

Lecture 15

Uniform convergence

overfitting

PAC learnability of finite classes.

No free lunch theorem

+ some proof witness

Last lecture :

Recall:

+ Uniform convergence. (UC)

Class C has the uniform convergence property if $\forall \epsilon, \delta \in (0,1)$, dist D

$\exists m$ (as a function of $\epsilon, \delta, \mathcal{H}$, but not D since we don't know D). s.t. for a training set of size m :

$$\Pr_{T \sim D^m} \left[\forall c \in C : |\hat{\text{err}}_T(c) - \text{err}(c)| \leq \epsilon \right] \geq 1 - \delta$$

Uniform convergence implies agnostic PAC learnability via EMR.

+ ERM could go very wrong if we overfit.

$$\hat{R}(x) = \begin{cases} y_i & x_i \in T \\ 0 & x_i \notin T \end{cases}$$

training set



0 empirical error } error 1 on any dist
with a continuous domain

ERM has really bad error! ↴

*

ERM works for a finite class C if we have enough samples.

- Problem setup:

samples $(x_1, y_1), \dots, (x_m, y_m) \sim D$

$$c \in C : \text{err}(c) := \Pr_{(x, y) \sim D} [c(x) \neq y]$$

Realizable case

Assume $\exists c^* \in C$ s.t. $\text{err}(c^*) = 0$

- Goal

find $\hat{c} \in C$ s.t. with probability

$$1 - \delta, \quad \text{err}(\hat{c}) \leq \varepsilon.$$

- Proof

Bad hypotheses $C_B := \{c \in C \mid \text{err}(c) > \varepsilon\}$

$$\hat{\text{err}}_T(c) := \frac{|\{(x, y) \in T \mid c(x) \neq y\}|}{|T|}$$

↑
training set

Misleading training samples

$$M := \{T \mid \exists c \in C_B \text{ s.t. } \hat{\text{err}}_T(c) = 0\}$$

Upon observing T , we may pick c that is a bad choice, but it "looked" good from ERM perspective, since

$$\hat{\text{err}}_T(c) = 0.$$

Our goal is to show observing a dataset $T \in M$ happens only with probability 0.

This is sufficient to prove \star .

fix $c \in C_B$

what is the probability of

$$\hat{\text{err}}_T(c) = 0$$

$$\Pr_{T \sim D^n} [\hat{\text{err}}_T(c) = 0]$$

$$= \Pr_{T \sim D^n} [\forall (x, y) \in T . c(x) = y]$$

iid samples $\rightarrow = \left(\Pr_{(x, y) \sim D} [c(x) = y] \right)^m$

$\text{err}(c) > \epsilon \rightarrow < (1 - \epsilon)^m \leq e^{-\epsilon m}$

Now, we are ready to bound

$$\Pr_{T \sim D^m} [T \in M]$$

$$= \Pr_{T \sim D^m} [\exists c \in C_B \text{ st. } \hat{\text{err}}_T(c) > 0]$$

$$= \sum_{c \in C_B} \Pr_{T \sim D^m} [\hat{\text{err}}_T(c) = 0]$$

$$\leq |C_B| \cdot e^{-\epsilon m} \leq |C| \cdot e^{-\epsilon m}$$

$$\text{set } m = \frac{\log(|C|/\delta)}{\epsilon}$$

$$\Rightarrow \Pr [\text{outputting a misleading } c]$$

$$\leq \delta$$

□

The agnostic case:

what if there is no perfect $c \in C$?

$$\forall c \in C \quad \text{err}(c) > 0$$

Goal

Find $\hat{c} \in C$ s.t.

$$\text{err}(\hat{c}) < \min_{c \in C} \text{err}(c) + \epsilon$$

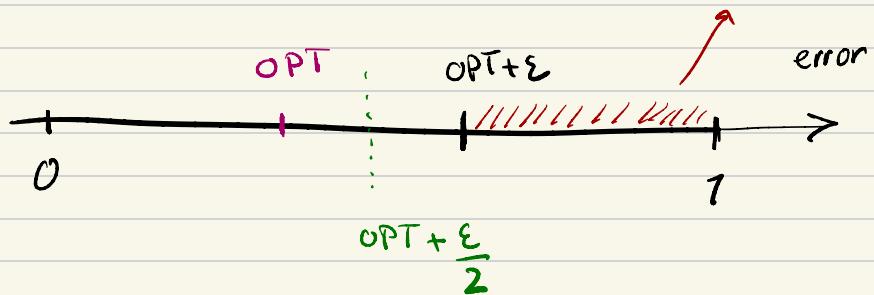
$\underbrace{\qquad\qquad\qquad}_{= \text{OPT}}$

the best possible option

Uniform convergence implies agnostic PAC learnability via EMR.

$$UC \Rightarrow \forall c \in C_B \quad \hat{\text{err}}_s(c) > \text{OPT} + \frac{\epsilon}{2}$$

$$UC \Rightarrow c^* = \text{the best option} \quad \hat{\text{err}}_s(c^*) \leq \text{OPT} + \epsilon$$



Exercise!

Suppose we have a finite class C ,

and $m = O\left(\frac{(\log |C|/\delta)}{\epsilon^2}\right)$. then w. p. at least $1-\delta$, for all $c \in C$, we have:

$$|\hat{\text{err}}_s(c) - \text{err}(c)| < \frac{\epsilon}{2}$$

No free lunch theorem says if
there is no universal learner ;
for a complex C even when
 E_{app} is 0 , $E_{est} \gg$ constant
with some constant probability
[unless we have $\Omega(1/X)$ samples]

suppose we have a set of $2n$ points

There are 2^{2m} possible labelings
of these $2m$ points.

Suppose C is the class of 2^{2m} func.
that assigns these labelings to these
points.

Assume this is the true labeling.

Fix a labeling of the points \uparrow

Now assume D is the uniform distribution on the $2m$ points with their label.

$T \leftarrow$ Draw m samples from D
(WLOG assume they are unique)

How many function in C label

T correctly? 2^m

$$P := \{c \in C \mid \hat{\text{err}}_T(c) = 0\}$$

\hookrightarrow promising hypothesis. $|P| = 2^{m/2}$

How many of them has error

$< \epsilon$?

c is misleading if $\begin{cases} \text{err}(c) > \epsilon \\ \text{and } \hat{\text{err}}_T(c) = 0 \end{cases}$

$$M := \{c \in C \mid \text{err}(c) > \epsilon \text{ and } \hat{\text{err}}_T(c) = 0\}$$

$$|M| = \frac{|M|}{|P|} \cdot |P|$$

$$= 2^m \cdot \Pr_{c \sim_P} [c \in M]$$

c makes
≥ m.ε
mistakes
in expectation

$$= 2^m \cdot \Pr \left[\frac{\# \text{mistakes}}{m} < \epsilon \right]$$

$$= 2^m \left(1 - \Pr \left[\frac{\# \text{mistakes}}{m} < \frac{1}{2} - \left(\frac{1}{2} - \epsilon \right)^2 \right] \right)$$

$$> 2^m \left(1 - e^{-2m(\frac{1}{2}-\epsilon)^2} \right)$$

↑

Hoeffding bound $\geq 2^{m/2} \cdot 0.99$

$\epsilon \leq \frac{1}{4}$ $m \geq 40$ ↑

\Rightarrow 0.99% of the promising concept
are bad!