

IT&CS: CS 229r  
LECTURE 11

3/5/2019

COMMUNICATION COMPLEXITY LOWER BOUNDS

- ① INNER PRODUCT FUNCTION
- ② DISTRIBUTIONAL COMPLEXITY
- ③ DISCREPANCY
- ④ LOWER BOUND FOR IP
- ⑤ BEYOND PRODUCT DISTRIBUTIONS: SET DISJOINTNESS
- ⑥ INFORMATION COMPLEXITY



Last time:

Defined Comm. Comp. ~~Model~~ Model: Alice X  $\rightleftarrows$  Bob Y

-  $CC(f)$  = def. complexity of computing  $f$  = # bits exchanged

-  $\Pi$  = Protocol  $\Pi(x, y)$ : Output of protocol under input  $x, y$ .

-  $CC^{Priv}(f)$ ;  $CC^{Pub}(f)$  = complexity with private  $\geq$  public randomness.

$CC(f) \geq \log \text{rank}(M_f)$ . How about  $CC^{Pub}(f)$ ?

• Inner Product function

$$IP(x, y) \triangleq \sum x_i y_i \pmod{2}$$

•  $CC^{Pub}(IP) = \Omega(n)$ . How do we prove this.

- Rank insufficient! (rank(Identity) =  $2^n$ ;  $CC^{Pub}(EQ) = O(1)$ )

- Idea 1: Put distribution  $\mu$  on  $(x, y)$

$$D_{\epsilon, \mu}(f) \triangleq \min_g \{ CC(g) \}$$

st  $\delta_{\mu}(f, g) \leq \epsilon$

$$\delta_{\mu}(f, g) \triangleq \Pr_{(x, y) \sim \mu} [f(x, y) \neq g(x, y)]$$

Claim:  $CC^{Pub}(f) \geq \frac{D_{\epsilon, \mu}(f)}{\log 1/\epsilon}$

Proof: Don't need randomness if  $(x, y)$  random.

- Idea 2:  $CC \leq$  "Discrepancy"  $\leq$  "eigenvalue".

$M_{\mu, f}$ : w.l.o.g.  $f: \text{Domain} \rightarrow \{+1, -1\}$   
 $\mu$  also a matrix

$$M_{\mu, f}(x, y) = \mu(x, y) \cdot f(x, y).$$

- $\text{Disc}(M) \triangleq \max_{\substack{S \subseteq \{0,1\}^n \\ T \subseteq \{0,1\}^n}} \left| \sum_{x,y} \mathbb{1}_S(x) \cdot \mathbb{1}_T(y) \cdot M(x,y) \right|$
- if  $\Pi$  is a  $k$ -bit protocol for  $f$  with 0-error then  $\text{Disc}(M) \geq 2^{-k}$ .
- if  $\Pi$  is  $k$ -bit protocol for  $f$  with  $\epsilon$ -error then  $\text{Disc}(M) \geq 2^{-k} (1-2\epsilon)$ .
- $CC_{\mu,\epsilon}(f) \leq k \Rightarrow \text{Disc}(M) \geq 2^{-k} (1-2\epsilon)$   
or  $\text{Disc}(M) < 2^{-k} (1-2\epsilon) \Rightarrow CC_{\mu,\epsilon}(f) > k$ .

Idea 3:  $\text{Disc}(M)$  vs. eigenvalues

$$\begin{aligned} \text{Disc}(M) &\leq \max_{X_S, X_T \in \{0,1\}^{2^n}} \sum_{x,y} X_S(x) \cdot X_T(y) \cdot M(x,y) \\ &\leq \max_{\substack{u,v \in \{0,1\}^{2^n} \\ \|u\|_2, \|v\|_2 \leq 2^{n/2}}} \sum_{x,y} u^T M \cdot v \\ &= \lambda_{\max}(M) \cdot 2^n \end{aligned}$$

$$\Rightarrow \lambda_{\max}(M) \leq 2^{-n-k} \Rightarrow \text{Disc}(M) \leq 2^{-k} \Rightarrow CC_{\mu,\epsilon}(f) > k-1$$

Disc  $\mu = ?$  for IP?

