Algorithmic Foundations of Learning

# Lecture 5 Covering Numbers Bounds for Rademacher Complexity. Chaining

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### Recap: Binary Classification

Only a finite number of elements in *A* matter: those giving different labels

Growth function (Definition 4.2)

$$\tau_{\mathcal{A}}(n) := \sup_{x_1, \dots, x_n \in \mathbb{R}^d} |\mathcal{A} \circ \{x_1, \dots, x_n\}|$$

(Proposition 4.3)

$$\operatorname{Rad}(\mathcal{A} \circ \{x_1, \dots, x_n\}) \le \sqrt{\frac{2\log \tau_{\mathcal{A}}(n)}{n}}$$

#### (Proposition 4.13)

$$\operatorname{Rad}(\mathcal{A} \circ \{x_1, \dots, x_n\}) \leq \sqrt{\frac{2\operatorname{VC}(\mathcal{A})\operatorname{log}(en/\operatorname{VC}(\mathcal{A}))}{n}}$$

**Question:** Can we use same idea in regression, isolating elements that matter? **Yes!** We need covering/packing numbers, metric arguments (no combinatorics) **NB:** This will also help in classification, allowing to remove log(en/VC(A))

## Covering and Packing Numbers

A pseudometric space  $(S, \rho)$  is a set S and a function  $\rho : S \times S \to \mathbb{R}_+$  (called a *pseudometric*) such that, for any  $x, y, z \in S$  we have:

- $\rho(x,y) = \rho(y,x)$  (symmetry)
- $\rho(x,z) \le \rho(x,y) + \rho(y,z)$  (triangle inequality)
- $\blacktriangleright \ \rho(x,x) = 0$

A metric space is obtained if one further assumes that  $\rho(x,y) = 0$  implies x = y

#### Covering and Packing Numbers (Definition 4.14)

Let  $(\mathcal{S}, \rho)$  be a pseudometric space,  $\varepsilon > 0$ 

The set C ⊆ S is a ε-cover of (S, ρ) if for every x ∈ S there exists y ∈ C such that ρ(x, y) ≤ ε. The set C ⊆ S is a minimal ε-cover if there is no other ε-cover with lower cardinality. The cardinality of any minimal ε-cover is the ε-covering number, denoted by Cov(S, ρ, ε)

▶ The set  $\mathcal{P} \subseteq S$  is a  $\varepsilon$ -packing of  $(S, \rho)$  if for every  $x, x' \in \mathcal{P}$  we have  $\rho(x, x') > \varepsilon$ . The set  $\mathcal{P} \subseteq S$  is a maximal  $\varepsilon$ -packing if there is no other  $\varepsilon$ -packing with greater cardinality. The cardinality of any maximal  $\varepsilon$ -packing is the  $\varepsilon$ -packing number, denoted by Pack $(S, \rho, \varepsilon)$ 

## Covering and Packing Numbers. Properties

Duality (Proposition 4.15)

$$\operatorname{Cov}(\mathcal{S},\rho,\varepsilon) \leq \operatorname{Pack}(\mathcal{S},\rho,\varepsilon) \leq \operatorname{Cov}(\mathcal{S},\rho,\varepsilon/2)$$

Covering and packing numbers typically grow exponentially with the dimension

 $\begin{array}{l} \mbox{Bounded Balls (Proposition 4.16)}\\ \mathcal{B}^d_r := \{y \in \mathbb{R}^d : \|y\| \leq r\} \mbox{ be the } d\mbox{-dim. ball with radius } r \geq 0. \mbox{ If } \varepsilon \leq r, \mbox{ then}\\ \hline \left( \frac{r}{\varepsilon} \right)^d \leq {\tt Cov}(\mathcal{B}^d_r, \|\cdot\|, \varepsilon) \leq {\tt Pack}(\mathcal{B}^d_r, \|\cdot\|, \varepsilon) \leq \left( \frac{3r}{\varepsilon} \right)^d \end{array}$ 

**Proof:** Volume argument

Covering and packing numbers grow exponentially also w.r.t. the **VC dimension**. This, along with chaining, will allow us to remove the log-term in Prop. 4.13

### Back to Regression...

 $\blacktriangleright \ \mathcal{A} \subseteq \mathcal{B} := \{ a : \mathcal{X} = \mathbb{R}^d \to \mathbb{R} \}$ 

▶ Given data  $x = \{x_1, ..., x_n\} \in \mathcal{X}^n$ , define data-dependent pseudonorms on  $\mathcal{A}$ :

$$|a||_{p,x} := \left(\frac{1}{n} \sum_{i=1}^{n} |a(x_i)|^p\right)^{1/p} \qquad ||a||_{\infty,x} := \max_i |a(x_i)|$$

