

Chebyshev Polynomials, Approximate Degree, and Their Applications

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Boolean Functions

- Boolean function $f : \{-1, 1\}^n \rightarrow \{-1, 1\}$



$$\text{AND}_n(x) = \begin{cases} -1 & \text{(TRUE)} & \text{if } x = (-1)^n \\ 1 & \text{(FALSE)} & \text{otherwise} \end{cases}$$

Approximate Degree

- A real polynomial p ϵ -approximates f if

$$|p(x) - f(x)| < \epsilon \quad \forall x \in \{-1, 1\}^n$$

- $\widetilde{\deg}_\epsilon(f)$ = minimum degree needed to ϵ -approximate f
- $\widetilde{\deg}(f) := \deg_{1/3}(f)$ is the **approximate degree** of f

Threshold Degree

Definition

Let $f : \{-1, 1\}^n \rightarrow \{-1, 1\}$ be a Boolean function. A polynomial p sign-represents f if $\text{sgn}(p(x)) = f(x)$ for all $x \in \{-1, 1\}^n$.

Definition

The threshold degree of f is $\min \deg(p)$, where the minimum is over all sign-representations of f .

- An equivalent definition of threshold degree is $\lim_{\epsilon \rightarrow 1} \widetilde{\deg}_{\epsilon}(f)$.

Why Care About Approximate and Threshold Degree?

Upper bounds on $\widetilde{\deg}_\epsilon(f)$ and $\deg_\pm(f)$ yield efficient learning algorithms.

- $\epsilon \approx 1/3$: Agnostic Learning [KKMS05]
- $\epsilon \approx 1 - 2^{-n^\delta}$: Attribute-Efficient Learning [KS04, STT12]
- $\epsilon \rightarrow 1$ (i.e., $\deg_\pm(f)$ upper bounds): PAC learning [KS01]

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- $\epsilon \rightarrow 1$ (i.e., $\text{deg}_{\pm}(f)$ upper bounds): PAC learning [KS01]
- Upper bounds on $\widetilde{\text{deg}}_{1/3}(f)$ also imply fast algorithms for differentially private data release [TUV12, CTUW14].

Why Care About Approximate and Threshold Degree?

Lower bounds on $\widetilde{\deg}_\epsilon(f)$ yield lower bounds on:

- Quantum query complexity [BBCMW98, AS01, Amb03, KSW04]
- Communication complexity [She08, SZ08, CA08, LS08, She12]
 - Lower bounds hold for a communication problem **related** to f .
 - Technique is called the **Pattern Matrix Method** [She08].
- Circuit complexity [MP69, Bei93, Bei94, She08]
- Oracle Separations [Bei94, BCHTV16]

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- Lower bounds on $\widetilde{\text{deg}}(f)$ also yield efficient secret-sharing schemes [BIVW16]

Details of Communication Applications

Lower bounds on $\widetilde{\deg}_\epsilon(f)$ and $\deg_{\pm}(f)$ yield communication lower bounds (often in a black-box manner) [Sherstov 2008]

- $\epsilon \approx 1/3$: BQP^{cc} lower bounds.
- $\epsilon \approx 1 - 2^{-n^\delta}$: PP^{cc} lower bounds
- $\epsilon \rightarrow 1$ (i.e., $\deg_{\pm}(f)$ lower bounds): UPP^{cc} lower bounds.

Example 1: The Approximate Degree of AND_n

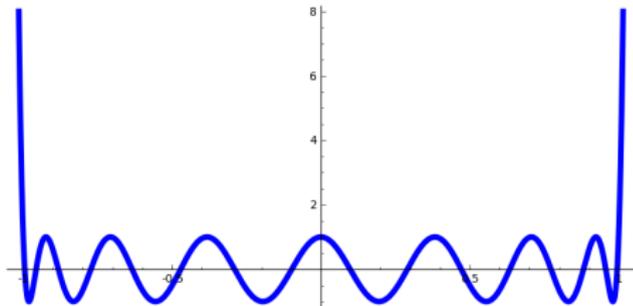
Example: What is the Approximate Degree of AND_n ?

