

LAST TIME :

- Definition of Weak Learning.
- ADABOOST: Training:  $\{(x_1, y_1), \dots, (x_m, y_m)\}$ .  
 $D_t(i) = \gamma_m$   
For  $t=1, \dots, T$ ,
  - Use WL under  $D_t$  to get  $h_t$
  - Let  $\underline{\varepsilon}_t = \Pr_{x \sim D_t} [h_t(x) \neq y_t]$ ; let  $r_t = \gamma_2 - \varepsilon_t \quad // \quad r_t \geq \gamma \quad (0, \varepsilon_t \leq \frac{1}{2} - \gamma)$
  - Choose  $\underline{\alpha}_t = \frac{1}{2} \log \left( \frac{1 - \varepsilon_t}{\varepsilon_t} \right)$
  - $D_{t+1}(i) = D_t(i) e^{-\alpha_t y_t h_t(x_i)} / Z_{t+1}$ .

Output: ~~H~~  $\text{sign} \left( \sum_{t=1}^T \alpha_t h_t(\cdot) \right)$  as classifier.

Theorem: Provided  $T \geq \frac{1}{2r^2} \log(2m)$ , then training error of  $H$  on the sample is 0.

Suppose that WL (weak learning algorithm) always outputs a hypothesis from some class  $H$ , whose VC-dimension is  $d$ .

$$TH_{n,T} = \left\{ \text{sign} \left( \underbrace{\sum_{i=1}^T \alpha_i h_i(\cdot)} \right) \mid h_i \in H_n, \alpha_i \in \mathbb{R} \right\}.$$

what is  $VC(D(TH_{n,T}))$ ?

(Exercise):  $VC(D(TH_{n,T})) \leq c \cdot T \cdot d \log T$ .

(Compute the growth function of the composition).

[Provided  $m \geq \frac{k_0}{\varepsilon} \left( \log \frac{1}{\delta} + c \cdot T \cdot d \log T \log \frac{1}{\varepsilon} \right)$  then the hypothesis output by Adaboost has error  $\leq \varepsilon$  w.p.  $\geq 1 - \delta$ .

[Appealing to VC Theorem].

$$\underline{m} \geq \left( \frac{k_0}{\varepsilon} \cdot \underbrace{\frac{1}{2r^2} \log(2m)d}_{\text{from exercise}} + \log \left( \frac{1}{2r^2} \log(2m)d \right) \right) + \underbrace{\frac{k_0}{\varepsilon} \log \frac{1}{\delta}}_{\text{from VC theorem}}$$

$$\begin{cases} \underline{m} \geq a \cdot \log(bm) \\ f(x) = x - a \log \underline{x} \geq 0 \quad a \geq c \log a \end{cases}$$

## PAC Learning :

- Several concept classes that are PAC learnable.
  - CONJUNCTIONS, HALFSPACES, 3-CNF, ...
- Occam's Razor / VC Theory
  - Consistent Learning  $\Rightarrow$  PAC learning  
(Settles information-theoretic/statistical complexity of learning).
- Weak & strong learning are equivalent.
- Are there hard learning problems for computational reasons?
  - If  $NP \neq RP$ , then the class 3-term DNF is not (properly) PAC-learnable using 3-term DNF.
- Is there a concept class that is hard to learn even improperly (algorithm can output a hypothesis from a larger class.).
  - If a certain assumption related to RSA holds, then there exists  $C$  that is not efficiently PAC-learnable.

Let  $p, q$  be two large primes, both of them 2048 bits long, and of the form  $3k+2$ .

Let  $N = pq$  [Factoring  $N$  is believed to be hard.]

(All arithmetic is mod  $N$ ).

$$\varphi(N) = (p-1)(q-1) \quad (\text{Euler's totient function})$$

$$\mathbb{Z}_N^* = \{i \mid 0 < i < N, \gcd(i, N) = 1\}, \quad |\mathbb{Z}_N^*| = \varphi(N)$$

(Group under multiplication mod  $N$ ).

We know that  $3 \times \varphi(N)$ .

$$\text{Let } f_N : \mathbb{Z}_N^* \rightarrow \mathbb{Z}_N^*, \quad f_N(y) = y^3 \pmod{N}$$

Claim:  $f_N$  is a bijection.

Proof: Since  $3 \times \varphi(N)$ ,  $\gcd(3, \varphi(N)) = 1$

Euler's theorem:  
 $\forall a \in \mathbb{Z}_N^*$ ,  
 $a^{\varphi(N)} \equiv 1 \pmod{N}$

$$\exists d \in \mathbb{Z}, \text{ s.t. } 3d \equiv 1 \pmod{\varphi(N)}$$

$$\boxed{\left. \begin{array}{l} \gcd(a, b) = g; \exists m, n \in \mathbb{Z}, g = m \cdot a + n \cdot b. \end{array} \right\} \quad 3d = 1 + d' \varphi(N)}$$

$$(f_N(y))^d = (y^3)^d \equiv y^{3d} \equiv y^{1+d' \varphi(N)} \equiv y \pmod{N}$$

$$f_N^{-1} : \mathbb{Z}_N^* \rightarrow \mathbb{Z}_N^*, \quad f_N^{-1}(x) = x^d \pmod{N}$$

$f_N$  is easy to compute using  $N$ .  $\rightarrow$  [PUBLIC KEY]

$f_N^{-1}$  is hard to compute without knowing  $d$   $\rightarrow$  [PRIVATE KEY]

Discrete Cube Root Problem: Two primes of the form  $(3k+2)$ ,  $p \neq q$  are chosen,  $N = p \cdot q$ ,  $\varphi(N) = (p-1)(q-1)$ ,  $3 \times \varphi(N)$ , Given  $N$  and  $x \in \mathbb{Z}_N^*$  as input, output  $y$ , s.t.  $y^3 \equiv x \pmod{N}$ .