• Simply uniform.  $\mu(x, y) = \frac{1}{4^n} \forall x, y$

• ~~Disc~~  $\lambda_{\max}(M_{\mu, IP(n)}) = ?$

$$M_{\mu, IP(n)} = M_{\mu, IP(1)}^{\otimes n}$$

$$IP(1)(x, y) = x \cdot y \quad x, y \in \{0, 1\}$$

$$M_{\mu, IP(1)} = \begin{bmatrix} 1/4 & 1/4 \\ 1/4 & -1/4 \end{bmatrix}$$

$$\lambda_{\max}(M_{\mu, IP(1)}) = \frac{1}{\sqrt{8}}$$

$$\lambda(M_{\mu, IP(n)}) = \lambda(M_{\mu, IP(1)})^n = \frac{1}{8^{n/2}} = \frac{1}{2^n} \cdot \frac{1}{2^{n/2}}$$

$$\Rightarrow \text{Disc}(M) \leq 2^{-n/2} \Rightarrow \mathbb{E} D_{\mu, \frac{1}{4}}(IP) \geq \frac{n}{2} - 1$$

Is  $n/2$  right? On uniform dist?

How about worst-case?

Exercises...

## SET DISJOINTNESS

$$\text{DISJ}^n \stackrel{?}{=} \text{DISJ}^n(X, Y) = 1 \quad \text{if } \exists i \text{ s.t. } X_i = Y_i = 1 \\ = 0 \quad \text{o.w.}$$

$$(\text{DISJ}^n(X, Y) = \bigvee_{i=1}^n (X_i \wedge Y_i))$$

Challenge with Disjointness: Want Distribution with  $X \perp Y$

But then  $|X|, |Y| \approx \sqrt{n}$  & in this case  $\exists \tilde{O}(\sqrt{n})$  bit protocol.

Exercise: Give an  $\tilde{O}(\sqrt{n})$  protocol for all  $\mu = \mu_x \times \mu_y$ .

## History

- Babai-Frankl-Simon:  $\Omega(\sqrt{n})$  on Unif distribution
- Kalyanasundaram + Schnitger:  $\Omega(n)$  ? on ?
- Razborov:  $\Omega(n)$  on complex dist.
- Bar-Yossef-Jayram-Kumar-Sivakumar:  $\Omega(n)$  on

$$\mu_{XY} = (\mu_{X_i Y_i})^n$$

$$(X_i, Y_i) \perp (X_{-i}, Y_{-i}) !$$

# INFORMATION COMPLEXITY

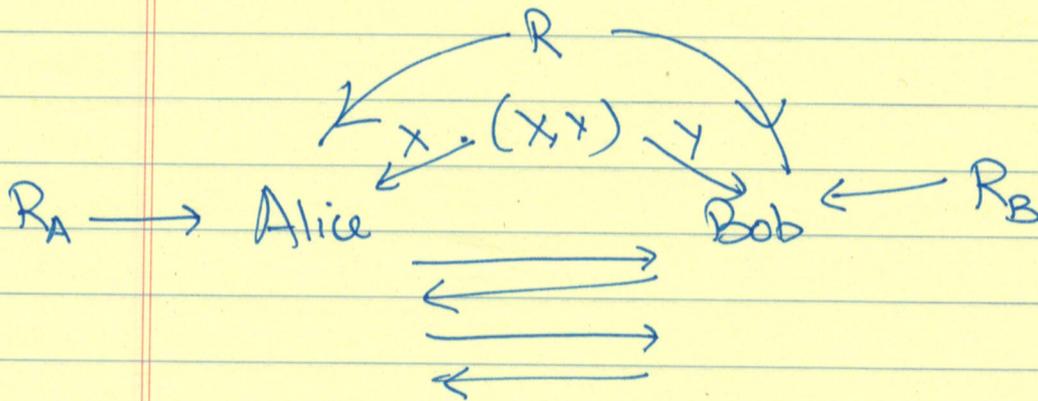
- Information-theoretic measure bounding communication complexity.

$$- IC_u(f, \pi) \triangleq I((X, Y); \pi) \quad [(X, Y) \sim u]$$

$$IC_u(f) \triangleq \min_{\pi \mid \pi \text{ solves } f} (IC_u(f, \pi))$$

"Information learned by observer about X, Y from  $\pi$ "

- More carefully.



