

CS 2429 - Foundations of Communication Complexity

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Lecturer: Toniann Pitassi

Scribe Notes by: Lila Fontes

1 Review of complexity classes

We've discussed P^{cc} , RP^{cc} , BPP^{cc} , NP^{cc} , and $coNP^{cc}$. For the regular (not communication complexity) classes, we think that $P = RP = BP$, but for the communication classes, we have seen separations:

- $P^{cc} \subsetneq RP^{cc}$ by EQUALITY.
- $RP^{cc} \subsetneq BPP^{cc}$ by GT.
- $BPP^{cc} \subsetneq NP^{cc}$ by SET-DISJOINTNESS.
- NP^{cc} and $coNP^{cc} \not\subseteq BPP^{cc}$ by GT.
- $NP^{cc} \not\subseteq$ and $\not\supseteq coNP^{cc}$ by SET-DISJOINTNESS.

IP is not in any of these classes.

Definition Function f has an *unbounded error* communication complexity protocol P if P is a randomized protocol such that

$$\forall x, y \Pr[P(x, y) = f(x, y)] > \frac{1}{2}$$

$U(f) \stackrel{\text{def}}{=} \text{least cost of an unbounded error protocol for } f$

$PP^{cc} \stackrel{\text{def}}{=} \text{set of all functions that have unbounded error protocols of cost poly log } n.$

Thus RP^{cc} , BPP^{cc} , and NP^{cc} are special cases of PP^{cc} .

Theorem 1 (Paturi-Simon) $U(f) = \log(\text{sign-rank}(M_f)) \pm O(1)$ where $\text{sign-rank}(M_f) \stackrel{\text{def}}{=} \text{the minimum rank of any matrix } M' \text{ that sign-agrees (entry-by-entry) with } M.$

Notice that the sign-rank of a matrix can be *much* smaller than its rank.

Theorem 2 (Forster) *Linear bounds for $U(\text{IP})$ by giving lower bounds on $\text{sign-rank}(M_{\text{IP}})$, i.e. $\text{IP} \notin PP^{cc}$.*

2 Variable partition models

In the standard model, the inputs x and y are partitioned in a *fixed* way amongst the two players.

Definition (*Best/any partition model*)

Let $f : \{0, 1\}^m \mapsto \{0, 1\}$. Let S, T be a partition of $\{1, \dots, m\}$ into two equal-sized sets. Then the minimum deterministic complexity over the “best” partition is:

$$D^{\text{best}}(f) \stackrel{\text{def}}{=} \min_{S, T} D^{S, T}(f)$$

And the maximum deterministic complexity over the “worst” partition is:

$$D^{\text{worst}}(f) \stackrel{\text{def}}{=} \max_{S, T} D^{S, T}(f)$$

It is harder to obtain lower bounds for $D^{\text{best}}(f)$.

Theorem 3 (Hayes) *Fixed partition lower bounds imply best partition lower bounds for a related function.*

2.1 More about IP

Definition Let G be a d -regular bipartite graph (with adjacency matrix A) on $[n] \times [n]$.

$$\text{GRAPH-IP}_A \stackrel{\text{def}}{=} \sum_{i, j} A(i, j) x_i y_j \pmod{2}$$

(This is analogous to $\text{IP}(X, Y) = \sum_i x_i y_i \pmod{2}$.) M_G is the normalized version of A . λ_2 is the second-largest eigenvalue of M_G .

Theorem 4 (Alor-Boppana(?)) *For all sufficiently large n , a random d -regular bipartite graph has $\lambda_2 = \Theta(\frac{1}{\sqrt{d}})$ with high probability.*

Lemma 5 (Expander mixing lemma) *Let G be a d -regular graph on $V_1 \times V_2$ with $|V_1| = |V_2| = n$. Let $A \subseteq V_1, B \subseteq V_2$. Then the number of edges between A and B is $\geq \frac{d|A| \cdot |B|}{n} - \lambda_2 d \sqrt{|A| \cdot |B|}$. When $|A| = |B| > \lambda_2 n$, then there exists at least one edge between A and B .*

Theorem 6 *Let G be a bipartite d -regular graph (with adjacency matrix A) on $V_1 \cup V_2$, with $\lambda_2 = \frac{1}{\sqrt{d}}$ and $d \geq 4$. If the best-partition communication complexity of $\text{GRAPH-IP}_A(x, y) \leq f(n)$, then the fixed partition communication complexity of $\text{IP}(x, y) \leq O(f(n))$.*

Proof Let $V = V_1 \cup V_2$; let $P = P_1, P_2$ be the partition of $V_1 \cup V_2$ such that GRAPH-IP_A is easy ($\leq f(n)$) with respect to this partition. Assume WLOG that P_1 contains $V'_1 \subset V_1$ of size $\geq \frac{n}{2}$, and similarly for V'_2 .

