 1 \right\}$$

$$\lambda_3 = \left\| n \mathbb{E}(R^2(X_1, \cdot)) \right\|_{\infty}^{\frac{1}{2}}$$

$$\lambda_4 = \sup_{x_1, x_2} |R(x_1, x_2)|$$

We apply the above result with  $R(x_1, x_2) = \sum_{l, k} (\psi_{ek}(x_1) - \langle \psi_{ek}, \eta \rangle) (\psi_{ek}(x_2) - \langle \psi_{ek}, \eta \rangle)$  which is symmetric and degenerate under  $\mathbb{P}_\eta$ . We begin by bounding  $\lambda_1, \lambda_2, \lambda_3, \lambda_4$  for our problem.

$$\lambda_1 = \frac{n(n-1)}{2} \mathbb{E}_\eta (R^2(X_1, X_2)) \leq \frac{n(n-1)}{2} \|\eta\|_{\infty}^2 2^j \quad (\text{We have done this calculation many times before})$$

$$\leq B^2 \cdot n^2 \cdot 2^j$$

~~To~~ To control  $\lambda_2$  consider any  $\phi(x_1)$  and  $\xi(x_2)$  s.t.

$$\mathbb{E}_\eta (\phi^2(X_1)) \leq 1 \quad \text{and} \quad \mathbb{E}_\eta (\xi^2(X_2)) \leq 1.$$

$$\Rightarrow \mathbb{E}_\eta (R(x_1, x_2) \phi(x_1) \xi(x_2)) = \mathbb{E}_\eta \left( (K_{V_j}(x_1, x_2) - \mathbb{E}_\eta(K_{V_j}(x_1, x_2) | x_1) - \mathbb{E}_\eta(K_{V_j}(x_1, x_2) | x_2) + \mathbb{E}_\eta(K_{V_j}(x_1, x_2))) \phi(x_1) \xi(x_2) \right)$$

First note

$$\left| \mathbb{E}_\eta (K_{V_j}(x_1, x_2) \phi(x_1) \xi(x_2)) \right| = \left| \int \int K_{V_j}(x_1, x_2) \phi(x_1) \eta(x_1) \xi(x_2) \eta(x_2) dx_1 dx_2 \right|$$

$$= \left| \int \Pi_{V_j}(\xi \eta)(x_2) \xi(x_2) \eta(x_2) dx_2 \right|$$

$$\bullet = \left| \int \Pi_{V_j}(\mathcal{G}\eta)(x_2) \Pi_{V_j}(\mathbb{E}\eta)(x_2) dx_2 \right|$$

$$\leq \sqrt{\int \mathcal{G}^2(x_2) \eta^2(x_2) dx_2} \sqrt{\int \mathbb{E}^2(x_2) \eta^2(x_2) dx_2} \leq B^2$$

similarly,  $\left| \mathbb{E}_\eta \left( \mathbb{E}_\eta (K_{V_j}(x_1, x_2) \cancel{\mathcal{G}\eta(x_1)} | x_1) \mathcal{G}(x_1) \mathbb{E}(x_2) \right) \right|$

$$= \left| \iiint \left( \int K_{V_j}(x_1, x') \eta(x') dx' \right) \mathcal{G}(x_1) \mathbb{E}(x_2) \eta(x_1) \eta(x_2) dx_1 dx_2 \right|$$

$$= \left| \iint \Pi_{V_j}(\eta)(x_1) \mathcal{G}(x_1) \eta(x_1) \mathbb{E}(x_2) \eta(x_2) dx_2 \right|$$

$$= \left| \int \Pi_{V_j}(\eta)(x_1) \Pi_{V_j}(\mathcal{G}\eta)(x_1) dx_1 \right| \left| \int \mathbb{E}(x_2) \eta(x_2) dx_2 \right|$$

$$\leq \sqrt{\int \eta^2(x) dx} \sqrt{\int \mathcal{G}^2(x) \eta^2(x) dx} \sqrt{\int \mathbb{E}^2(x) \eta^2(x) dx} \leq B^2$$

similarly  $\mathbb{E}_\eta \left( \mathbb{E}_\eta (K_{V_j}(x_1, x_2)) \mathcal{G}(x_1) \mathbb{E}(x_2) \right) \leq B^2$