$$\widetilde{\text{deg}}(\text{AND}_n) = \Theta(\sqrt{n}).$$

- Upper bound: Use **Chebyshev Polynomials**.
- Markov's Inequality: Let $G(t)$ be a univariate polynomial s.t. $\text{deg}(G) \leq d$ and $\sup_{t \in [-1,1]} |G(t)| \leq 1$. Then

$$\sup_{t \in [-1,1]} |G'(t)| \leq d^2.$$

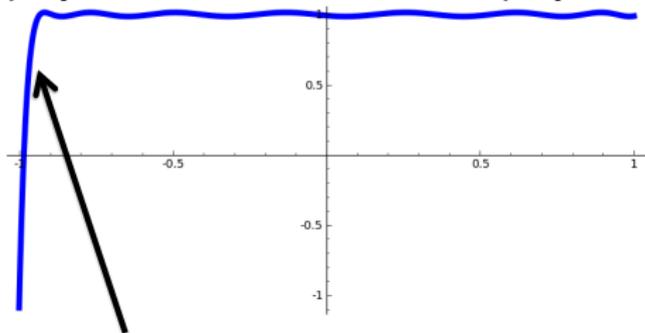
- Chebyshev polynomials are the extremal case.



Example: What is the Approximate Degree of AND_n ?

$$\widetilde{\text{deg}}(\text{AND}_n) = O(\sqrt{n}).$$

- After shifting and scaling, can turn degree $O(\sqrt{n})$ Chebyshev polynomial into a univariate polynomial $Q(t)$ that looks like:



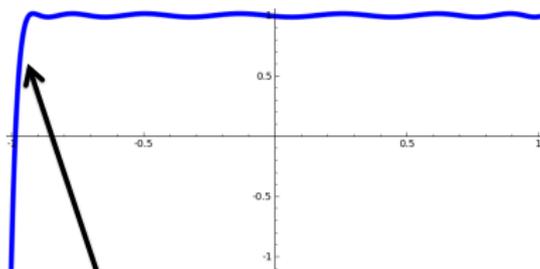
$$Q(-1+2/n) = 2/3$$

- Define n -variate polynomial p via $p(x) = Q(\sum_{i=1}^n x_i/n)$.
- Then $|p(x) - \text{AND}_n(x)| \leq 1/3 \quad \forall x \in \{-1, 1\}^n$.

Example: What is the Approximate Degree of AND_n ?

[NS92] $\widetilde{\text{deg}}(\text{AND}_n) = \Omega(\sqrt{n})$.

- Lower bound: Use **symmetrization**.
- Suppose $|p(x) - \text{AND}_n(x)| \leq 1/3 \quad \forall x \in \{-1, 1\}^n$.
- There is a way to turn p into a univariate polynomial p^{sym} that looks like this:



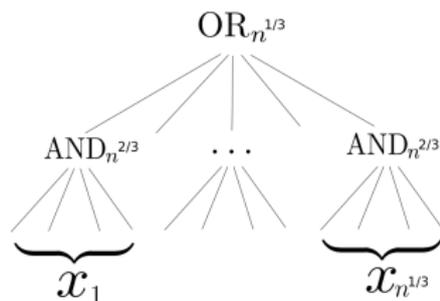
$$Q(-1+2/n) \geq 2/3$$

- Claim 1: $\text{deg}(p^{\text{sym}}) \leq \text{deg}(p)$.
- Claim 2: Markov's inequality $\implies \text{deg}(p^{\text{sym}}) = \Omega(n^{1/2})$.

Example 2: The Threshold Degree of the
Minsky-Papert DNF

The Minsky-Papert DNF

- The Minsky-Papert DNF is $MP(x) := OR_{n^{1/3}} \circ AND_{n^{2/3}}$.



The Minsky-Papert DNF

- Claim: $\deg_{\pm}(\text{MP}) = \tilde{\Theta}(n^{1/3})$.
- The $\Omega(n^{1/3})$ lower bound was proved by Minsky and Papert in 1969 via a symmetrization argument.
 - More generally, $\deg_{\pm}(\text{OR}_t \circ \text{AND}_b) \geq \Omega(\min(t, b^{1/2}))$.

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 - More generally, $\deg_{\pm}(\text{OR}_t \circ \text{AND}_b) \geq \Omega(\min(t, b^{1/2}))$.
- We will prove the matching upper bound:

$$\deg_{\pm}(\text{OR}_t \circ \text{AND}_b) \leq \tilde{O}(\min(t, b^{1/2})).$$

- First, we'll construct a sign-representation of degree $O((b \log t)^{1/2})$ using Chebyshev approximations to AND_b .
- Then we'll construct a sign-representation of degree $\tilde{O}(t)$ using rational approximations to AND_b .