GOAL: find $S \subset V'_1, T \subset V'_2$ such that the edges between S and T are a perfect matching, and $|S|$ and $|T| = O(n)$.

1. Use expander mixing lemma. Initially, let $A_0 = V'_1, B_0 = V'_2; |A_0| = |B_0| = \frac{n}{2}$.

2. Choose an edge $e = (i, j)$ from $A \times B$. (Such an edge exists by the expander mixing lemma.) Remove all neighboring vertices of edge: $A_1 = A_0 - \text{nbrs}(j)$ and $B_1 = B_0 - \text{nbrs}(i)$. Repeat this step on A_1 and B_1 .

By the expander mixing lemma, we can continue for s steps as long as $|A_s|$ and $|B_s| \geq \lambda_n = \frac{n}{\sqrt{d}}$, i.e., $\frac{n}{2} - ds \geq \frac{n}{\sqrt{d}}$.

Consider an instance of IP where Alice has x of size s and Bob has y of size s . Alice creates x' , an instance of GRAPH-IP_A on n bits with partition P , as follows: the bits of x are put in one-to-one correspondence with elements of S ; all other bits of x' are zero. Bob does the same, matching his y to corresponding bits of T . This is done nonuniformly; Alice and Bob share graph G ahead-of-time.

For any function that has large complexity under one partition, we construct a function GRAPH-IP that has large complexity under *any* partition.

2.2 Examples

2.2.1 Q -decision trees

Usually we think of a decision tree for a boolean function $f(\vec{x})$ as having one bit x_i of \vec{x} at each node, with the edges to its two children labelled by values 0 and 1 for x_i .

In Q decisions trees, each node is instead labelled with any function from the function class Q (e.g., $x_1 \wedge x_5$, $x_3 \vee x_2$).

Let $\text{worst}_Q \stackrel{\text{def}}{=} \max_{q \in Q} D^{\text{worst}}$. Let $\text{best}_Q \stackrel{\text{def}}{=} \min_{q \in Q} D^{\text{best}}$.

Lemma 7 $T_Q(f) \geq \frac{D^{\text{worst}}(f)}{\text{worst}_Q}$

Proof Fix an arbitrary partition of the inputs into two disjoint sets. Alice and Bob simulate the tree. At every query, they compute the function $q(x)$ that is being queried at that node. Each step takes $\leq \text{worst}_Q$ bits of communication complexity. They take a total $T_Q(f)$ number of steps. Total communication complexity = $T_Q(f) \cdot \text{worst}_Q$.

2.2.2 Turing machine time-space tradeoff

Consider a multitape Turing machine, with a read-only input tape and several read-write work tapes.

Lemma 8 Let $f : \{0, 1\}^n \times \{0, 1\}^n \rightarrow \{0, 1\}$. Let M be a multitape Turing machine running in time $T(n)$ and space $S(n)$ that computes f on inputs of size $m = 3n$, such that

- M accepts $\{x0^n y \mid f(x, y) = 1\}$
- M rejects $\{x0^n y \mid f(x, y) = 0\}$

Then $D(f) = O\left(\frac{T(n)S(n)}{n}\right)$.

In particular, if f has $O(n)$ communication complexity, then $T(n)S(n) \geq O(n^2)$.

Why?

We'll show that, given a Turing machine, we can construct a communication complexity protocol simulating it.

The input tape of M looks like: $\boxed{x} \mid \boxed{0^n} \mid \boxed{y}$. Alice simulates M 's computation until input tape head moves over to y , then sends the state and the tapes' contents to Bob (for a cost of $O(S(n))$ bits). Bob simulates M 's computation until the input tape head moves over to x , then transfers the state and tapes' contents to Alice. They continue in this manner until the simulated computation has halted.

The number of transfers is at most $T(n)/n$, since the middle pad of n zeroes forces Alice and Bob to do a lot of work. (If the zeroes were not there, then we would consider the number of reversals. . .) Each transfer uses $O(S(n))$ bits, for a total deterministic protocol cost of $D(f) = O\left(\frac{T(n)S(n)}{n}\right)$.

2.2.3 Circuit depth lower bounds

This material is from Karchmov and Wigderson (sp?).

Consider a function $f : \{0, 1\}^n \rightarrow \{0, 1\}$ and the relation

$$R_f = \{(x, y, i) \mid x \in f^{-1}(1), y \in f^{-1}(0), x_i \neq y_i\}$$

Define $cc(R_f)$ as the minimum number of bits of communication required in a protocol in which player 1 gets $x \in f^{-1}(1)$ and player 2 gets $y \in f^{-1}(0)$. The protocol outputs an i such that $x_i = y_i$.

Theorem 9 For any boolean function $f : \{0, 1\}^n \rightarrow \{0, 1\}$, the minimum depth of a circuit over $\{\wedge, \vee, \neg\}$ is equal to $cc(R_f)$.