$$\Rightarrow \lambda_2 \leq 4\pi B^2.$$

To control  $\lambda_3$ , fix  $x_2 \in [0, 1]$  and consider

$$\mathbb{E}_\eta(R^2(x_1, x_2)) = \mathbb{E}_\eta \left[ K_{V_j}(x_1, x_2) - \mathbb{E}_\eta [K_{V_j}(x_1, x_2) | x_1] \right. \\ \left. - \mathbb{E}_\eta [K_{V_j}(x_1, x_2) | x_2 = x_2] + \mathbb{E}_\eta [K_{V_j}(x_1, x_2)] \right]$$

$$\leq 4 \mathbb{E} \left( K_{V_j}^2(x_1, x_2) \right) + \mathbb{E} \left( \mathbb{E}_\eta [K_{V_j}(x_1, x_2) | x_1]^2 \right)$$

$$\leq \mathbb{E}_\eta \left[ K_{V_j}(x_1, x_2) - \mathbb{E}_\eta (K_{V_j}(x_1, x_2)) \right]^2 + \mathbb{E}_\eta \left[ \mathbb{E}_\eta (K_{V_j}(x_1, x_2) | x_1) - \mathbb{E}_\eta (K_{V_j}(x_1, x_2)) \right]^2$$

$$\text{Now, } \mathbb{E}_\eta \left[ K_{V_j}(x_1, x_2) - \mathbb{E}_\eta(K_{V_j}(x_1, x_2)) \right]^2$$

$$\leq 2 \mathbb{E}_\eta \left( \sum_{\ell, k} \psi_{\ell k}(x_2) \psi_{\ell k}(x_2) \right)^2 + 2 \int \left( \sum_{\ell, k} \psi_{\ell k}(x_2) \psi_{\ell k}(x_2) \right)^2 \eta(x_2) dx_2$$

$$\leq 2B^2 \cdot 2^j + 2B \sum_{\ell, k} \psi_{\ell k}^2(x_2) \leq 8B \cdot 2^j \quad \left( \text{for each } x_2 \sum_{\ell, k} \psi_{\ell k}^2(x_2) \leq 1+2+2^2+\dots+2^j \leq 2^{j+1} \right)$$

similarly one can also show,

$$\mathbb{E}_\eta \left[ \mathbb{E}_\eta(K_{V_j}(x_1, x_2) | x_1) - \mathbb{E}_\eta(K_{V_j}(x_1, x_2)) \right]^2 \leq 8B \cdot 2^j$$

$$\Rightarrow \text{for each } x_2 \in [0, 1], \mathbb{E}_\eta(R^2(x_1, x_2)) \leq 16B \cdot 2^j$$

$$\Rightarrow \lambda_3 \leq (16Bn \cdot 2^j)^{1/2}$$

$$\lambda_4 = \sup_{x_1, x_2} |R(x_1, x_2)| \quad R(x_1, x_2) = K_{V_j}(x_1, x_2) - \mathbb{E}_\eta(K_{V_j}(x_1, x_2) | x_1 = x_1) - \mathbb{E}_\eta(K_{V_j}(x_1, x_2) | x_2 = x_2) + \mathbb{E}_\eta(K_{V_j}(x_1, x_2))$$

$$|K_{V_j}(x_1, x_2)| \leq \sum_{\ell=-1}^j \sum_{k=0}^{2^{j-\ell}-1} |\psi_{\ell k}(x_1)| |\psi_{\ell k}(x_2)|$$

$$\leq 2^{j+1}$$

$$\Rightarrow \lambda_4 \leq 4 \cdot 2^{j+1}$$

$$\text{Collecting our bounds: } \lambda_1^2 \leq B^2 \cdot n^2 \cdot 2^j$$

$$\lambda_2 \leq 4nB^2$$

$$\lambda_3 \leq 4\sqrt{Bn \cdot 2^j}$$

$$\lambda_4 \leq 4 \cdot 2^{j+1} = 8 \cdot 2^j$$

Therefore, plugging these bounds in the lemma we get

$$\mathbb{P}_\gamma \left( \left| \sum_{i_1 \neq i_2} R(x_{i_1}, x_{i_2}) \right| \geq C \left[ B n^{3/2} \sqrt{u} + 4 n B^2 u + 4 \sqrt{B n^{3/2}} u^{3/2} + 8 2^j u^2 \right] \right) \leq 6 e^{-u}$$

