

Last time:

computational hardness of learning

\mathcal{C} = all $\text{poly}(n)$ -size Boolean circuits

can learn
with $\text{poly}(n)$
many examples,
in $\text{expl}(\text{poly}(n))$
time

based on existence of pseudorandom function families

- mapping the boundary of efficient learnability
- start hardness of learning based on public-key cryptography (trapdoor 1-way permutations)

Today: • hardness of learning based on trapdoor 1-way permutations (public-key cryptography)

• specific (conjectured) trapdoor 1-way perm.:

"discrete cube roots"

• Hardness assump. about \Rightarrow certain "simple" Bool. functions (that have $\text{poly}(n)$ size circuits) are hard to learn

In fact, even $\text{poly}(n)$ size Bool. formulas.

alternative:

• Ask Me Anything review session for exam

Reminder: Closed-book, closed-note assessment this Thurs 12/04 (be on time!)

Questions?

We understand

- permut.
- one-way perm.
- trapdoor one-way perm. (TOWP)

Public-Key Cryptosystem: PKC scheme allowing Bob

to send an ^(encrypted) msg to Alice in such a way that an eavesdropper Eve can't infer the underlying msg even seeing everything B sends to A (but A can decrypt the encrypted msg).

This follows directly from TOPW.
Here's how:

"trapdoor" → A keeps this info secret!

Setup: • A creates a TOPW (chooses primes p, q ; mult. $pq = N$)
"encryp. fn": f , the
"decryp. fn": f^{-1} .

A knows trapdoor info ($p + q$), so can eff.

compute f^{-1} on any point

• A publishes alg. for computing f . (Publishes N .)

To send a secure msg z to A, Bob:

- computes $f(z)$
- sends $f(z)$ to A.

→ A applies her alg for computing f^{-1} to $f(y)$,
+ gets $f^{-1}(f(y)) = y$. ☺

• What about Eve? She sees $f(z)$ but lacks trapdoor info, so can't compute f^{-1} on $f(z)$ + can't recover y .

RSA

(TOPW)

Key conn. between PKC + learning: if scheme is secure, the decryption fns f^{-1} are hard to learn.

Why? Sp's there's an eff. learning alg.^A to learn decryp. fns.

Crypto/leavesdrop.
world:

E gets some $f(z)$,
wants to invert f & get z
i.e. compute f^{-1} on $f(z)$.

Key point: Eve can generate
data set needed by A!

Does this by drawing
 y^1, y^2, \dots, y^m & computing
 $f(y^1), \dots, f(y^m)$, & using

$(f(y^1), y^1)$
 $(f(y^2), y^2)$
 \vdots
 $(f(y^m), y^m)$ } distrib. is
identical to
dist. of.

Learning world:

learning alg.^A gets labeled
ex's

$(x^1, f^{-1}(x^1))$
 $(x^2, f^{-1}(x^2))$
 \vdots
 $(x^m, f^{-1}(x^m))$ } x^i 's
unif.
rand.

computes, outputs hi-acc. hyp.
 h (so on fresh ex. y ,
whp $\underline{h(y) = f^{-1}(y)}$).

PKC

So, if TOWP exist, the decryp. fns (f^{-1} 's)
are a hard-to-learn class of fns.

$X = [0, 1]$

$\mathcal{C} =$ intervals like $[.38, .417]$

$|\mathcal{C}| =$ infinite

$\text{vcdim}(\mathcal{C}) \leq 2:$

• + • - • + no interval lab. 3
pts this way.

$\mathcal{E} = \left\{ \begin{array}{l} \{1\} \\ \{2\} \\ \vdots \end{array} \right\}$

is a " (1)

$h_1 = \{1\}$

adv: $x^1 = 1$

$h_1(x^1) = 1 + \text{Yes}$

adv: no, sorry, $c(x^1) = c(1) = 0$
WRONG

(2) too " "

^{OCMB alg}
Def of "A has MB M for \mathcal{E} ":

\forall seq of ex $(x^1, x^2, \dots) \in X$

\forall target conc. $c \in \mathcal{E}$,

if c is target conc. \forall (x^1, x^2, \dots) is seq of ex,
alg makes $\leq M$ mist.

$\mathcal{E} = \left\{ \{1\}, \{2\}, \{3\}, \dots \right\}$

$|\mathcal{E}| = \infty$

$$VCOIM(e) = 1$$

3, 5, 1, 4, 9

$$\frac{3}{22}, \frac{5}{22}, \frac{1}{22}, \frac{4}{22}, \frac{9}{22}$$

$$Z_t = \sum_{i=1}^m y_t(i) \exp(-\alpha_t y_i h_t(x^i))$$

hyp h error $err_{\mathcal{D}}(h, c)$

$$\text{"adv of } h" = \frac{1}{2} - err_{\mathcal{D}}(h, c)$$

$$err \in (0, \frac{1}{2}): \quad 0 < \gamma < \frac{1}{2}$$

#1 PS 5:

(i) argued for ± 1 valued hyp's h
target c :

can view adv. either in terms of

$$\frac{1}{2} - err_{\mathcal{D}}(h, c), \text{ or in terms of}$$

$$\frac{1}{2} \cdot \mathbb{E}_{x \sim \mathcal{D}} [h(x)c(x)]$$

- h perfect: $\epsilon = 1$. adv. $\frac{1}{2}$
 - h 50% error: adv. = 0, ~~adv. 0~~
-

(ii) : if f is a low-wt LTF over $\{\pm 1\}^n$, $f = \text{sign}(\sum_{i=1}^n w_i x_i)$

$$w_i \in \mathbb{Z}, \quad \sum_{i=1}^n |w_i| = W \text{ odd,}$$

for any dist \mathcal{D} , $\exists i \in [n]$ s.t.

either $\mathbb{E}[f(x) x_i] \geq \frac{1}{W}$ or

$$\mathbb{E}[f(x) \cdot (-x_i)] \geq \frac{1}{W}.$$