

Machine Learning Theory 2026

Lecture 5

Tim van Erven

Focus on binary classification:

- ▶ Review
- ▶ Remaining proof:
growth function controls uniform convergence

Uniform Convergence Upper Bound with VC-Dimension

Theorem

Consider binary classification. Suppose $\text{VCdim}(\mathcal{H}) \leq v < \infty$. Then there exists an absolute constant $C > 0$ such that

$$\sup_{h \in \mathcal{H}} |L_{\mathcal{D}}(h) - L_S(h)| \leq \epsilon \quad \text{with probability} \geq 1 - \delta,$$

whenever

$$m \geq C \frac{v \ln(1/\epsilon) + \ln(1/\delta) + 1}{\epsilon^2}.$$

Proof Approach

Growth function: $\tau_{\mathcal{H}}(m) = \max_{|\mathcal{C}|=m} |\mathcal{H}_{\mathcal{C}}|$

- ▶ Interpretation: How many truly different hypotheses are there when we only observe m inputs $\mathcal{C} = \{\mathbf{x}_1, \dots, \mathbf{x}_m\}$?

Proof Approach

Growth function: $\tau_{\mathcal{H}}(m) = \max_{|\mathcal{C}|=m} |\mathcal{H}_{\mathcal{C}}|$

- Interpretation: How many truly different hypotheses are there when we only observe m inputs $\mathcal{C} = \{x_1, \dots, x_m\}$?

Part I: Growth function controls uniform convergence:

$$\sup_{h \in \mathcal{H}} |L_{\mathcal{D}}(h) - L_S(h)| \leq c \sqrt{\frac{\ln \tau_{\mathcal{H}}(m)}{m}} + c \sqrt{\frac{\ln(4/\delta)}{m}} \quad \text{with probability } \geq 1 - \delta$$

Part II: VC-dimension controls growth function (Sauer's Lemma):

$$\ln \tau_{\mathcal{H}}(m) \leq v \ln \left(\frac{em}{v} \right) \quad \text{for } m > v.$$

- Finish: combine Parts I and II, and find lower bound on m s.t.
 $\sup_{h \in \mathcal{H}} |L_{\mathcal{D}}(h) - L_S(h)| \leq \epsilon.$

**Proof Part I:
Growth Function Controls Uniform
Convergence**

Part I: Proof Outline

Lemma (Two-sided Bound)

Consider binary classification. Then there exists an absolute constant $c > 0$ such that, for any $\delta \in (0, 1]$,

$$\sup_{h \in \mathcal{H}} |L_{\mathcal{D}}(h) - L_S(h)| \leq c \sqrt{\frac{\ln \tau_{\mathcal{H}}(m)}{m}} + c \sqrt{\frac{\ln(4/\delta)}{m}} \quad w.p. \geq 1 - \delta.$$

Part I: Proof Outline

Lemma (Two-sided Bound)

Consider binary classification. Then there exists an absolute constant $c > 0$ such that, for any $\delta \in (0, 1]$,

$$\sup_{h \in \mathcal{H}} |L_{\mathcal{D}}(h) - L_S(h)| \leq c \sqrt{\frac{\ln \tau_{\mathcal{H}}(m)}{m}} + c \sqrt{\frac{\ln(4/\delta)}{m}} \quad w.p. \geq 1 - \delta.$$

Note: could measure loss in binary classification differently.
Sufficient to show:

Lemma (One-sided Bound)

For any loss function $\ell(h, \mathbf{X}, Y) = \tilde{\ell}(h(\mathbf{X}), Y)$ with range $[0, 1]$:

$$\sup_{h \in \mathcal{H}} \{L_{\mathcal{D}}(h) - L_S(h)\} \leq c \sqrt{\frac{\ln \tau_{\mathcal{H}}(m)}{m}} + c \sqrt{\frac{\ln(2/\delta)}{m}} \quad w.p. \geq 1 - \delta.$$

One-sided Bound \Rightarrow Two-sided Bound

$$\text{Let } z = \sup_{h \in \mathcal{H}} \{L_D(h) - L_S(h)\}, \quad z' = \sup_{h \in \mathcal{H}} \{L_S(h) - L_D(h)\}$$

Applying one-sided bound with $\ell' = 1 - \ell$
controls z' , because

$$\begin{aligned} L'_D(h) - L'_S(h) &= \mathbb{E}[1 - \ell(h, x, y)] \\ &\quad - \frac{1}{n} \sum_{i=1}^n (1 - \ell(h, x_i, y_i)) \\ &= \frac{1}{n} \sum_{i=1}^n \ell(h, x_i, y_i) - \mathbb{E}[\ell(h, x, y)] \\ &= L_S(h) - L_D(h) \end{aligned}$$