A Sign-Representation for $\text{OR}_t \circ \text{AND}_b$ of degree $\tilde{O}(b^{1/2})$

- Let p_1 be a (Chebyshev-derived) polynomial of degree $O(\sqrt{b \cdot \log t})$ approximating AND_b to error $\frac{1}{8t}$.
- Let $p = \frac{1}{2} \cdot (1 - p_1)$.
- Then $\frac{1}{2} - \sum_{i=1}^t p(x_i)$ sign-represents $\text{OR}_t \circ \text{AND}_b$.

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- Then $\frac{1}{2} - \sum_{i=1}^t p(x_i)$ sign-represents $\text{OR}_t \circ \text{AND}_b$.
 - If $\text{AND}_b(x_i) = \text{FALSE}$ for all i , then

$$\frac{1}{2} - \sum_{i=1}^t p(x_i) \geq \frac{1}{2} - t \cdot \frac{1}{8t} \geq 3/8.$$

- If $\text{AND}_b(x_i) = \text{TRUE}$ for even one i , then

$$\frac{1}{2} - \sum_{i=1}^t p(x_i) \leq \frac{1}{2} - 7/8 + (t-1) \cdot \frac{1}{8t} \leq -1/4.$$

A Sign-Representation for $\text{OR}_t \circ \text{AND}_b$ of degree $\tilde{O}(t)$

- Fact: there exist p_1, q_1 of degree $O(\log b \cdot \log t)$ such that

$$\left| \text{AND}_b(x) - \frac{p_1(x)}{q_1(x)} \right| \leq \frac{1}{8t} \text{ for all } x \in \{-1, 1\}^b.$$

- Let $\frac{p(x)}{q(x)} = \frac{1}{2} \cdot \left(1 - \frac{p_1(x)}{q_1(x)} \right)$.

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- Claim: The following polynomial sign-represents $\text{OR}_t \circ \text{AND}_b$.

$$r(x) := \left(\frac{1}{2} \cdot \prod_{1 \leq i \leq t} q^2(x_i) \right) - \sum_{i=1}^t \left(p(x_i) \cdot q(x_i) \cdot \prod_{1 \leq i' \leq t, i' \neq i} q^2(x_{i'}) \right).$$

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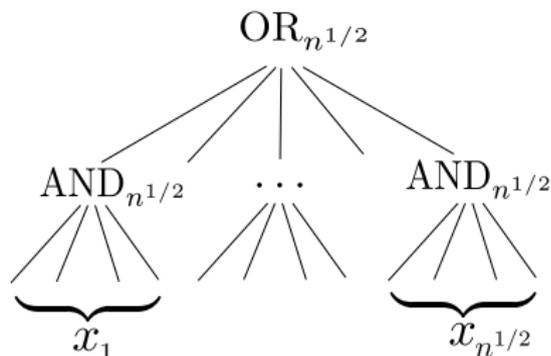
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- Proof: $\text{sgn}(\text{OR}_t \circ \text{AND}_b(x)) = \frac{1}{2} - \sum_{i=1}^t \frac{p(x_i)}{q(x_i)} = \frac{1}{2} - \sum_{i=1}^t \frac{p(x_i) \cdot q(x_i)}{q^2(x_i)} = \frac{r(x)}{\prod_{i=1}^t q^2(x_i)}$. The denominator of the RHS is non-negative, so throw it away w/o changing the sign.

Recent Progress on Lower Bounds: Beyond Symmetrization

Beyond Symmetrization

- Symmetrization is “lossy”: in turning an n -variate poly p into a univariate poly p^{sym} , we throw away information about p .
- Challenge problem: What is $\widetilde{\text{deg}}(\text{OR-AND}_n)$?



