

$$f = \sum_{j=1}^{\infty} \theta_j \varphi_j$$

$$f \in W^{\text{pen}}(\beta) \Rightarrow \theta \in (\mathcal{H})^{\beta}$$

$$f \in \mathcal{W}^{\beta} : \left\{ \sum_{j=1}^{\infty} j^{2\beta} \theta_j^2 \leq 1 \right\}$$

$$j=1, 2, \dots, N, \quad \hat{\theta}_j = \frac{1}{n} \sum_{i=1}^n Y_i \varphi_j(X_i)$$

$$(\|\varphi_j\|_2 = 1)$$

$$\mathbb{E}[\hat{\theta}_j] = \langle f^*, \varphi_j \rangle_n$$

$$\text{Var}(\hat{\theta}_j) = \frac{1}{n^2} \sum_{i=1}^n \varphi_j^2(X_i/n) = \frac{1}{n}$$

$$\|\varphi_j\|_n = 1$$

$$\mathbb{E} \left[\int_0^1 (\hat{f}_n(x) - f^*(x))^2 dx \right] = \sum_{j=1}^{\infty} \mathbb{E} (\hat{\theta}_j - \theta_j^*)^2$$

$$= \sum_{j=1}^N \mathbb{E} (\hat{\theta}_j - \theta_j^*)^2 + \sum_{j=N+1}^{\infty} (\theta_j^*)^2$$

$$= \sum_{j=1}^N \left[\frac{1}{n} + \left(\langle f^*, \varphi_j \rangle_n - \langle f^*, \varphi_j \rangle \right)^2 \right] + \sum_{j=N+1}^{\infty} (\theta_j^*)^2$$

$$\leq \frac{N}{n} + \frac{\sum_{j=N+1}^{\infty} j^{2\beta} (\theta_j^*)^2}{N^{2\beta}} + \sum_{j=1}^N \alpha_j^2$$

$$\frac{N}{n} + \frac{1}{N^{2\beta}}$$

$$N = n^{\frac{1}{2\beta+1}}$$

(Ignore α)

$$\text{MISE} \leq n^{-\frac{2\beta}{2\beta+1}}$$

Following this calculation.

$$\mathbb{E} \left[\|\hat{f}_n - f^*\|_n^2 \right] \leq n^{-\frac{2\beta}{2\beta+1}}$$

MISE: need to bound α ($f^* = \sum_{j=1}^{+\infty} \theta_j \varphi_j$)

$$\alpha_{ij} = \sum_{i=1}^{+\infty} \theta_i^* \left(\langle \varphi_i, \varphi_j \rangle_n - \langle \varphi_i, \varphi_j \rangle_{\mathcal{L}^2} \right) \quad (j \leq N < n)$$

$$\text{If } i, j \leq n. \quad \langle \varphi_i, \varphi_j \rangle_n = \begin{cases} 1 & i=j \\ 0 & i \neq j \end{cases}$$

$$\alpha_{ij} = \sum_{i=N+1}^{+\infty} \left(\langle \varphi_i, \varphi_j \rangle_n - \langle \varphi_i, \varphi_j \rangle_{\mathcal{L}^2} \right) \theta_i^*$$

$$\left(\|\varphi\|_{\infty} \leq \sqrt{2} \right)$$

$$\leq 2 \sum_{i=N+1}^{+\infty} |\theta_i^*|$$

$$\sum_{i=N+1}^{+\infty} |\theta_i^*| \leq \left[\sum_{i=N+1}^{+\infty} i^{2\beta} \cdot (\theta_i^*)^2 \right]^{1/2} \cdot \left[\sum_{i=N+1}^{+\infty} i^{-2\beta} \right]^{1/2}$$

$$\left(\beta > \frac{1}{2} \right) \leq C \cdot n^{\frac{1}{2} - \beta}$$

$$\text{MISE} \leq \frac{N}{n} + N^{-2\beta} + N \cdot n^{-2\beta}$$

Want to take $N = \left\lfloor n^{\frac{1}{2\beta+1}} \right\rfloor$

In order for $\text{MISE} \sim n^{-\frac{2\beta}{2\beta+1}}$
we need $N \cdot n^{-2\beta} \lesssim n^{-\frac{2\beta}{2\beta+1}}$

which requires $\beta \geq 1$.