$$\Rightarrow \mathbb{P}_\gamma \left( \left| \sum_{i_1 \neq i_2} R(x_{i_1}, x_{i_2}) \right| \geq 8 C_0 B^2 \left[ n 2^{j/2} \sqrt{u} + n u + \sqrt{n} 2^{j/2} u^{3/2} + 2^j u^2 \right] \right) \leq 6 e^{-u}$$

$$\Rightarrow \mathbb{P}_\gamma \left( \left| \frac{1}{n(n-1)} \sum_{i_1 \neq i_2} R(x_{i_1}, x_{i_2}) \right| \geq 16 C_0 B^2 \left[ \frac{2^{j/2}}{n} \sqrt{u} + \frac{u}{n} + \frac{2^{j/2}}{n^{3/2}} u^{3/2} + \frac{2^j}{n^2} u^2 \right] \right) \leq 6 e^{-u}$$

Now,  $2^j u^{3/2} \leq u + u^2$  by AM-GM inequality.

$$\Rightarrow \mathbb{P}_\gamma \left( \left| \frac{1}{n(n-1)} \sum_{i_1 \neq i_2} R(x_{i_1}, x_{i_2}) \right| \geq 16 C_0 B^2 \left[ \frac{2^{j/2}}{n} \sqrt{u} + \frac{u}{n} \left( \frac{2^{j/2}}{\sqrt{n}} + 1 \right) + \frac{2^{j/2}}{n^{3/2}} u^2 \left( 1 + \frac{2^{j/2}}{\sqrt{n}} \right) \right] \right) \leq 6 e^{-u}$$

$$\Rightarrow \mathbb{P}_\gamma \left( \left| \hat{\chi}_n(j) - \mathbb{E}_\gamma \hat{\chi}_n(j) \right| \geq a_1 \sqrt{u} + a_2 u + a_3 u^2 \right) \leq 6 e^{-u} \quad \text{where } a_1, a_2, a_3 \text{ are as above.}$$

If  $h(u)$  is such that  $a_1 \sqrt{h(u)} + a_2 h(u) + a_3 h^2(u) \leq u$

then,

$$\begin{aligned} \mathbb{P}_\gamma \left( \left| \hat{\chi}_n(j) - \mathbb{E}_\gamma \hat{\chi}_n(j) \right| \geq u \right) &\leq \mathbb{P}_\gamma \left( \left| \hat{\chi}_n(j) - \mathbb{E}_\gamma \hat{\chi}_n(j) \right| \geq a_1 \sqrt{h(u)} \right. \\ &\quad \left. + a_2 h(u) + a_3 h^2(u) \right) \\ &\leq 6 e^{-h(u)} \end{aligned}$$

letting  $h(u) = \frac{1}{3} \min \{ b_1 u^2, b_2 u, b_3 \sqrt{u} \}$  with  $b_1 = 1/a_1^2$ ,  $b_2 = 1/a_2$  and  $b_3 = 1/\sqrt{a_3}$

we have,

$$\mathbb{P}_\gamma \left( \left| \hat{\chi}_n(j) - \mathbb{E}_\gamma \hat{\chi}_n(j) \right| \geq u \right) \leq 6 \exp \left\{ -\frac{1}{3} \min \left( \frac{u^2}{a_1^2}, \frac{u}{a_2}, \frac{\sqrt{u}}{\sqrt{a_3}} \right) \right\}$$

where  $a_1 = 16 C_0 B^2 \sqrt{\frac{2^j}{n^2}}$ ,  $a_2 = \frac{16 C_0 B^2}{n} \left( \sqrt{\frac{2^j}{n}} + 1 \right)$ ,  $a_3 = 16 C_0 B^2 \cdot \frac{2^{j/2}}{n^{3/2}} \left( 1 + \sqrt{\frac{2^j}{n}} \right)$

this also implies that

$$\begin{aligned} \mathbb{E}_\eta (|\hat{\chi}_n(j) - \mathbb{E}_\eta \hat{\chi}_n(j)|^{2q}) &= 2q \int_0^\infty u^{2q-1} \mathbb{P}_\eta (|\hat{\chi}_n(j) - \mathbb{E}_\eta \hat{\chi}_n(j)| > u) du \\ &\leq 12q \left[ \int_0^\infty u^{2q-1} e^{-b_1 u^2} du + \int_0^\infty u^{2q-1} e^{-b_2 u} du + \int_0^\infty u^{2q-1} e^{-b_3 \sqrt{u}} du \right] \\ &\leq 12q \left( \frac{\Gamma(q)}{2b_1^q} + \frac{\Gamma(2q)}{b_2^{2q}} + \frac{2\Gamma(4q)}{b_3^{4q}} \right) \end{aligned}$$

