

# Introduction to Machine Learning

Machine Learning: Jordan Boyd-Graber University of Maryland RADEMACHER COMPLEXITY

## **Content Questions**

**Administrivia Questions** 



What is the Rademacher complexity of a hypothesis set reduced to a single hypothesis?

(1)

$$\mathscr{R}_{m}(H) = \mathbb{E}_{S \sim D^{m}, \sigma} \left[ \sup_{h \in H} \frac{1}{m} \sum_{i=1}^{m} \sigma_{i} h(z_{i}) \right]$$
(1)
(2)

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(2)(3)

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$$= \mathbb{E}_{S \sim D^{m}} \left[ \frac{1}{m} \sum_{i=1}^{m} 0 \cdot \sigma_{i} h_{0}(z_{i}) \right]$$
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What is the Rademacher complexity of a hypothesis set reduced to a single hypothesis?

$$\mathcal{R}_{m}(H) = \mathbb{E}_{S \sim D^{m}, \sigma} \left[ \sup_{h \in H} \frac{1}{m} \sum_{i=1}^{m} \sigma_{i} h(z_{i}) \right]$$
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(3)  
$$= \mathbb{E}_{S \sim D^{m}} \left[ \frac{1}{m} \sum_{i=1}^{m} 0 \cdot \sigma_{i} h_{0}(z_{i}) \right] = 0$$
(4)

(5)

# Prove

$$\mathscr{R}_m(\alpha H) = |\alpha|\mathscr{R}_m(H)$$

If  $\alpha \ge 0$ 

If  $\alpha$  < 0

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(6)  
$$\sup_{h \in H} \sum_{i=1}^{m} \alpha \sigma_{i} h(x_{i}) =$$
(7) If  $\alpha < 0$   
$$\alpha \sup_{h \in H} \sum_{i=1}^{m} \sigma_{i} h(x_{i})$$
(8)

m

m

# Prove

$$\mathscr{R}_m(\alpha H) = |\alpha|\mathscr{R}_m(H)$$

If  $\alpha \ge 0$ 

If  $\alpha$  < 0

$$\sup_{h\in\alpha H}\sum_{i=1}^{m}\sigma_{i}h(x_{i})=$$
 (6)

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 (8)

$$\sup_{h \in \alpha H} \sum_{i=1}^{m} \sigma_i h(x_i) =$$
(9)

$$\sup_{h\in H}\sum_{i=1}^{m}\alpha\sigma_{i}h(x_{i}) =$$
(10)

$$(-\alpha) \sup_{h \in H} \sum_{i=1}^{m} (-\sigma_i) h(x_i) \qquad (11)$$

# Prove

$$\mathscr{R}_m(\alpha H) = |\alpha|\mathscr{R}_m(H)$$

If  $\alpha \ge 0$ 

If  $\alpha < 0$ 

$$\sup_{h \in \alpha H} \sum_{i=1}^{m} \sigma_{i} h(x_{i}) = (6) \qquad \sup_{h \in \alpha H} \sum_{i=1}^{m} \sigma_{i} h(x_{i}) = (9)$$

$$\sup_{h \in H} \sum_{i=1}^{m} \alpha \sigma_{i} h(x_{i}) = (7) \qquad \sup_{h \in H} \sum_{i=1}^{m} \alpha \sigma_{i} h(x_{i}) = (10)$$

$$\alpha \sup_{h \in H} \sum_{i=1}^{m} \sigma_{i} h(x_{i}) \qquad (8) \qquad (-\alpha) \sup_{h \in H} \sum_{i=1}^{m} (-\sigma_{i}) h(x_{i}) \qquad (11)$$
Since  $\sigma_{i}$  and  $-\sigma$  have the same distribution,  $\mathscr{R}_{m}(\alpha H) = |\alpha| \mathscr{R}_{m}(H)$ 

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$$= \frac{1}{m} \mathbb{E}_{\vec{\sigma},S} \left[ \sup_{h \in \mathcal{H}, h' \in \mathcal{H}'} \sum_{i=1}^{m} \sigma_i(h(x_i) + h'(x_i)) \right]$$
(13)

(14)

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(13)

 $= \frac{1}{m} \mathbb{E}_{\vec{\sigma},S} \left[ \sup_{h \in H, h' \in H'} \sum_{i=1}^{m} \sigma_i h(x_i) + \sup_{h \in H, h' \in H'} \sum_{i=1}^{m} \sigma_i h'(x_i) \right]$ (14)

(15)

# Prove

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(14)
$$= \frac{1}{m} \mathbb{E}_{\vec{\sigma},S} \left[ \sup_{h \in H} \sum_{i=1}^{m} \sigma_i h(x_i) \right] + \frac{1}{m} \mathbb{E}_{\vec{\sigma},S} \left[ \sup_{h' \in H'} \sum_{i=1}^{m} \sigma_i h(x_i) \right]$$
(15)

### **VC Dimension**

To show VC dimension of a set of points

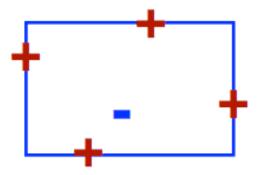
- Show that **a** set of *d* can be shattered
- Show that **no** set of d + 1 can be shattered

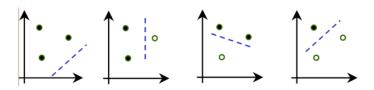
**Axis Aligned Rectangles** 

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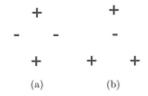


Figure 3.2 Unrealizable dichotomies for four points using hyperplanes in  $\mathbb{R}^2$ . (a) All four points lie on the convex hull. (b) Three points lie on the convex hull while the remaining point is interior.



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In general, the VC dimension of *d*-dimensional hyperplanes is d + 1

Show that the VC dimension of a finite hypothesis set H is at most  $\lg |H|$ .

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- If a set has d points, there are 2<sup>d</sup> ways to do that
- Each configuration requires a different hypothesis
- Solving for the number of hypotheses gives lg |H|

### Next time

- Getting more practical
- SVMs
- Excellent theoretical properties