Then

$$\begin{aligned} \sup_{h \in H} |L_D(h) - L_S(h)| &= \max\{z, z'\} \\ &\leq C \sqrt{\frac{\ln \mathcal{E}_H(m)}{m}} + C \sqrt{\frac{\ln(4/\delta')}{m}} \quad \text{w.p.} \geq 1 - \delta \end{aligned}$$

by one-sided bounds for z and z' with $\delta' = \frac{\delta}{2}$
+ union bound.

Approach for One-Sided Bound

Lemma (One-sided Bound)

For any loss function $\ell(h, \mathbf{X}, Y) = \tilde{\ell}(h(\mathbf{X}), Y)$ with range $[0, 1]$:

$$\sup_{h \in \mathcal{H}} \{L_{\mathcal{D}}(h) - L_S(h)\} \leq c \sqrt{\frac{\ln \tau_{\mathcal{H}}(m)}{m}} + c \sqrt{\frac{\ln(2/\delta)}{m}} \quad w.p. \geq 1 - \delta.$$

Remark:

- ▶ Book first derives suboptimal dependence on δ in Chapter 6
- ▶ I am taking a shortcut through Chapters 6, 26 and 28

Approach for One-Sided Bound

Lemma (One-sided Bound)

For any loss function $\ell(h, \mathbf{X}, Y) = \tilde{\ell}(h(\mathbf{X}), Y)$ with range $[0, 1]$:

$$\sup_{h \in \mathcal{H}} \{L_{\mathcal{D}}(h) - L_S(h)\} \leq c \sqrt{\frac{\ln \tau_{\mathcal{H}}(m)}{m}} + c \sqrt{\frac{\ln(2/\delta)}{m}} \quad \text{w.p.} \geq 1 - \delta.$$

Proof consists of 3 steps:

1. **Concentration:** Abbreviate $Z = \sup_{h \in \mathcal{H}} \{L_{\mathcal{D}}(h) - L_S(h)\}$. Then, for any loss function $\ell(h, \mathbf{X}, Y)$ with range $[0, 1]$,

$$Z \leq \mathbb{E}[Z] + c \sqrt{\frac{\ln(2/\delta)}{m}} \quad \text{w.p.} \geq 1 - \delta.$$

Approach for One-Sided Bound

Lemma (One-sided Bound)

For any loss function $\ell(h, \mathbf{X}, Y) = \tilde{\ell}(h(\mathbf{X}), Y)$ with range $[0, 1]$:

$$\sup_{h \in \mathcal{H}} \{L_{\mathcal{D}}(h) - L_S(h)\} \leq c \sqrt{\frac{\ln \tau_{\mathcal{H}}(m)}{m}} + c \sqrt{\frac{\ln(2/\delta)}{m}} \quad \text{w.p.} \geq 1 - \delta.$$

Proof consists of 3 steps:

1. **Concentration:** Abbreviate $Z = \sup_{h \in \mathcal{H}} \{L_{\mathcal{D}}(h) - L_S(h)\}$. Then, for any loss function $\ell(h, \mathbf{X}, Y)$ with range $[0, 1]$,

$$Z \leq \mathbb{E}[Z] + c \sqrt{\frac{\ln(2/\delta)}{m}} \quad \text{w.p.} \geq 1 - \delta.$$

2. **Symmetrization:** For any loss function:

$$\mathbb{E}[Z] \leq 2 \mathbb{E}[\mathcal{R}(\ell, \mathcal{H}, S)].$$

Approach for One-Sided Bound

Lemma (One-sided Bound)

For any loss function $\ell(h, \mathbf{X}, Y) = \tilde{\ell}(h(\mathbf{X}), Y)$ with range $[0, 1]$:

$$\sup_{h \in \mathcal{H}} \{L_{\mathcal{D}}(h) - L_S(h)\} \leq c \sqrt{\frac{\ln \tau_{\mathcal{H}}(m)}{m}} + c \sqrt{\frac{\ln(2/\delta)}{m}} \quad \text{w.p.} \geq 1 - \delta.$$

Proof consists of 3 steps:

