

# Information Complexity vs. Communication Complexity: Hidden Layers Game

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Final Project Presentation for Information Theory in TCS

# Introduction

- ▶ Review of IC vs CC
- ▶ Hidden Layers Game
- ▶ Upper Bound of IC
- ▶ Intuition for lower bound of CC

# Communication Complexity and Information Complexity

## Communication Complexity

$CC(f; \epsilon)$  is the smallest number of bits that Alice and Bob need to exchange to compute  $f$  with error probability  $\epsilon$ .

## Information Complexity

- ▶ The protocol  $\pi$  on the pair of (random) inputs  $(X; Y) \sim \mu$  gives the transcript  $\Pi = \Pi(X; Y)$
- ▶ The information cost of a protocol  $\Pi$  is the amount of information that the protocol reveals to Alice and Bob about their input.
- ▶ the amount revealed to Alice – who knows  $X$  – about  $Y$  is given by the conditional mutual information  $I(Y; \Pi|X)$ .

information cost of  $\Pi$  is given by:

$$IC_{\mu}(\pi) = I(Y; \Pi|X) + I(X; \Pi|Y)$$

# Information Complexity

(continued) The task of finding information complexity of  $f$  is the task of minimizing the information complexity of the protocol for  $f$ :

$$IC_{\mu} = \inf_{\text{protocol } \pi \text{ performing } f} IC_{\mu}(\pi)$$

## IC vs CC

Information complexity can be viewed as the interactive analogue of Shannon's entropy.

Equality between information and communication complexity is equivalent to compression theorem in the interactive setting: whether it is possible to compress an interactive conversation into its information content like we compress a single message.

# A problem with large CC and small IC

## Hidden Layers Game problem

Conjectured in [Bra13] with lower bound proved in [GKR16]

- ▶  $k$  is a parameter used in the problem
- ▶ IC upper bound =  $O(\log k)$
- ▶ CC Lower Bound =  $\Omega(k)$

Exponential separation!

In fact proved separation with external IC (stronger result)

Using embedding of set disjointness inputs.

# Hidden Layers Game

Hidden Layers Game is a sampling problem.

Parameters:

- ▶ strings over an alphabet  $\Sigma$  of size  $k$
- ▶ another parameter  $N = 2^n$ . fix  $N = 2^n = 2^{2^k}$ .

Input:

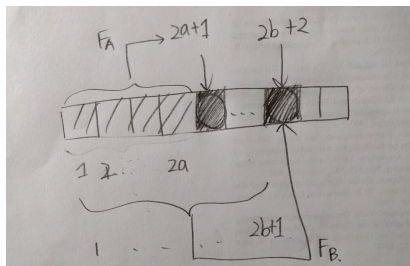
- ▶ Alice and Bob are given a pair of numbers  $a, b \sim \{0, \dots, N-1\}$  (i.e. two  $n$ -bit numbers that take  $\Omega(\log n)$  communication to compare)
- ▶ Alice is given a uniformly random function  $F_A : \Sigma^{2^a} \rightarrow \Sigma$  (the function is only known to Alice)
- ▶ Bob is given a uniformly random function  $F_B : \Sigma^{2^{b+1}} \rightarrow \Sigma$  (the function is only known to Bob)

# Hidden Layers Game

Alice and Bob need to sample a uniformly random string  $s \in \Sigma^{2N}$  subject to the constraints:

- ▶  $s_{2a+1} = F_A(s_{1 \dots 2a})$
- ▶  $s_{2b+2} = F_B(s_{1 \dots 2b+1})$

In other words, they want a  $2N$ -symbol string over the alphabet, where its first  $2a$ -symbols substring can be mapped to its  $(2a+1)$ th symbol by Alice's function and its first  $(2b+1)$ -symbols substring can be mapped to its  $(2b+2)$ th symbol by Bob's function.



## Naive Protocol and IC upper bound

Naive Protocol  $\pi_0$  for hidden layers game  $H$

- ▶ in odd rounds Alice samples the next symbol of  $s$  and in even rounds Bob does.
- ▶ In rounds  $i \neq 2a + 1$ , Alice just sends a uniformly random  $s_i \sim \Sigma$ . In round  $i = 2a + 1$ , Alice computes and sends  $si = F_A(s_{1..2a})$ .
- ▶ Bob does the similar thing for even rounds

Communication complexity =  $\Theta(N \log k) = \Theta(2^{2^k} \log k)$  ( $2N$  rounds, we can view the encoding of each char  $s_i$  as  $\log k$  since the alphabet has size  $k$ ).