History of the OR-AND Tree

Upper bounds

$$[\text{HMW03}] \quad \widetilde{\text{deg}}(\text{OR-AND}_n) = O(n^{1/2})$$

Lower bounds

$$[\text{NS92}] \quad \Omega(n^{1/4})$$

$$[\text{Shi01}] \quad \Omega(n^{1/4} \sqrt{\log n})$$

$$[\text{Amb03}] \quad \Omega(n^{1/3})$$

[Aar08] Reposed Question

$$[\text{She09}] \quad \Omega(n^{3/8})$$

$$[\text{BT13}] \quad \Omega(n^{1/2})$$

$$[\text{She13}] \quad \Omega(n^{1/2}), \text{ independently}$$

Linear Programming Formulation of Approximate Degree

What is best error achievable by **any** degree d approximation of f ?
Primal LP (Linear in ϵ and coefficients of p):

$$\begin{aligned} \min_{p, \epsilon} \quad & \epsilon \\ \text{s.t.} \quad & |p(x) - f(x)| \leq \epsilon \quad \text{for all } x \in \{-1, 1\}^n \\ & \deg p \leq d \end{aligned}$$

Dual LP:

$$\begin{aligned} \max_{\psi} \quad & \sum_{x \in \{-1, 1\}^n} \psi(x) f(x) \\ \text{s.t.} \quad & \sum_{x \in \{-1, 1\}^n} |\psi(x)| = 1 \\ & \sum_{x \in \{-1, 1\}^n} \psi(x) q(x) = 0 \quad \text{whenever } \deg q \leq d \end{aligned}$$

Dual Characterization of Approximate Degree

Theorem: $\deg_\epsilon(f) > d$ iff there exists a “dual polynomial”
 $\psi: \{-1, 1\}^n \rightarrow \mathbb{R}$ with

- (1) $\sum_{x \in \{-1, 1\}^n} \psi(x) f(x) > \epsilon$ “high correlation with f ”
- (2) $\sum_{x \in \{-1, 1\}^n} |\psi(x)| = 1$ “ L_1 -norm 1”
- (3) $\sum_{x \in \{-1, 1\}^n} \psi(x) q(x) = 0$, when $\deg q \leq d$ “pure high degree d ”

A **lossless** technique. Strong duality implies any approximate degree lower bound can be witnessed by dual polynomial.

Goal: Construct an explicit dual polynomial
 $\psi_{\text{OR-AND}}$ for OR-AND

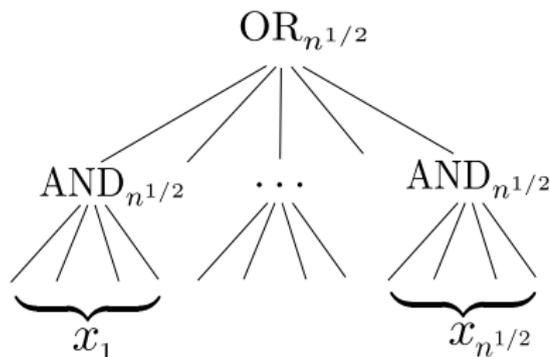
Constructing a Dual Polynomial

- By [NS92], there are dual polynomials
$$\psi_{\mathbf{OUT}} \text{ for } \widetilde{\text{deg}}(\text{OR}_{n^{1/2}}) = \Omega(n^{1/4}) \quad \text{and}$$
$$\psi_{\mathbf{IN}} \text{ for } \widetilde{\text{deg}}(\text{AND}_{n^{1/2}}) = \Omega(n^{1/4})$$
- Both [She13] and [BT13] combine $\psi_{\mathbf{OUT}}$ and $\psi_{\mathbf{IN}}$ to obtain a dual polynomial $\psi_{\mathbf{OR-AND}}$ for OR-AND.
- The combining method was proposed in independent earlier work by [Lee09] and [She09].

The Combining Method [She09, Lee09]

$$\psi_{\text{OR-AND}}(x_1, \dots, x_{n^{1/2}}) := C \cdot \psi_{\text{OUT}}(\dots, \text{sgn}(\psi_{\text{IN}}(x_i)), \dots) \prod_{i=1}^{n^{1/2}} |\psi_{\text{IN}}(x_i)|$$

(C chosen to ensure $\psi_{\text{OR-AND}}$ has L_1 -norm 1).