1. **Concentration:** Abbreviate $Z = \sup_{h \in \mathcal{H}} \{L_{\mathcal{D}}(h) - L_S(h)\}$. Then, for any loss function $\ell(h, \mathbf{X}, Y)$ with range $[0, 1]$,

$$Z \leq \mathbb{E}[Z] + c \sqrt{\frac{\ln(2/\delta)}{m}} \quad \text{w.p.} \geq 1 - \delta.$$

2. **Symmetrization:** For any loss function:

$$\mathbb{E}[Z] \leq 2 \mathbb{E}[\mathcal{R}(\ell, \mathcal{H}, S)].$$

3. For any loss $\ell(h, \mathbf{X}, Y) = \tilde{\ell}(h(\mathbf{X}), Y)$ with range $[0, 1]$:

$$\mathcal{R}(\ell, \mathcal{H}, S) \leq \sqrt{\frac{2 \ln |\mathcal{H}_S|}{m}} \leq \sqrt{\frac{2 \ln \tau_{\mathcal{H}}(m)}{m}} \quad \text{for all } S.$$

Step 1: Concentration

To show: loss $\ell(h, x, y) \in [0, 2]$

$$Z = \sup_{h \in \mathcal{H}} L_D(h) - L_S(h)$$

$$Z \leq \mathbb{E}[Z] + C \sqrt{\frac{\ln(2/\delta)}{m}} \quad \text{w.p.} \geq 1 - \delta$$

Proof:

some complicated function
 $Z = f(A_1, \dots, A_m)$ for $A_i = (x_i, y_i)$

Bounded differences property:

* If change $A_i \rightarrow A'_i$, then

Z changes by at most $\frac{1}{m}$

(because $L_S(h) = \frac{1}{m} \sum_{i=1}^m \ell(h, x_i, y_i)$)

changes by at most $\frac{1}{m}$)

McDiarmid's Inequality

Suppose A_1, \dots, A_m are independent random variables, and $f: A^m \rightarrow \mathbb{R}$ satisfies for all i

$$\sup_{\substack{a_1, \dots, a_m \\ a_i}} |f(a_1, \dots, a_m) - f(a_1, \dots, a_{i-1}, a_i', a_{i+1}, \dots, a_m)| \leq b.$$

Then, with probability $\geq 1 - \delta$,

$$|f(A_1, \dots, A_m) - \mathbb{E}[f(A_1, \dots, A_m)]| \leq b \sqrt{\frac{m}{2} \ln\left(\frac{2}{\delta}\right)}$$

z satisfies this with $b = z/m$:

$$\begin{aligned} |z - \mathbb{E}[z]| &\leq \sqrt{\frac{\ln(2/\delta)}{2m}} \quad \text{w.p. } \geq 1 - \delta \\ &\leq c \sqrt{\frac{\ln(2/\delta)}{m}} \quad \text{for } c \geq \frac{1}{\sqrt{2}} \end{aligned}$$

□

Rademacher Complexity

How much can the losses of $h \in \mathcal{H}$ on S
correlate with random errors?

Rademacher random variables: Let $\sigma = (\sigma_1, \dots, \sigma_m) \in \{-1, +1\}^m$ be i.i.d. with $\Pr(\sigma_i = -1) = \Pr(\sigma_i = +1) = 1/2$.

Rademacher complexity:

$$\mathcal{R}(\ell, \mathcal{H}, S) = \frac{1}{m} \mathbb{E}_{\sigma} \left[\sup_{h \in \mathcal{H}} \sum_{i=1}^m \sigma_i \ell(h, \mathbf{X}_i, Y_i) \right]$$

- Interpret $\sum_{i=1}^m \sigma_i \ell(h, \mathbf{X}_i, Y_i)$ as correlation of losses with random errors

Step 2: Symmetrization

$$\mathcal{R}(\ell, \mathcal{H}, S) = \frac{1}{m} \mathbb{E}_{\sigma} \left[\sup_{h \in \mathcal{H}} \sum_{i=1}^m \sigma_i \ell(h, \mathbf{X}_i, Y_i) \right]$$

Lemma

$$\mathbb{E} \left[\sup_{h \in \mathcal{H}} \{L_{\mathcal{D}}(h) - L_S(h)\} \right] \leq 2 \mathbb{E} \left[\mathcal{R}(\ell, \mathcal{H}, S) \right]$$

Step 2: Symmetrization

$$\mathcal{R}(\ell, \mathcal{H}, S) = \frac{1}{m} \mathbb{E}_{\sigma} \left[\sup_{h \in \mathcal{H}} \sum_{i=1}^m \sigma_i \ell(h, \mathbf{X}_i, Y_i) \right]$$

Lemma

$$\mathbb{E}_S \left[\sup_{h \in \mathcal{H}} \{L_{\mathcal{D}}(h) - L_S(h)\} \right] \leq 2 \mathbb{E}_S [\mathcal{R}(\ell, \mathcal{H}, S)]$$

Amazing because:

- ▶ $\sup_{h \in \mathcal{H}} \{L_{\mathcal{D}}(h) - L_S(h)\}$ may be large for very unlikely S
- ▶ But Rademacher complexity $\mathcal{R}(\ell, \mathcal{H}, S)$ is small for all S !