The pseudonorms induce the following pseudometrics:

$$\|a-b\|_{p,x} := \left(\frac{1}{n} \sum_{i=1}^{n} |a(x_i) - b(x_i)|^p\right)^{1/p} \quad \|a-b\|_{\infty,x} := \max_i |a(x_i) - b(x_i)|$$

#### (Proposition 5.1)

For any  $x = \{x_1, \ldots, x_n\} \in \mathcal{X}^n$ ,  $1 \le p \le q$ , and  $\varepsilon > 0$ , we have

$$\operatorname{Cov}(\mathcal{A}, \|\cdot\|_{p,x}, \varepsilon) \leq \operatorname{Cov}(\mathcal{A}, \|\cdot\|_{q,x}, \varepsilon)$$

$$\operatorname{Pack}(\mathcal{A}, \|\cdot\|_{p,x}, \varepsilon) \leq \operatorname{Pack}(\mathcal{A}, \|\cdot\|_{q,x}, \varepsilon)$$

Thus, in what follows it is enough to prove results for small values of p

### Bound on Rademacher Complexity via Covering Numbers

#### (Proposition 5.2)

For any 
$$x=\{x_1,\ldots,x_n\}\in \mathcal{X}^n$$
, let  $\sup_{a\in\mathcal{A}}\|a\|_{2,x}\leq c_x.$  Then,

$$\mathtt{Rad}(\mathcal{A} \circ x) \leq \inf_{\varepsilon > 0} \Big\{ \varepsilon + \frac{\sqrt{2}\,c_x}{\sqrt{n}} \sqrt{\log \mathtt{Cov}(\mathcal{A}, \|\,\cdot\,\|_{1,x},\varepsilon)} \Big\}$$

#### Proof:

Fix  $x \in \mathcal{X}^n$ ,  $\varepsilon > 0$ . Let  $\mathcal{C} \subseteq \mathcal{A}$  be a minimal  $\varepsilon$ -cover of  $(\mathcal{A}, \|\cdot\|_{1,x})$ For any  $a \in \mathcal{A}$  let  $\tilde{a} \in \mathcal{C}$  be such that  $\|a - \tilde{a}\|_{1,x} \leq \varepsilon$ 

$$\begin{split} \operatorname{Rad}(\mathcal{A} \circ x) &\leq \operatorname{\mathbf{E}} \sup_{a \in \mathcal{A}} \frac{1}{n} \sum_{i=1}^{n} \Omega_{i}(a(x_{i}) - \tilde{a}(x_{i})) + \operatorname{\mathbf{E}} \sup_{a \in \mathcal{A}} \frac{1}{n} \sum_{i=1}^{n} \Omega_{i} \tilde{a}(x_{i}) \\ &\leq \varepsilon + \operatorname{\mathbf{E}} \max_{a \in \mathcal{C}} \frac{1}{n} \sum_{i=1}^{n} \Omega_{i} a(x_{i}) \\ &\leq \varepsilon + \max_{a \in \mathcal{C}} \sqrt{\sum_{i=1}^{n} a(x_{i})^{2} \frac{\sqrt{2 \log |\mathcal{C}|}}{n}} \qquad \text{by Massart's lemma} \\ &\leq \varepsilon + c_{x} \sqrt{\frac{2 \log \operatorname{Cov}(\mathcal{A}, \| \cdot \|_{1,x}, \varepsilon)}{n}} \qquad \text{as } |\mathcal{C}| = \operatorname{Cov}(\mathcal{A}, \| \cdot \| \end{split}$$

 $\cdot \parallel_{1,x}, \varepsilon$ 

## Improved Result using Chaining

#### (Proposition 5.3)

For any 
$$x=\{x_1,\ldots,x_n\}\in \mathcal{X}^n$$
 and  $\sup_{a\in\mathcal{A}}\|a\|_{2,x}\leq c_x$  we have

$$\operatorname{Rad}(\mathcal{A} \circ x) \leq \inf_{\varepsilon \in [0, c_x/2]} \left\{ 4\varepsilon + \frac{12}{\sqrt{n}} \int_{\varepsilon}^{c_x/2} \mathrm{d}\nu \sqrt{\log \operatorname{Cov}(\mathcal{A}, \| \cdot \|_{2, x}, \nu)} \right\}$$

