

## Assumption modification

Chanwoo Lee, December 4, 2020

**Assumption 1** (Boundary noise). There exist constants  $\alpha \in (0, 1]$  and  $C > 0$ , such that

$$\max_{\pi \in \Pi'} \mathbb{P}_{\mathbf{X}} (|p(\mathbf{X}) - \pi| \leq t/H) \leq C \left( \frac{t}{H} \right)^{\frac{\alpha}{1-\alpha}}, \quad \text{for all } t \in [0, 1], \quad (1)$$

where  $\Pi' \subset \Pi$  with  $|\Pi| - |\Pi'| \leq m$  and  $m$  is a finite number independent on  $H$ . When  $\alpha = 1$ , the inequality (1) reads  $\mathbb{P}(|p(\mathbf{X}) - \pi| \leq t/H) = 0$ .

**Theorem 0.1.** Suppose (1) is satisfied with  $\alpha \in (0, 1)$ . Then, with the condition that  $H \leq \frac{C_0}{\max_{\pi \in \Pi'} [R_{\pi}(S) - R_{\pi}(S_{\text{bayes}})]^{1-\alpha}}$ ,

$$\mathbb{P}_{\mathbf{X}}[S \Delta S_{\text{bayes}}] \leq C_1 [R_{\pi}(S) - R_{\pi}(S_{\text{bayes}}(\pi))]^{\alpha},$$

for all sets  $S \in \mathbb{R}^{d_1 \times d_2}$ , levels  $\pi \in \Pi'$ . If (1) is satisfied with  $\alpha = 1$ , Then, with no condition on  $H$ ,

$$\mathbb{P}_{\mathbf{X}}[S \Delta S_{\text{bayes}}] \leq C_2 H [R_{\pi}(S) - R_{\pi}(S_{\text{bayes}}(\pi))],$$

for all sets  $S \in \mathbb{R}^{d_1 \times d_2}$ , levels  $\pi \in \Pi'$ .

**Theorem 0.2** (Nonparametric regression via weighted classifications). Let  $p(\mathbf{X})$  be a regression function satisfying (1), and  $\bar{p}(\mathbf{X})$  the linear combination of weighted classifiers based on our method. Then, there exists a constant  $C_3 > 0$  such that

$$R_{\text{reg}}(\bar{p}) - R_{\text{reg}}(p) \leq 4\mathbb{E}_{\mathbf{X}} |\bar{p}(\mathbf{X}) - p(\mathbf{X})| \leq \frac{2}{H} + C_3 H^{\mathbb{1}\{\alpha=1\}} \max_{\pi \in \Pi} [R_{\pi}(\bar{S}(\pi)) - R_{\pi}(S_{\text{bayes}}(\pi))]^{\alpha},$$

for all resolution parameter  $H = |\Pi| \in \mathbb{N}_+$ .

**Remark 1.** We have two cases of the bound

1. when  $\alpha \in (0, 1)$ , We have

$$\begin{aligned} \mathbb{E}_{\mathbf{X}} |\bar{p}(\mathbf{X}) - p(\mathbf{X})| &\leq C_3 \max_{\pi \in \Pi} [R_{\pi}(\bar{S}(\pi)) - R_{\pi}(S_{\text{bayes}}(\pi))]^{\alpha} + C_4 \max_{\pi \in \Pi} [R_{\pi}(\bar{S}(\pi)) - R_{\pi}(S_{\text{bayes}}(\pi))]^{1-\alpha} \\ &\leq \underbrace{C_3 \left( \frac{r(s_1 + s_2) \log d}{n} \right)^{(1-\alpha)/(2-\alpha)}}_{\text{reduction error}} + \underbrace{C_4 \left( \frac{r(s_1 + s_2) \log d}{n} \right)^{\alpha/(2-\alpha)}}_{\text{statistical error}} + \underbrace{C_5 a_n^{\alpha}}_{\text{approximation error}} \end{aligned}$$

2. when  $\alpha = 1$ ,

$$\mathbb{E}_{\mathbf{X}} |\bar{p}(\mathbf{X}) - p(\mathbf{X})| \leq \underbrace{C_3 \frac{1}{H}}_{\text{reduction error}} + \underbrace{C_4 H \left( \frac{r(s_1 + s_2) \log d}{n} \right)}_{\text{statistical error}} + \underbrace{C_5 a_n^{\alpha}}_{\text{approximation error}}$$

We can bound the convergence rate setting  $H = \mathcal{O}(\sqrt{(n)})$ .

**Remark 2.** One way to make our theorem organized without distinguishing  $\alpha \in (0, 1)$  and  $\alpha = 1$  is to change Theorem 0.1 as

**Theorem 0.3.** Suppose (1) is satisfied with  $\alpha \in (0, 1]$ , then (1) implies

$$\mathbb{P}_{\mathbf{X}}[S \Delta S_{\text{bayes}}] \leq C_1 H [R_{\pi}(S) - R_{\pi}(S_{\text{bayes}}(\pi))]^{\alpha},$$

for all sets  $S \in \mathbb{R}^{d_1 \times d_2}$ , levels  $\pi \in \Pi'$ .

Then our main bound becomes

$$\mathbb{E}_{\mathbf{X}} |\bar{p}(\mathbf{X}) - p(\mathbf{X})| \leq \underbrace{C_3 \frac{1}{H}}_{\text{reduction error}} + \underbrace{C_4 H \left( \frac{r(s_1 + s_2) \log d}{n} \right)^{\alpha/(2-\alpha)}}_{\text{statistical error}} + \underbrace{C_5 a_n^\alpha}_{\text{approximation error}}$$