Consequence:

- ▶ Can measure complexity of \mathcal{H} conditional on S
- ▶ So only restriction of \mathcal{H} to inputs $\mathbf{X}_1, \dots, \mathbf{X}_m$ in S matters!

Step 2: "Symmetrization"

To show: $R(\ell, \mathcal{H}, S) = \frac{1}{n} \mathbb{E} \left[\sup_{h \in \mathcal{H}} \sum_{i=1}^n \sigma_i \ell(h, x_i, y_i) \right]$

$$\mathbb{E} \left[\sup_{h \in \mathcal{H}} L_D(h) - L_S(h) \right] \leq 2 \mathbb{E} [R(\ell, \mathcal{H}, S)]$$

Proof: Let $S' = \left(\begin{smallmatrix} y_1' \\ x_1' \end{smallmatrix} \right), \dots, \left(\begin{smallmatrix} y_n' \\ x_n' \end{smallmatrix} \right)$ be independent sample.

$$\mathbb{E} \left[\sup_{h \in \mathcal{H}} L_D(h) - L_S(h) \right] = \mathbb{E} \left[\sup_{h \in \mathcal{H}} \mathbb{E} [L_{S'}(h)] - L_S(h) \right]$$

$$= \mathbb{E} \left[\sup_{h \in \mathcal{H}} \mathbb{E} [L_{S'}(h) - L_S(h)] \right] \leq \mathbb{E} \left[\sup_{S, S'} \sup_{h \in \mathcal{H}} L_{S'}(h) - L_S(h) \right]$$

$$= \frac{1}{n} \mathbb{E} \left[\sup_{S, S'} \sum_{i=1}^n \{ \ell(h, x_i', y_i') - \ell(h, x_i, y_i) \} \right]$$

Homogenize the two samples

N.B. If we swap any $\begin{pmatrix} y_i \\ x_i \end{pmatrix}$ and $\begin{pmatrix} y'_i \\ x'_i \end{pmatrix}$ between S and S' , then their distribution does not change.

Hence, for any $\sigma_i \in \{-1, +1\}$

$$\begin{aligned} & \frac{1}{n} \mathbb{E} \left[\sup_{S, S'} \sum_{i=1}^m \{ \ell(h, x_i, y_i) - \ell(h, x_i, y'_i) \} \right] \\ &= \frac{1}{n} \mathbb{E} \left[\sup_{S, S'} \sum_{i=1}^m \sigma_i \{ \ell(h, x_i, y'_i) - \ell(h, x_i, y_i) \} \right] \\ &= \frac{1}{n} \mathbb{E} \left[\sup_{S, S, S'} \sum_{i=1}^m \sigma_i \{ \ell(h, x'_i, y_i) - \ell(h, x_i, y_i) \} \right] \\ &\leq \frac{1}{n} \mathbb{E} \left[\sup_{S, S, S'} \sum_{i=1}^m \sigma_i \ell(h, x'_i, y_i) + \sup_{h \in \mathcal{H}} \sum_{i=1}^m -\sigma_i \ell(h, x_i, y_i) \right] \\ & \quad \text{(using that } -\sigma \text{ has same distribution as } \sigma) \\ &= \frac{2}{n} \mathbb{E} \left[\sup_{h \in \mathcal{H}} \sum_{i=1}^m \sigma_i \ell(h, x_i, y_i) \right] = 2 \mathbb{E} [R(\ell, \mathcal{H}, S)] \quad \square \end{aligned}$$

Step 3: Bound the Rademacher Complexity

Lemma

For any loss function $\ell(h, \mathbf{X}, Y) = \tilde{\ell}(h(\mathbf{X}), Y)$ with range $[0, 1]$ and any sample S :

$$\mathcal{R}(\ell, \mathcal{H}, S) \leq \sqrt{\frac{2 \ln |\mathcal{H}_S|}{m}} \leq \sqrt{\frac{2 \ln \tau_{\mathcal{H}}(m)}{m}}.$$

