

- Last time:
- "Chernoff bounds" (tail bounds on sums of indep. random variables) + applic. to hypothesis testing
 - learning by finding consistent hyp. from a fixed class $\mathcal{H}$ "CHF"
 - "Occam's Razor" ("cardinality version")

- Today:
- Applic. of $\mathcal{V}$: learning sparse disj., using few examples, with a hypothesis that is a pretty sparse disj., via "greedy set cover heuristic"
 - start proper vs. improper learning:
 - can efficiently improperly learn 3-term DNF;
 - can't "properly" " " " " , unless $NP=RP$

Admin: PS 2 due, PS 3 out
Rocco OH this week:

Wed 4-6 CEP5R 620

Questions?

Let's ^{PAC} learn $\mathcal{C} = \{ \text{all length-}k \text{ mon disj.} \}$!
over $X = \{0,1\}^n$

Winnow: OLCMB alg with $M = O(k \cdot \log n)$ mist.

Conversion

$\Rightarrow$ PAC alg. w/ $O\left(\frac{M}{\epsilon} \cdot \ln\left(\frac{M}{\delta}\right)\right)$ ex. " "

" Hyp. is weird; an LTF.

? Can we do this with mon. disj. hyp ?

Y via thm from last time:
we'll give an ^{algorithmic} way to find a consist.
hyp., given an ex., from

$$H_m = \{ \text{all mon conj. over } x_1, \dots, x_m \} \\ \text{of length } \leq k \cdot \ln m$$

The alg. engine: "greedy heuristic" for Set Cover.

Here's a problem:

SET COVER

Input: family of r sets $S_1, S_2, \dots, S_r$
each $S_i \subseteq \{1, \dots, m\}$ "universe"

Goal: Use min # of S_i 's to cover all elts of universe.

Ex:

$$m = 7$$

$$S_1 = 1, 2, 3, 4, 5$$

$$S_2 = 1, 3, 5, 7$$

$$S_3 = 2, 3, 4, 6$$

$$S_4 = 3, 4, 7$$

S_2, S_3 is
optimal
solution

Culture: This is an "NP-complete" problem:

!!
~

almost certainly no poly-time alg., to find optimal sol.

": There's a highly eff. alg. to find a sol. that's provably not much worse than opt: "greedy heuristic".

GH:

First step: • Take the S_i s.t. $|S_i|$ largest.
• Delete all elts in S_i from each remaining S_j (update S_j 's)

Next step: Repeat (using new S_j 's)

Do this until all of $\{1, \dots, m\}$ covered.

Ex:

$m=7$

$S_1 = 1, 2, 3, 4, 5$

$S_2 = \cancel{1}, \cancel{2}, \cancel{3}, 7$

$S_3 = \cancel{2}, \cancel{3}, 4, 6$

$S_4 = \cancel{3}, \cancel{4}, 7$

GH: • first set it chooses is S_1 .

• Update:

$S_2 = 7$

$S_3 = 6$

$S_4 = 7$

• Pick S_3 ; update
Pick S_4 ; done.

Found S_1, S_3, S_4 : sol. size 3, not 2.

Claim:

Let $OPT =$ size of optimal sol. (#sets).

GH always finds a sol. of $\leq OPT \cdot \ln(m)$ sets.

Pf:

Fact: Let $U \subseteq \{1, \dots, m\}$ be a set of "uncovered" elts.
There must be some S_i (some $i \in [r]$) that covers
 $\geq \frac{|U|}{\text{OPT}}$ elts of U .

Pf: Some coll. of OPT many S_i 's covers all of $[m]$,
hence covers U ; so one of them covers $\geq \frac{|U|}{\text{OPT}}$
elts of U , or else together couldn't cover U .

Consider execution of GH.

Let $U_i = \{\text{elts of } [m] \text{ that are uncovered after stages } 1, \dots, i\}$.

$$U_0 = [m]$$

Next $(i+1)$ st step: covers $\geq \frac{|U_i|}{\text{OPT}}$ elts of U_i .

[By FACT above, some original S_j originally covered $\geq \frac{|U_i|}{\text{OPT}}$ elts of U_i -- & still does; updates didn't affect uncovered elts.]

So

$$|U_{i+1}| \leq |U_i| - \frac{|U_i|}{\text{OPT}} = |U_i| \cdot \left(1 - \frac{1}{\text{OPT}}\right).$$

$$|U_0| = m, \text{ so } |U_i| \leq m \cdot \left(1 - \frac{1}{\text{OPT}}\right)^i.$$

$$i = \text{OPT} \cdot \ln(m): |U_i| \leq m \left(1 - \frac{1}{\text{OPT}}\right)^{\text{OPT} \ln m} < m \cdot \left(\frac{1}{e}\right)^{\ln m} = 1$$

$$\left(1 - \frac{1}{x}\right)^x < \frac{1}{e}$$

$$x \geq 1$$

$$\text{so } U_{\text{OPT} \cdot \ln m} = 0. \quad \smile$$

Back to Learning!

