

A Proofs of Theorems

In this section, we give proofs of theorems.

A.1 Decomposition of generalization error in PU classification

Assume that $\pi^* := p(y = 1)$ is the true class prior of the positive class. Subsequently,

$$\begin{aligned}
\mathbf{E}_{p(\mathbf{x}, y)}[\ell_{0-1}(yf(\mathbf{x}))] &= \int_{\mathbf{R}^d} \sum_y \ell_{0-1}(yf(\mathbf{x})) p(\mathbf{x}, y) d\mathbf{x} \\
&= \int_{\mathbf{R}^d} \sum_y \tilde{\ell}(yf(\mathbf{x})) \left(\frac{y+3}{2} \right) p(\mathbf{x}, y) d\mathbf{x} \\
&= \int_{\mathbf{R}^d} \sum_y \tilde{\ell}(yf(\mathbf{x})) (2p(\mathbf{x}, y = +1) + p(\mathbf{x}, y = -1)) d\mathbf{x} \\
&= \pi^* \int_{\mathbf{R}^d} \tilde{\ell}(f(\mathbf{x})) p(\mathbf{x} | y = +1) d\mathbf{x} + \int_{\mathbf{R}^d} \sum_y \tilde{\ell}(yf(\mathbf{x})) p(\mathbf{x}, y) d\mathbf{x} \\
&= \pi^* \mathbf{E}_{p(\mathbf{x}|y=+1)} [\tilde{\ell}(f(\mathbf{x}))] + \mathbf{E}_{p(\mathbf{x}, y)} [\tilde{\ell}(yf(\mathbf{x}))]. \tag{14}
\end{aligned}$$

This decomposition is the key idea of our error bounds.

A.2 Proof of Theorem 1

Note that $\tilde{\ell}$ maps to $[0, 1]$, but if $y = +1$ it maps to $[0, 1/2]$. We apply *McDiarmid's inequality* and obtain

$$\Pr \left\{ \mathbf{E}_{p(\mathbf{x}|y=+1)} [\tilde{\ell}(f(\mathbf{x}))] - \frac{1}{n} \sum_{i=1}^n \tilde{\ell}(f(\mathbf{x}_i)) \geq \epsilon \right\} \leq \exp \left(-\frac{2\epsilon^2}{n(1/2n)^2} \right).$$

Equating the right-hand side of the above inequality to $\delta/2$ gives us that with probability at least $1 - \delta/2$,

$$\mathbf{E}_{p(\mathbf{x}|y=+1)} [\tilde{\ell}(f(\mathbf{x}))] - \frac{1}{n} \sum_{i=1}^n \tilde{\ell}(f(\mathbf{x}_i)) \leq \sqrt{\frac{\ln(2/\delta)}{8n}}.$$

Apply *McDiarmid's inequality* again and obtain that with probability at least $1 - \delta/2$,

$$\mathbf{E}_{p(\mathbf{x}, y)} [\tilde{\ell}(yf(\mathbf{x}))] - \frac{1}{n'} \sum_{j=1}^{n'} \tilde{\ell}(y'_j f(\mathbf{x}'_j)) \leq \sqrt{\frac{\ln(2/\delta)}{2n'}}.$$

Combining these two concentration inequalities and Eq. (14) completes the proof. \square

A.3 Proof of Theorem 2

Definition 3 ([15], Definitions 3.1 and 3.2). *Let \mathcal{F} be a class of functions. Let $\mathbf{x}_1, \dots, \mathbf{x}_n$ be independent observations drawn according to $p(\mathbf{x})$, and $\sigma_1, \dots, \sigma_n$ be independent uniformly $\{\pm 1\}$ -valued random variables, i.e., Rademacher variables. The empirical Rademacher complexity of \mathcal{F} conditioned on $\mathbf{x}_1, \dots, \mathbf{x}_n$ is defined by*

$$\widehat{\mathcal{R}}_n(\mathcal{F}) := \mathbf{E}_{\sigma_1, \dots, \sigma_n} \left\{ \sup_{f \in \mathcal{F}} \frac{1}{n} \sum_{i=1}^n \sigma_i f(\mathbf{x}_i) \right\},$$

and the Rademacher complexity of \mathcal{F} is defined by

$$\mathcal{R}_n(\mathcal{F}) := \mathbf{E}_{\mathbf{x}_1, \dots, \mathbf{x}_n} \left\{ \widehat{\mathcal{R}}_n(\mathcal{F}) \right\}.$$

Denote by $\mathcal{R}_n(\mathcal{F})$ the Rademacher complexity w.r.t. $p(\mathbf{x} \mid y = +1)$, and $\mathcal{R}'_{n'}(\mathcal{F})$ the Rademacher complexity w.r.t. $p(\mathbf{x})$. By Theorem 5.5 of [15] and the condition that $C_k = \sup_{\mathbf{x} \in \mathcal{R}^d} \sqrt{k(\mathbf{x}, \mathbf{x})}$, we get

$$\begin{aligned}\mathcal{R}_n(\mathcal{F}) &\leq \frac{C_\alpha C_k}{\sqrt{n}}, \\ \mathcal{R}'_{n'}(\mathcal{F}) &\leq \frac{C_\alpha C_k}{\sqrt{n'}}.\end{aligned}\tag{15}$$

Next, we need the following lemmas.