## Naive Protocol and IC upper bound

$s$  is sampled uniformly from the subset  $S$  of strings which satisfy the two constraints.

The size of  $S$ ,  $|S| = k^{2N-2}$ ; uniformly random except  $(2a+1)$ th and  $(2b+2)$ th symbols.

Thus the KL-divergence between  $s$  and the uniform distribution on  $\Sigma^{2N}$  is  $2 \log k$ .

## Naive Protocol and IC upper bound

The transcript of  $\pi_0$  is distributed exactly as the output  $s$  of  $H$  given  $a, F_A, b, F_B$ .

Denote  $\mu$  as the distribution of the inputs  $a, F_A, b, F_B$  to  $H$ .

$$\begin{aligned} IC_\mu(H) &= IC_\mu(\pi_0) = I_\mu(s; a, F_A, b, F_B) \\ &= \mathbf{E} \mathbb{D}(s|a; F_A, b, F_B || s) = 2 \log k \end{aligned}$$

## CC Lower Bound Intuition 1: Disjointness

- ▶ A randomly selected string  $t \in \Sigma^{2N}$  has a probability of exactly  $1/k$  of being consistent with Alice's input:  
 $t$  just needs its  $(2a + 1)$ th symbol happen to satisfy  
 $t_{2a+1} = F_A(t_{1..2a})$   
Same for Bob.
- ▶ So  $t$  has probability  $1/k^2$  to be consistent with both Alice and Bob

# CC Lower Bound Intuition 1: Disjointness

Protocol 1:

- ▶ Using public randomness and no communication; sample  $k^2$  strings  $s_1, \dots, s_{k^2}$  drawn uniformly at random from  $\Sigma^{2N}$
- ▶ Let  $A$  be the subset (of approximately  $k$ ) strings satisfying Alice's constraint
- ▶ Let  $B$  be the subset satisfying Bob's constraint
- ▶ Alice and Bob communicate to determine whether  $A \cap B = \emptyset$ , if not, they output the first element of  $A \cap B$ ; otherwise they repeat the entire process.

# CC Lower Bound Intuition 1: Disjointness

## Correctness

- ▶ the first string in the intersection between  $A$  and  $B$  must satisfy distribution of  $s$
- ▶ The probability that  $A \cap B \neq \emptyset$  is approximately  $1 - 1/e$ , and the process will terminate after an expected constant number of iterations.

## Lower bound

- ▶ CC upper bound for disjointness of two sets with size  $k$  is  $O(k)$ .
- ▶ if we can reduce to Disjointness...
- ▶ CC lower bound for disjointness of two sets with size  $k$  is  $\Omega(k)$ .

## CC Lower Bound Intuition 2: Greater Than(GT)

Protocol 2:

- ▶ find a  $c$  such that  $a \leq c \leq b$  or  $a \geq c \geq b$ ,  
wlog assume that  $a \leq c \leq b$
- ▶ Use public randomness and no communication, generate strings  $t_1, t_2.. \in \Sigma^{2c+1}$  uniformly randomly
- ▶ Alice sends Bob the index of the first string  $s_0$  satisfying her constraint
- ▶ Using public randomness and no communication, generate strings  $r_1, r_2.. \in \Sigma^{2N}$  which extend  $s_0$  with uniformly random symbols
- ▶ Bob sends Alice the index of the first string  $s$  satisfying his constraint. This  $s$  is the output.

## CC Lower Bound Intuition 2: Greater Than(GT)

The first step of comparing  $a, b$  requires CC of the Greater Than function.

As discussed above, the probability of a string to be acceptable is  $1/k$ , and therefore communicating the index of the first acceptable string requires  $O(\log k)$  bits.

### Lower bound for GT

$a$  and  $b$  are  $n$  – bit numbers.

$n = \log N$ . Therefore the lb for GT here is

$$\Omega(\log n) = \Omega(\log \log N) = \Omega(k).$$

# Sampling vs Decision?

- ▶ Can this sampling problem be generalized to to a decision problem?
- ▶ if no such decision problem exists, what property makes protocols for decision problems easier to compress?
- ▶ Sampling problems require a lot of public randomness.  
Decision problems protocols: the answer is determined by messages sent by Alice and Bob.



# Sampling vs Decision?

- ▶ Exponential separation of IC and CC for Boolean functions has been shown in [GKR15].
- ▶ With the introduction of a lower bound method: Relative discrepancy method.
- ▶ But is Relative discrepancy method to separate all boolean functions?
- ▶ Actually No! More in my report.

Questions?



Mark Braverman.

A hard-to-compress interactive task?

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