$\subseteq k \cdot \ln m$

We'll give an alg which, given a set S of m ex. labeled by a length- k mon disj, outputs a "small" consist. mon. disj.

(So H_m will be $\{all\}$;
 $|H_m|$ will be $< 2^{\epsilon m}$ for suitable m , & done.)

The learning alg:

- 1) Run elim alg. on our m -ex sample:
 (start w/ $h = x_1 \vee \dots \vee x_n$,
 for each neg ex z , if $z_i = 1$ remove x_i from h).

This gives a mon disj h , consist. w/ examples;
 wlog this h is $x_1 \vee \dots \vee x_r$.

Note: any sub-disj. of $x_1 \vee \dots \vee x_r$ is cons. with the neg. ex. in the sample.

- 2) Goal: find small sub-disj. of $x_1 \vee \dots \vee x_r$ that's consist. w/ all the pos examples.
 I.e. want small sub-collection of $x_1, \dots, x_r$ that "covers" all (at most m) pos ex in sample.
 x_i covers j^{th} pos ex $\Leftrightarrow x_i = 1$ in that example.
 This is a set cover problem!
- $x_i \leftrightarrow$ set S_i played
 pos ex $j \leftrightarrow$ elt $j \in [m]$.

Use GH to find a coll of $\leq \underline{OPT \cdot \ln(m)}$

x_i 's to cover all pos ex.

$OPT \leq k$ b/c target is a mon disj of length $\leq k$.

So we have an eff alg. which, given a sample of m ex lab. by length- k mon disj, finds a consistent $h \in \mathcal{H}_m := \{ \text{length at most } k \cdot \ln m \text{ mon disj} \}$.

Have $|\mathcal{H}_m| \leq n^{k \ln m}$.

So as long as m satisfies



$$n^{k \ln m} \leq \delta e^{\epsilon m}$$

using a sample of size that m + running above alg. is an (ϵ, δ) PAC learner.

Verify:

$$m \geq 2 \cdot \left(\frac{1}{\epsilon} \cdot k \cdot (\ln n) \cdot \ln \frac{1}{\delta} \right) \cdot \log \left(\frac{1}{\epsilon} \cdot k \cdot (\ln n) \cdot \ln \frac{1}{\delta} \right)$$

suffices to ensure $\star$. Why?

Need $\star$, i.e.

$$k \cdot \ln(m) \cdot \ln(n) \leq \ln \delta + \epsilon m, \text{ i.e.}$$

$$k \cdot \ln(m) \cdot \ln(n) + \ln \frac{1}{\delta} \leq \epsilon m$$

So suff for m to sat.

$$\underline{k \cdot \ln(m) \ln(n) \cdot \ln \frac{1}{\delta}} \leq \epsilon m, \text{ i.e.}$$

$$a, b \geq 2$$



$$a+b \leq ab$$

$$\frac{K \cdot \ln(n) \cdot \ln\left(\frac{1}{\epsilon}\right)}{\epsilon} \leq \frac{m}{\ln m}$$

A

Want as small an m as poss, s.t.

$$A \leq \frac{m}{\ln m}$$

$$m = e^A?$$

$$\text{RHS} = \frac{e^A}{A} \gg A$$

Try something:

would $m = A$ work?

No: $A \stackrel{?}{\leq} \frac{A}{\ln A}$ false $\neg$

would $m = A \ln A$ work?

no $A \stackrel{?}{\leq} \frac{A \ln A}{\ln(A \ln A)}$ < 1 so didn't work...

would $m = 2A \ln A$ work?

YES! $A \stackrel{?}{\leq} \frac{2A \ln A}{\ln(2A \ln A)} = \frac{A \ln(A^2)}{\ln(2A \ln A)}$

> 1 + worked.

Proper vs Improper Learning

Take-home message: learning problems which

are easy if you use the right $\mathcal{H}$ can become
hard if / / / wrong $\mathcal{H}$.

$\mathcal{C} =$ all 3-term DNFs $T_1 \vee T_2 \vee T_3$
over $X = \{0,1\}^n$.

Q: Does there exist a poly-time alg to
PAC learn $\mathcal{C}$?

① Y, if we use a different $\mathcal{H}$:

$\mathcal{H} =$ all 3-CNF formulas;

② N if we insist on proper learning.

①: Recall "de Morgan's" law: for T/F vars
 a, b, c, d , have

$$(a \wedge b) \vee (c \wedge d) \equiv (\overline{a \vee c}) \wedge (\overline{a \vee d}) \wedge (\overline{b \vee c}) \wedge (\overline{b \vee d}).$$

LHS T: $\downarrow$ T, so c, d both T ✓

LHS F: $F + F$; say a, c both F: F.

Next time: use this for learning.