Remark: $\hat{f}_{n,N}$ relies on $\{ \varphi_j \}_{j=1}^{+\infty}$ being orthonormal
orthonormal in $L^2[0,1]$.

Local poly estimator

Warmup: Nadaraya-Watson

$$\hat{f}_n(x) = \frac{\sum_{j=1}^n Y_j K\left(\frac{x_j - x}{h}\right)}{\sum_{j=1}^n K\left(\frac{x_j - x}{h}\right)}$$

K : some (well-behaved) kernel.

$$W_{n,i}(x) = \frac{K\left(\frac{x_i - x}{h}\right)}{\sum_{j=1}^n K\left(\frac{x_j - x}{h}\right)}$$

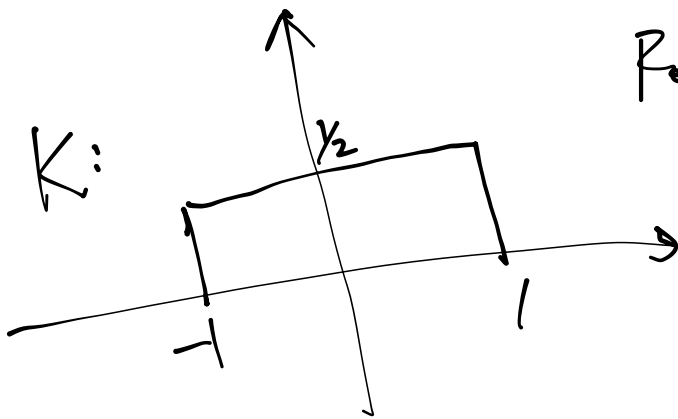
$$\begin{aligned} \text{Bias: } b(x_0) &= E[\hat{f}_n(x_0)] - f^*(x_0) \\ &= \sum_{i=1}^n W_{n,i}(x_0) \cdot (f^*(x_i) - f^*(x_0)). \end{aligned}$$

$$\text{Variance: } \sigma^2(x_0) = \sum_{i=1}^n W_{n,i}^2(x_0).$$

Assume $f^* \in \Sigma(\beta)$. i.e. $|f^*(x) - f^*(y)| \leq |x - y|^\beta$

for $\beta \in (0, 1]$.

$$|b(x_0)| \leq \sum_{i=1}^n |W_{n,i}(x_0)| \cdot |x_i - x_0|^\beta$$



For x_i 's s.t. $|x_i - x_0| > h$

$$K\left(\frac{x_i - x_0}{h}\right) = 0$$

$$\Rightarrow W_{n,i}(x_0) = 0.$$

$$|b(x_0)| \leq \sum_{i=1}^n |W_{n,i}(x_0)| \cdot h^\beta = h^\beta$$

$$\sigma^2(x_0) = \sum_{i=1}^n W_{n,i}(x_0)^2 \leq \max_i |W_{n,i}(x_0)| \cdot \underbrace{\sum_{i=1}^n |W_{n,i}(x_0)|}_{=1}.$$

$$W_{n,i}(x_0) = \frac{K\left(\frac{x_i - x_0}{h}\right)}{\sum_{j=1}^n K\left(\frac{x_j - x_0}{h}\right)}$$

$$\leq \left| \{j: |x_j - x_0| \leq h\} \right|^{-1}.$$

Equi-spaced design $h > n^{-1}$.

$$\left| \{j : |x_j - x_0| \leq h\} \right| \geq nh.$$

$$\text{MSE}(x_0) \lesssim h^{2\beta} + \frac{1}{nh}$$

$$h_n^* = n^{\frac{-1}{2\beta+1}} \implies \text{MSE}(x_0) \lesssim n^{\frac{-2\beta}{2\beta+1}}.$$