

# Supplemental Material

## A Proofs

When bounding the Rademacher complexity for Lipschitz continuous loss classes (such as the hinge loss or the squared loss), the following lemma is often very helpful.

**Lemma A.1** (Talagrand’s lemma [41]). *Let  $l : \mathbb{R} \rightarrow \mathbb{R}$  be a loss function that is  $L$ -Lipschitz continuous and  $l(0) = 0$ . Let  $\mathcal{F}$  be a hypothesis class of real-valued functions and denote its loss class by  $\mathcal{G} := l \circ \mathcal{F}$ . Then the following inequality holds:*

$$R_n(\mathcal{G}) \leq 2LR_n(\mathcal{F}).$$

We can use the above result to prove Lemma 3.

*Proof of Lemma 3.* Since the LATENTSVDD loss function is 1-Lipschitz with  $l(0) = 0$ , by Lemma A.1, it is sufficient to bound  $R(\mathcal{F}_{\text{SVDD}}(z))$ . To this end, it holds

$$\begin{aligned} R(\mathcal{F}_{\text{SVDD}}(z)) &\stackrel{\text{def.}}{=} \mathbb{E} \left[ \sup_{\mathbf{c}, \Omega: 0 \leq \|\mathbf{c}\|^2 + \Omega \leq \lambda} \frac{1}{n} \sum_{i=1}^n \sigma_i (\Omega \right. \\ &\quad \left. + 2\langle \mathbf{c}, \Psi(\mathbf{x}_i, z) \rangle - \|\Psi(\mathbf{x}_i, z)\|^2) \right] \\ &\leq \mathbb{E} \left[ \sup_{\Omega: -\lambda \leq \Omega \leq \lambda} \frac{1}{n} \sum_{i=1}^n \sigma_i \Omega \right] \\ &\quad + 2\mathbb{E} \left[ \sup_{\mathbf{c}: \|\mathbf{c}\|^2 \leq \lambda} \frac{1}{n} \sum_{i=1}^n \sigma_i (\langle \mathbf{c}, \Psi(\mathbf{x}_i, z) \rangle) \right] \\ &\quad + \underbrace{\mathbb{E} \left[ -\frac{1}{n} \sum_{i=1}^n \sigma_i \|\Psi(\mathbf{x}_i, z)\|^2 \right]}_{=0 \text{ (by symmetry of } \sigma_i \text{)}}. \quad (\text{A.3.1}) \end{aligned}$$

Note that the term to the right is zero because the Rademacher variables are random signs, independent of  $\mathbf{x}_1, \dots, \mathbf{x}_n$ . The term to the left can be bounded as follows:

$$\begin{aligned} \mathbb{E} \left[ \sup_{\Omega: -\lambda \leq \Omega \leq \lambda} \frac{1}{n} \sum_{i=1}^n \sigma_i \Omega \right] &= \lambda \mathbb{E} \left[ \left| \frac{1}{n} \sum_{i=1}^n \sigma_i \right| \right] \\ &\stackrel{(*)}{\leq} \lambda \sqrt{\mathbb{E} \left[ \frac{1}{n^2} \sum_{i,j=1}^n \sigma_i \sigma_j \right]} \\ &= \frac{\lambda}{\sqrt{n}}. \quad (\text{A.3.2}) \end{aligned}$$

where for  $(*)$  we employ Jensen’s inequality. Moreover, applying the Cauchy-Schwarz inequality and Jensen’s in-

equality, respectively, we obtain

$$\begin{aligned} &\mathbb{E} \left[ \sup_{\mathbf{c}: \|\mathbf{c}\|^2 \leq \lambda} \frac{1}{n} \sum_{i=1}^n \sigma_i (\langle \mathbf{c}, \Psi(\mathbf{x}_i, z) \rangle) \right] \\ &\stackrel{\text{C.-S.}}{\leq} \mathbb{E} \left[ \sup_{\mathbf{c}: \|\mathbf{c}\|^2 \leq \lambda} \|\mathbf{c}\| \left\| \frac{1}{n} \sum_{i=1}^n \sigma_i \Psi(\mathbf{x}_i, z) \right\| \right] \\ &\stackrel{\text{Jensen}}{\leq} \sqrt{\lambda \mathbb{E} \left[ \frac{1}{n^2} \sum_{i,j=1}^n \sigma_i \sigma_j \langle \Psi(\mathbf{x}_i, z), \Psi(\mathbf{x}_j, z) \rangle \right]} \\ &= \sqrt{\lambda \frac{1}{n^2} \sum_{i=1}^n \|\Psi(\mathbf{x}_i, z)\|^2} \\ &\leq B \sqrt{\frac{\lambda}{n}} \quad (\text{A.3.3}) \end{aligned}$$

