## One-against-all

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**Theorem.** Let  $\hat{\eta}_1, \ldots, \hat{\eta}_K \colon \mathcal{X} \to [0, 1]$  be estimates of conditional probability functions  $x \mapsto \mathbb{P}(Y = k \mid X = x)$  for  $k = 1, \ldots, K$ , and let

$$\epsilon := \mathbb{E}\left[\max_{k=1,\dots,K} \left| \hat{\eta}_k(X) - \mathbb{P}(Y = k \mid X) \right| \right]$$

Let  $\hat{f}: \mathcal{X} \to \{1, \dots, K\}$  be the one-against-all classifier based on  $\hat{\eta}_1, \dots, \hat{\eta}_K$ , i.e.,

$$\hat{f}(x) = \operatorname*{arg\,max}_{k=1,\ldots,K} \hat{\eta}_k(x), \quad x \in \mathcal{X},$$

(with ties broken arbitrarily), and let  $f^* \colon \mathcal{X} \to \{1, \dots, K\}$  be the Bayes optimal classifier. Then

$$\mathbb{P}(\hat{f}(X) \neq Y) - \mathbb{P}(f^{\star}(X) \neq Y) \le 2\epsilon.$$

*Proof.* Fix  $x \in \mathcal{X}$ ,  $y^* := f^*(x)$ , and  $\hat{y} := \hat{f}(x)$ . Let  $\eta_k(x) := \mathbb{P}(Y = k \mid X = x)$  for all  $k = 1, \ldots, K$ . Then

$$\begin{split} \mathbb{P}(\hat{f}(X) \neq Y \mid X = x) - \mathbb{P}(f^{\star}(X) \neq Y \mid X = x) &= \sum_{k \neq \hat{y}} \eta_k(x) - \sum_{k \neq y^{\star}} \eta_k(x) \\ &= \eta_{y^{\star}}(x) - \eta_{\hat{y}}(x) \\ &= \underbrace{\eta_{y^{\star}}(x) - \eta_{\hat{y}}(x)}_{\leq 0} + \eta_{y^{\star}}(x) - \widehat{\eta}_{y^{\star}}(x) + \widehat{\eta}_{\hat{y}}(x) - \eta_{\hat{y}}(x) \\ &\leq 2 \max_{k=1,...,K} |\widehat{\eta}_k(x) - \eta_k(x)|. \end{split}$$

Therefore, taking expectations with respect to X,

$$\mathbb{P}(\hat{f}(X) \neq Y) - \mathbb{P}(f^{\star}(X) \neq Y) \le 2 \cdot \mathbb{E}\left[\max_{k=1,\dots,K} \left| \hat{\eta}_k(X) - \eta_k(X) \right| \right].$$

The bound on the excess risk is tight. To see this, suppose for a given  $x \in \mathcal{X}$  (with  $y^* = f^*(x)$  and  $\hat{y} = \hat{f}(x)$ ), we have  $\hat{\eta}_{y^*}(x) = \hat{\eta}_{\hat{y}}(x) - \delta$ , but  $\eta_{y^*}(x) = \hat{\eta}_{y^*}(x) + \epsilon$  and  $\eta_{\hat{y}}(x) = \hat{\eta}_{\hat{y}}(x) - \epsilon$ . Then

$$\eta_{y^{\star}}(x) - \eta_{\hat{y}}(x) = (\hat{\eta}_{y^{\star}(x)} + \epsilon) - (\hat{\eta}_{\hat{y}}(x) - \epsilon)$$
$$= 2\epsilon - \delta$$

which tends to  $2\epsilon$  as  $\delta \to 0$ .