Lemma 4. Fix $\eta > 0$, then, for any $0 < \delta < 1$ with probability at least $1 - \delta$ over the repeated sampling of $\{(\mathbf{x}'_1, y'_1), \dots, (\mathbf{x}'_{n'}, y'_{n'})\}$ for evaluating the empirical error, every $f \in \mathcal{F}$ satisfies

$$\mathbf{E}_{p(\mathbf{x}, y)} [\tilde{\ell}(yf(\mathbf{x}))] - \frac{1}{n'} \sum_{j=1}^{n'} \tilde{\ell}_\eta(y'_j f(\mathbf{x}'_j)) \leq \frac{2}{\eta} \mathcal{R}'_{n'}(\mathcal{F}) + \sqrt{\frac{\ln(1/\delta)}{2n}}.$$

Proof. Note that both $\tilde{\ell}$ and $\tilde{\ell}_\eta$ map to $[0, 1]$, $\tilde{\ell}$ is lower bounded by $\tilde{\ell}_\eta$, and the Lipschitz constant of $\tilde{\ell}_\eta$ is $1/\eta$. Hence, this lemma is essentially same as the first half of Theorem 4.4 in [15]. \square

Lemma 5. Fix $\eta > 0$, then, for any $0 < \delta < 1$ with probability at least $1 - \delta$ over the repeated sampling of $\{\mathbf{x}_1, \dots, \mathbf{x}_n\}$ for evaluating the empirical error, every $f \in \mathcal{F}$ satisfies

$$\mathbf{E}_{p(\mathbf{x}|y=+1)} [\tilde{\ell}(f(\mathbf{x}))] - \frac{1}{n} \sum_{i=1}^n \tilde{\ell}_\eta(f(\mathbf{x}_i)) \leq \frac{1}{\eta} \mathcal{R}_n(\mathcal{F}) + \sqrt{\frac{\ln(1/\delta)}{8n}}.$$

Proof. If we fix $y = +1$, both $\tilde{\ell}$ and $\tilde{\ell}_\eta$ map to $[0, 1/2]$, and the Lipschitz constant of $\tilde{\ell}_\eta$ is $1/(2\eta)$. Then, the proof of this lemma is analogous with the proof of the first half of Theorem 4.4 in [15], while there are two difference points:

- When applying Theorem 3.1 of [15], note that both $\tilde{\ell}$ and $\tilde{\ell}_\eta$ map to $[0, 1/2]$, and consequently McDiarmid's inequality results in a tighter bound;
- When applying Lemma 4.2 of [15], note that $\tilde{\ell}_\eta$ is $(1/(2\eta))$ -Lipschitz continuous, and thus the contraction of Rademacher averages results in a tighter bound. \square

By Lemma 5 and (15), with probability at least $1 - \delta/2$ over the repeated sampling of $\{\mathbf{x}_1, \dots, \mathbf{x}_n\}$,

$$\mathbf{E}_{p(\mathbf{x}|y=+1)} [\tilde{\ell}(f(\mathbf{x}))] - \frac{1}{n} \sum_{i=1}^n \tilde{\ell}_\eta(f(\mathbf{x}_i)) \leq \frac{C_\alpha C_k}{\eta \sqrt{n}} + \sqrt{\frac{\ln(2/\delta)}{8n}}.$$

Similarly, by Lemma 4 and (15), with probability at least $1 - \delta/2$ over the repeated sampling of $\{(\mathbf{x}'_1, y'_1), \dots, (\mathbf{x}'_{n'}, y'_{n'})\}$,

$$\mathbf{E}_{p(\mathbf{x}, y)} [\tilde{\ell}(yf(\mathbf{x}))] - \frac{1}{n'} \sum_{j=1}^{n'} \tilde{\ell}_\eta(y'_j f(\mathbf{x}'_j)) \leq \frac{2C_\alpha C_k}{\eta \sqrt{n'}} + \sqrt{\frac{\ln(2/\delta)}{2n'}}.$$

Combining these two concentration inequalities and Eq. (14) completes the proof. \square