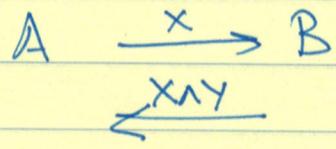
$$\pi = \pi(X, Y, R, R_A, R_B) \dots$$

$$IC_u = I((X, Y); \pi \mid R) \quad \left[ \begin{array}{l} \text{condition on } R; \\ R_A, R_B \text{ might} \\ \text{reduce information} \end{array} \right]$$

# Example

- AND(x,y) = x ∧ y      x,y ∈ {0,1}; μ = uniform.

- Naive Protocol: π<sub>naive</sub>

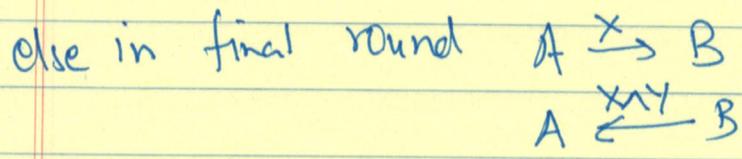


$$IC(\pi_{naive}) = \frac{1}{2} \cdot 1 + \frac{1}{2} \cdot 2 = \frac{3}{2}$$

- Better Protocol: t- rounds

in first t-1 rounds

- if Alice has 1 sends 1
- if Alice has 0 send 1 w.p. 1/2  
0 w.p. 1/2
- same with Bob.
- if either player outputs 0, stop & output 0.



$$IC \leq \frac{3}{4} \cdot \frac{1}{2} + \frac{1}{4} \cdot 2 = \frac{5}{4}$$

if either player has 0 learn one of the bits, but not both.

What distributions to use for DIC?

$\mu$ : (1) Pick  $Z \in \{0,1\}^n$  unif.

(2) for  $i=1$  to  $n$  do

if  $Z_i=0$   $X_i=0$

$Y_i \sim \text{Ber}(1/2)$

if  $Z_i=1$   $X_i \sim \text{Ber}(1/2)$

$Y_i = 0$ .

$\rightarrow$  Resulting dist = ~~(\*)~~  $\mu$ .

Funny:  $\pi=0$  is always correct!

Catch: will want  $\pi$  correct on every  $(X,Y)$  even those not in support of  $\mu$ !

~~will show~~

Define  $CIC_n \triangleq I((X,Y); \pi | Z)$

(1)  $CIC_n \geq n \cdot CIC_1$

(2)  $CIC_1 = \Omega(1)$ .

9

$$(1) I(XY; \pi | Z) \geq \sum_{i=1}^n I((X_i, Y_i); \pi | Z) \quad [\text{Standard}]$$

$$(2) I((X_i, Y_i); \pi | Z) \geq c_i c_n \stackrel{\Delta}{=} \min_{\tilde{\pi}} I(X_i, Y_i; \tilde{\pi} | Z) \quad [\text{Simulation}]$$

$$(1) I(XY; \pi | Z) = H(XY | Z) - H(XY | \pi, Z)$$

$$- H(X, Y | Z) = \sum_{i=1}^n H((X_i, Y_i) | Z, X_{<i}, Y_{<i})$$

$$= \sum_{i=1}^n H(X_i, Y_i | Z) \quad \text{s.t. } (X_i, Y_i) \sim Z - (X_{<i}, Y_{<i})$$

$$- H(XY | \pi, Z) = \sum_{i=1}^n H((X_i, Y_i) | \pi, Z, (X_{<i}, Y_{<i}))$$

$$\leq \sum_{i=1}^n H(X_i, Y_i | \pi, Z) \quad [\text{Conditioning } \dots]$$

(1) follows.

(2)  $\tilde{\pi}$  simulates  $\pi \dots$

$\uparrow$   
(X, Y)

needs

$(X, Y) \sim \mu^n \rightarrow$  generate  $Z_2 \dots Z_n$  using common randomness

$X_2 \dots X_n$   
 $Y_2 \dots Y_n$  using private randomness.

now simulate  $\pi$ .

- int. learned about  $X, Y$  is int. about  $X, Y$  in  $\pi | Z$