Going Back to our Actual Problem

$\eta \in \mathcal{P}(\alpha_0, M, B)$  and  $n \ll 2^{j_0}, 2^{j_1} \ll n^2$

$$\mathbb{E}_\eta ((\hat{\chi}_n(j) - \chi(\eta))^2) \leq c(M, B) n^{-8\alpha_0/4\alpha_0+1} + T_1$$

$$T_1 \leq \left\{ \mathbb{E}_\eta ((\hat{\chi}_n(j_1) - \chi(\eta))^{2q}) \right\}^{1/q} \left\{ \mathbb{P}_\eta (\hat{j} = j_1) \right\}^{1/p} \quad \text{for any } \frac{1}{p} + \frac{1}{q} = 1$$

$b, q \geq 1$

then we showed, for any  $n \ll 2^j \ll n^2$ ,

$$\mathbb{P}_\eta (\hat{j} = j_1) \leq \mathbb{P}_\eta \left[ |\hat{\chi}_n(j_0) - \mathbb{E}_\eta \hat{\chi}_n(j_0)| > \sqrt{\frac{C^* \log n}{4}} \sqrt{\frac{2^{j_0}}{n^2}} \right] + \mathbb{P}_\eta \left[ |\hat{\chi}_n(j_1) - \mathbb{E}_\eta \hat{\chi}_n(j_1)| > \sqrt{\frac{C^* \log n}{4}} \sqrt{\frac{2^{j_1}}{n^2}} \right]$$

We then showed

$$\begin{aligned} \mathbb{P}_\eta \left[ |\hat{\chi}_n(j) - \mathbb{E}_\eta \hat{\chi}_n(j)| > \sqrt{\frac{C^{**} \log n}{4}} \sqrt{\frac{2^j}{n^2}} \right] \\ \leq \exp\left(-\frac{C^{**}}{2B} \times \frac{2^j}{n}\right) + 6 \exp\left(-\frac{1}{3} \min\left\{ \frac{u^2}{a_1}, \frac{u}{a_2}, \frac{\sqrt{u}}{a_3} \right\}\right) \end{aligned}$$

with  $a_1, a_2, a_3$   
as on page (15)

We also have a bound on  $\mathbb{E}_\eta (|\hat{\chi}_n(j) - \mathbb{E}_\eta \hat{\chi}_n(j)|^{2q})$ .

$\therefore$  We have all the ingredients to tackle  $T_1$ .



It is easy to check that with our choice of  $j_{\text{opt}}$ ,

if  $u = \sqrt{c^{**} \log n} \sqrt{2^j/n^2}$  and  $j \in \{j_{\text{opt}}\}$ , then

$$\min \left\{ \frac{u^2}{a_1^2}, \frac{u}{a_2}, \frac{\sqrt{u}}{a_3} \right\} =$$

$$= \frac{1}{16c_0B^2} \left\{ \frac{c^{**} \log n \cdot 2^j/n^2}{2^j/n^2}, \frac{(c^{**} \log n \cdot 2^j/n^2)^{1/2}}{\frac{1}{n} (\sqrt{\frac{2^j}{n}} + 1)}, \frac{(c^{**} \log n \cdot 2^j/n^2)^{1/4}}{\left(\frac{2^{j/2}}{n^{3/2}} (1 + \sqrt{\frac{2^j}{n}})\right)^{1/2}} \right\}$$

$$= \frac{1}{(16c_0B^2)^2} \left\{ c^{**} \log n, \frac{(n^2 c^{**} \log n \cdot 2^j/n^2)^{1/2}}{(\sqrt{\frac{2^j}{n}} + 1)}, \frac{\left(\frac{n^3 c^{**} \log n \cdot 2^j/n^2\right)^{1/4}}{(1 + \sqrt{\frac{2^j}{n}})^{1/2}} \right\}$$