#### Proof (main ideas):

Fix  $x \in \mathcal{X}^n$ . Define family of covers: let  $\varepsilon_j = \frac{c_x}{2^j}$  and  $\mathcal{C}_j \subseteq \mathcal{A}$  be a minimal  $\varepsilon_j$ -cover of  $(\mathcal{A}, \|\cdot\|_{2,x})$ For any  $a \in \mathcal{A}, j \ge 1$  let  $a_j \in \mathcal{C}_j$  s.t.  $\|a - a_j\|_{2,x} \le \varepsilon_j$ . Use  $a = a - a_m + \sum_{j=1}^m (a_j - a_{j-1})$  (chain)

$$\operatorname{Rad}(\mathcal{A} \circ x) \leq \operatorname{\mathbf{E}} \sup_{a \in \mathcal{A}} \frac{1}{n} \sum_{i=1}^{n} \Omega_{i}(a(x_{i}) - a_{m}(x_{i})) + \operatorname{\mathbf{E}} \sup_{a \in \mathcal{A}} \frac{1}{n} \sum_{i=1}^{n} \Omega_{i} \sum_{j=1}^{m} (a_{j}(x_{i}) - a_{j-1}(x_{i}))$$

First term:

$$\sum_{i=1}^{n} \Omega_i(a(x_i) - a_m(x_i)) \le \sum_{i=1}^{n} |a(x_i) - a_m(x_i)| = n ||a - a_m||_{1,x} \le n ||a - a_m||_{2,x} \le n\varepsilon_m$$

Second term:  $\mathbf{E} \sup_{a \in \mathcal{A}} \frac{1}{n} \sum_{i=1}^{n} \Omega_i(a_j(x_i) - a_{j-1}(x_i)) \le \sup_{a \in \mathcal{A}} \|a_j - a_{j-1}\|_{2,x} \frac{\sqrt{2\log |\mathcal{C}_j||\mathcal{C}_{j-1}|}}{\sqrt{n}}$ 

$$\text{We get} \qquad \quad \text{Rad}(\mathcal{A} \circ x) \leq \varepsilon_m + \frac{12}{\sqrt{n}} \sum_{j=1}^m (\varepsilon_j - \varepsilon_{j+1}) \sqrt{\log \operatorname{Cov}(\mathcal{A}, \| \cdot \|_{2,x}, \varepsilon_j)} \leq \text{integral}$$

### Back to Classification...

$$(Proposition 5.5) \qquad (Theorem 5.6)$$

$$Pack(\mathcal{A}, \|\cdot\|_{p,x}, \varepsilon) \le \left(\frac{10}{\varepsilon^p} \log \frac{2e}{\varepsilon^p}\right)^{VC(\mathcal{A})} \implies Rad(\mathcal{A} \circ x) \lesssim \sqrt{\frac{VC(\mathcal{A})}{n}}$$

**Proof of Proposition 5.5 (main ideas):** W.I.o.g. p = 1. Fix  $x \in \mathcal{X}^n$  and  $\varepsilon > 0$ . Let  $\mathcal{P} \subseteq \mathcal{A}$  be a maximal  $\varepsilon$ -packing. For any  $a, b \in \mathcal{P}$ 

$$\varepsilon < \|a - b\|_{1,x} = \frac{1}{n} \sum_{i=1}^{n} |a(x_i) - b(x_i)| = \frac{1}{n} \sum_{i=1}^{n} \mathbbm{1}_{a(x_i) \neq b(x_i)} = \mathbf{P}(a(Z) \neq b(Z))$$

Let  $Z_1, \ldots, Z_m$  be m i.i.d. random variables distributed as Z (uniform in  $\{x_1, \ldots, x_n\}$ ):  $\mathbf{P}(|\mathcal{P} \circ \{Z_1, \ldots, Z_m\}| = |\mathcal{P}|)$ 

 $= \mathbf{P}(\text{For every } a, b \in \mathcal{P}, a \neq b, \text{ we have } a \circ \{Z_1, \dots, Z_m\} \neq b \circ \{Z_1, \dots, Z_m\})$ 

 $= 1 - \mathbf{P}(\text{There exists } a, b \in \mathcal{P}, a \neq b, \text{ such that } a \circ \{Z_1, \dots, Z_m\} = b \circ \{Z_1, \dots, Z_m\})$ 

 $> 1 - |\mathcal{P}|^2 (1 - \varepsilon)^m > 1 - |\mathcal{P}|^2 e^{-m\varepsilon}$  by union bound, independence, and packing property

Bound > 0 for  $m = \frac{2}{\epsilon} \log |\mathcal{P}| \Rightarrow$  there exists  $z_1, \ldots, z_m$  (probabilistic method)

$$|\mathcal{P}| = |\mathcal{P} \circ z| \le |\mathcal{A} \circ z| \le au_{\mathcal{A}}(m) = au_{\mathcal{A}}\left(rac{2}{arepsilon} \log |\mathcal{P}|
ight)$$

Proof follows by using Sauer-Shelah's lemma and computing an upper bound for the recursion