Step 3

To show: $\ell(h, x, y) = \tilde{\ell}(h(x), y) \in [0, 1]$

For any S : $\mathcal{R}(\ell, \mathcal{H}, S) \leq \sqrt{\frac{2 \ln |\mathcal{H}_S|}{m}}$

Proof: $m\mathcal{R}(\ell, \mathcal{H}, S) = \mathbb{E} \left[\sup_{h \in \mathcal{H}} \sum_{i=1}^m \sigma_i \tilde{\ell}(h(x_i), y_i) \right]$
 $= \mathbb{E} \left[\max_{h \in \mathcal{H}_S} \sum_{i=1}^m \sigma_i \hat{\ell}(h(x_i), y_i) \right]$

Let $Z_i(h) = \sigma_i \hat{\ell}(h(x_i), y_i) \in [-1, +1]$. Then $\mathbb{E}[Z_i(h)] = 0$

Hoeffding's Lemma (B.7 in Shai²):

Suppose Z takes values in $[a, b]$ and $\mathbb{E}[Z] = 0$. Then

$$\mathbb{E}[e^{\lambda Z}] \leq e^{\lambda^2(b-a)^2/8} \quad \text{for any } \lambda > 0.$$

$$m \cdot R(\ell, H, S) = \mathbb{E} \left[\max_{h \in H_S} \sum_{i=1}^m z_i(h) \right]$$

$$= \frac{1}{\lambda} \mathbb{E} \left[\ln \max_{h \in H_S} e^{\sum_{i=1}^m \lambda z_i(h)} \right] \quad \text{for any } \lambda > 0$$

$$\leq \frac{1}{\lambda} \mathbb{E} \left[\ln \sum_{h \in H_S} e^{\sum_{i=1}^m \lambda z_i(h)} \right]$$

(Jensen's inequality)

$$\leq \frac{1}{\lambda} \ln \left(\mathbb{E} \left[\sum_{h \in H_S} e^{\sum_{i=1}^m \lambda z_i(h)} \right] \right)$$

$$= \frac{1}{\lambda} \ln \left(\sum_{h \in H_S} \prod_{i=1}^m \mathbb{E} \left[e^{\lambda z_i(h)} \right] \right)$$

(Hoeffding's Lemma)

$$\leq \frac{1}{\lambda} \ln \left(\sum_{h \in H_S} \prod_{i=1}^m e^{\lambda^2/2} \right) = \frac{1}{\lambda} \ln |H_S| + \lambda \frac{m}{2}$$

$$\text{Take } \lambda = \sqrt{\frac{\ln |H_S|}{m/2}} : \quad = \sqrt{2m \ln |H_S|}$$

$$R(\ell, H, S) \leq \sqrt{\frac{2 \ln |H_S|}{m}}$$

□

Back to the Big Picture

Part I: Growth function controls uniform convergence:

$$\sup_{h \in \mathcal{H}} |L_{\mathcal{D}}(h) - L_S(h)| \leq c \sqrt{\frac{\ln \tau_{\mathcal{H}}(m)}{m}} + c \sqrt{\frac{\ln(4/\delta)}{m}} \quad \text{with probability } \geq 1 - \delta$$

Part II: VC-dimension controls growth function (Sauer's Lemma):

$$\ln \tau_{\mathcal{H}}(m) \leq v \ln \left(\frac{em}{v} \right) \quad \text{for } m > v.$$

Back to the Big Picture

Part I: Growth function controls uniform convergence:

$$\sup_{h \in \mathcal{H}} |L_{\mathcal{D}}(h) - L_S(h)| \leq c \sqrt{\frac{\ln \tau_{\mathcal{H}}(m)}{m}} + c \sqrt{\frac{\ln(4/\delta)}{m}} \quad \text{with probability } \geq 1 - \delta$$

Part II: VC-dimension controls growth function (Sauer's Lemma):

$$\ln \tau_{\mathcal{H}}(m) \leq v \ln \left(\frac{em}{v} \right) \quad \text{for } m > v.$$

For $m > v$:

$$\sup_{h \in \mathcal{H}} |L_{\mathcal{D}}(h) - L_S(h)| \leq c \sqrt{\frac{v \ln \left(\frac{em}{v} \right)}{m}} + c \sqrt{\frac{\ln(4/\delta)}{m}} \quad \text{with probability } \geq 1 - \delta$$

- ▶ Remaining: find lower bound on m s.t. bound is at most ϵ .