(Easy to solve if we can factor  $N$ )

## DCRA Assumption :

For every polynomial  $r(\cdot)$ ,  $\nexists$  algorithm that runs in time  $r(n)$  and that on input  $N \not\mid x$ , where  $N$  is as defined above,  $x \in \mathbb{Z}_N^*$  at random and  $n = \# \text{bits in } N$  output  $y$  s.t. w.p.  $\geq \gamma_{r(n)}$ ,  $y$  satisfies  $y^3 \equiv x \pmod{N}$ .

The probability is over random draws of  $p, q, n$  and any internal randomization of the algorithm.

Given  $(x_1, y_1), (x_2, y_2), \dots, (x_m, y_m)$ ,  $x_i, y_i \in \mathbb{Z}_N^*$ ,  $x_i \sim \text{Unif}(\mathbb{Z}_N^*)$  and  $y_i$  s.t.  $y_i^3 \equiv x_i \pmod{N}$ .

Can we output  $h: \mathbb{Z}_N^* \rightarrow \mathbb{Z}_N^*$  s.t.  $\cup p \geq 1 - \delta$

$$\Pr_{x \sim \text{Unif}(\mathbb{Z}_N^*)} [h(x) \neq y, \text{ where } y^3 \equiv x \pmod{N}] \leq \varepsilon.$$

$y$  is also uniform on  $\mathbb{Z}_N^*$  as  $f_N$  is a bijection.

Generating data is easy; Pick  $y_i \sim \text{Unif}(\mathbb{Z}_N^*)$ ,  $x_i = y_i^3 \pmod{N}$ .

$$f_N^{-1}: \mathbb{Z}_N^* \rightarrow \mathbb{Z}_N^*, \quad f_N^{-1}(x) = y \quad \text{s.t. } y^3 \equiv x \pmod{N}$$

$n = \# \text{bits in } N$ .

$$f_{N,i}^{-1}: \mathbb{Z}_N^* \rightarrow \{0, 1\} \quad \text{i}^{\text{th}} \text{ bit of } y$$

$$\{f_{N,1}^{-1}, \dots, f_{N,n}^{-1}\} \leftarrow \begin{array}{l} \text{at least one of these functions must} \\ \text{be hard to learn.} \end{array}$$

Otherwise set  $\varepsilon = \gamma_{n^2}$ ,  $\delta = \gamma_{n^2}$ .

Suppose we learn  $h_1, \dots, h_n$ , w.p.  $\geq 1 - n \cdot \delta \geq 1 - \frac{1}{n}$   
all  $h_i$  satisfy  $\text{err}(h_i) \leq \gamma_{n^2}$

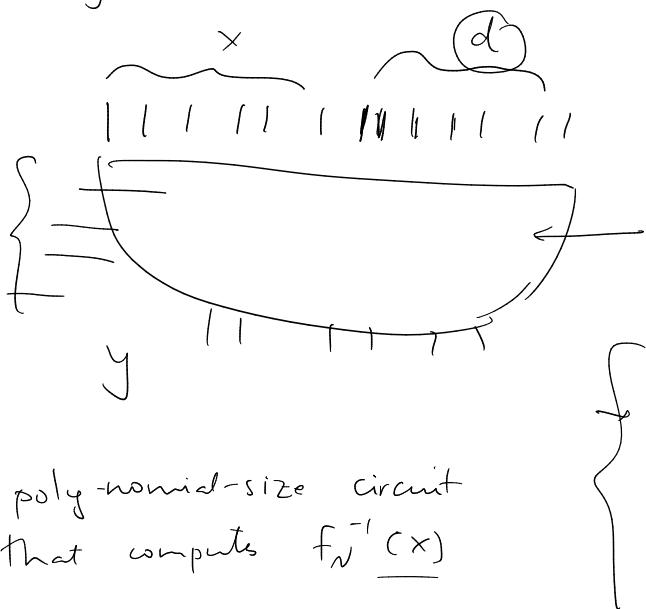
For  $x$  is picked at random, w.p.  $\geq 1 - \frac{1}{n}$ ,

$$h_1(x) h_2(x) \dots h_n(x) = y, \quad \text{s.t. } y^3 \equiv x \pmod{N}.$$

$$f_N^{-1} \leftarrow d$$

Turing Machine:  $M(x, d) \rightarrow y$  in polynomial time

$$\text{s.t. } y^3 \equiv x \pmod{N}$$



Polynomial-size circuit.