$$= \frac{1}{(16c_0B^2)^2} \left\{ c^{**} \log n, \frac{(c^{**} \log n \cdot 2^j)^{1/2}}{(1 + \sqrt{2^j/n})}, \frac{(c^{**} n \log n)^{1/4}}{(1 + \sqrt{2^j/n})^{1/2}} \right\}$$

$$= \frac{(c^{**} \log n)}{(16c_0B^2)^2} \neq n.$$

$$\Rightarrow \mathbb{P}_\eta (|\hat{x}_n(j) - \mathbb{E}_\eta(\hat{x}_n(j))| > \sqrt{c^{**} \log n} \sqrt{2^j/n^2})$$

$$\leq \exp\left(-\frac{c^{**}}{2B} \times \frac{2^j}{n}\right) + 6 \exp\left(-\frac{1}{3} \times \frac{c^{**} \log n}{(16c_0B^2)^2}\right) \quad \text{if } j \in \{j_{\text{opt}}\}$$

If  $c^{**} > 6(16c_0B^2)^2$ , then the above bound  $\leq (7/n)$

$$\therefore \mathbb{P}_\eta [|\hat{x}_n(j) - \mathbb{E}_\eta(\hat{x}_n(j))| > \sqrt{\frac{c^*}{4} \log n} \sqrt{2^j/n^2}]$$

$$\leq \exp\left(-\frac{c^*}{8B} \cdot \frac{2^j}{n}\right) + 6 \exp\left(-\frac{c^* \log n}{12(16c_0B)^2}\right)$$

Choose  $c^* > 24(16c_0B)^2$

$$\Rightarrow \mathbb{P}_\eta [|\hat{x}_n(j) - \mathbb{E}_\eta(\hat{x}_n(j))| > \sqrt{\frac{c^*}{4} \log n} \sqrt{2^j/n^2}] \leq 7/n \quad \text{if } j \in \{j_{\text{opt}}\}$$

We also have, if  $j \in \{j_0, j_1\}$  (j satisfying  $n \ll 2^j \ll n^2$ )

$$\mathbb{E}_\eta (|\hat{\chi}_n(j) - \mathbb{E}_\eta(\hat{\chi}_n(j))|^{2q})$$

$$\leq 12q \left( \frac{\Gamma(q)}{2b_1^q} + \frac{\Gamma(2q)}{b_2^{2q}} + \frac{2\Gamma(4q)}{b_3^{4q}} \right)$$

$$= 12q \left[ \frac{\Gamma(q)}{2} \times \frac{1}{(16C_0B^2)^q} a_1^{2q} + \Gamma(2q) \times a_2^{2q} + 2\Gamma(4q) a_3^{2q} \right]$$

$$\leq 12q \left[ \frac{\Gamma(q)}{2} + \Gamma(2q) + 2\Gamma(4q) \right] \max\{a_1^{2q}, a_2^{2q}, a_3^{2q}\}$$

$$\leq 12q \left[ \frac{\Gamma(q)}{2} + \Gamma(2q) + 2\Gamma(4q) \right] (16C_0B^2)^{2q} \left(\frac{2^j}{n^2}\right)^q \quad (\text{check by direct calculations})$$

$$\Rightarrow T_1 \leq \left[ \left\{ 12q \left( \frac{\Gamma(q)}{2} + \Gamma(2q) + 2\Gamma(4q) \right) \right\}^{\frac{1}{q}} \frac{2^{j_1}}{n^2} \right] \times \left( \frac{7}{n} \right)^{\frac{1}{p}} \times (16C_0B^2)^2$$

$$= (16C_0B^2) \frac{2^{j_1}}{n^2} \times \left( \frac{7}{n} \right)^{\frac{1}{p}} \times \left( 12q \left( \frac{\Gamma(q)}{2} + \Gamma(2q) + 2\Gamma(4q) \right) \right)^{\frac{1}{q}}$$

We need to make this smaller than  $2^{j_0}/n^2 = n^{-\frac{8\alpha_0}{4\alpha_0+1}}$

$\Rightarrow$  choose  $p$  sufficiently close to 1 (depending on  $\alpha_0$ ).

This completes the "proof" for adaptation over

$$0 < \alpha_0 \leq \alpha_1 < 1/4.$$