because  $\mathbb{P}(\|\Psi(\mathbf{x}_i, z)\| \leq B) = 1$ . Hence, inserting the results (A.3.2) and (A.3.3) into (A.3.1), yields the claimed result, that is,

$$\begin{aligned} R(\mathcal{G}_{\text{SVDD}}(z)) &\stackrel{\text{Lemma A.1}}{\leq} R(\mathcal{F}_{\text{SVDD}}(z)) \\ &\leq \frac{\lambda}{\sqrt{n}} + B \sqrt{\frac{\lambda}{n}} = \frac{\lambda + B\sqrt{\lambda}}{\sqrt{n}}. \quad (\text{A.3.4}) \end{aligned}$$

□

Next, we invoke the following result, taken from [23] (Lemma 8.1).

**Lemma A.2.** *Let  $\mathcal{F}_1, \dots, \mathcal{F}_l$  be hypothesis sets in  $\mathbb{R}^X$ , and let  $\mathcal{F} := \{\max(f_1, \dots, f_l) : f_i \in \mathcal{F}_i, i \in \{1, \dots, l\}\}$ . Then,*

$$R_n(\mathcal{F}) \leq \sum_{j=1}^l R_n(\mathcal{F}_j).$$

*Sketch of proof [23].* The idea of the proof is to write  $\max(h_1, h_2) = \frac{1}{2}(h_1 + h_2 + |h_1 - h_2|)$ , and then to show that

$$\mathbb{E} \left[ \sup_{h_1 \in \mathcal{F}_1, h_2 \in \mathcal{F}_2} \frac{1}{n} \sum_{i=1}^n |h_1(x_i) - h_2(x_i)| \right] \leq R_n(\mathcal{F}_1) + R_n(\mathcal{F}_2).$$

This proof technique also generalizes to  $l > 2$ . □

We can use Lemma A.2 and Lemma 3, to conclude the main theorem of this paper, that is, Theorem 2, which establishes generalization guarantees of the usual order  $O(1/\sqrt{n})$  for the proposed LATENTSVDD method.

*Proof of Theorem 2.* First observe that, because  $l$  is 1-Lipschitz,

$$R_n(\mathcal{G}_{\text{LATENTSVDD}}) \leq R_n(\mathcal{F}_{\text{LATENTSVDD}}).$$

Next, note that we can write

$$R_n(\mathcal{F}_{\text{LATENTSVDD}}) = \left\{ \max_{z \in \mathcal{Z}} (f_z) : f_z \in \mathcal{F}_{\text{SVDD}}(z) \right\}.$$

Thus, by Lemma 2 and Lemma 4,

$$\begin{aligned} R_n(\mathcal{F}_{\text{LATENTSVDD}}) &\leq |\mathcal{Z}| \max_{z \in \mathcal{Z}} R_n(\mathcal{F}_{\text{SVDD}}(z)) \\ &\leq |\mathcal{Z}| \frac{\lambda + B\sqrt{\lambda}}{\sqrt{n}}. \end{aligned}$$

Moreover, observe that the loss function in the definition of  $\mathcal{G}_{\text{LATENTSVDD}}$  can only range in the interval  $[0, B]$ . Thus, Theorem 2 in the main paper gives the claimed result, that is,

$$\begin{aligned} \mathbb{E}[\widehat{g}_n] - \mathbb{E}[g^*] &\leq 4R_n(\mathcal{G}_{\text{LATENTSVDD}}) + B\sqrt{\frac{2\log(2/\delta)}{n}} \\ &\leq 4|\mathcal{Z}| \frac{\lambda + B\sqrt{\lambda}}{\sqrt{n}} + B\sqrt{\frac{2\log(2/\delta)}{n}}. \end{aligned}$$

□