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Must verify:

- 1 $\psi_{\text{OR-AND}}$ has pure high degree $\geq n^{1/4} \cdot n^{1/4} = n^{1/2}$.
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Must verify:

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- 2 $\psi_{\text{OR-AND}}$ has high correlation with OR-AND. [BT13, She13]

Additional Recent Progress on Approximate and Threshold Degree Lower Bounds

(Negative) One-Sided Approximate Degree

- Negative one-sided approximate degree is an intermediate notion between approximate degree and threshold degree.
- A real polynomial p is a negative one-sided ϵ -approximation for f if

$$|p(x) - 1| < \epsilon \quad \forall x \in f^{-1}(1)$$

$$p(x) \leq -1 \quad \forall x \in f^{-1}(-1)$$

- $\widetilde{\text{odeg}}_{-, \epsilon}(f) = \min$ degree of a negative one-sided ϵ -approximation for f .

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- $\widetilde{\text{odeg}}_{-, \epsilon}(f) = \min$ degree of a negative one-sided ϵ -approximation for f .
- Examples: $\widetilde{\text{odeg}}_{-, 1/3}(\text{AND}_n) = \Theta(\sqrt{n})$; $\widetilde{\text{odeg}}_{-, 1/3}(\text{OR}_n) = 1$.

Recent Theorems: Part 1

Theorem (BT13, She13)

Let f be a Boolean function with $\widetilde{\text{odeg}}_{-,1/2}(f) \geq d$. Let $F = \text{OR}_t(f, \dots, f)$. Then $\widetilde{\text{deg}}_{1/2}(F) \geq d \cdot \sqrt{t}$.

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- Define $\text{GAPMAJ}_t: \{-1, 1\}^t \rightarrow \{-1, 1\}$ to be the partial function that equals:
 - -1 if at least $2/3$ of its inputs are -1
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 - undefined otherwise.

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Compare to:

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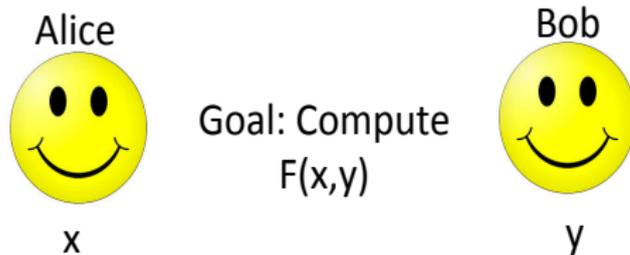
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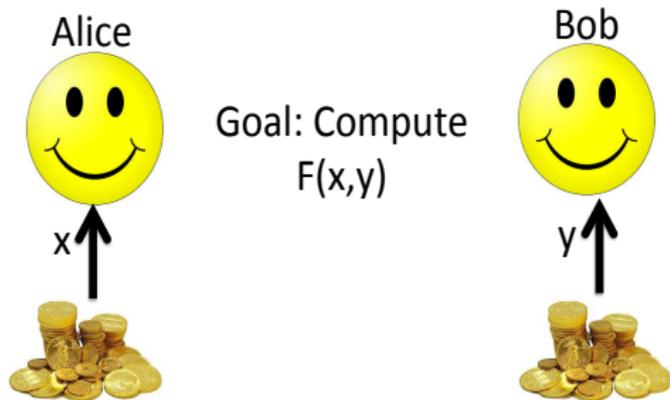
- Implies a number of new oracle separations:
 $\text{SZK}^A \not\subseteq \text{PP}^A$, $\text{SZK}^A \not\subseteq \text{PZK}^A$, and $\text{NIPZK}^A \not\subseteq \text{coNIPZK}^A$.

Applications to Communication Complexity

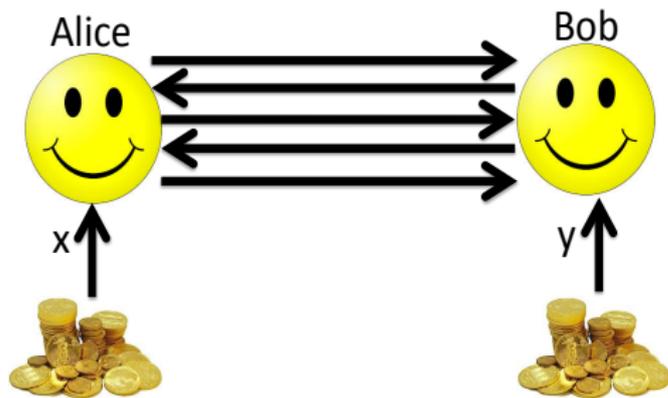
Definition of the UPP^{cc} Communication Model



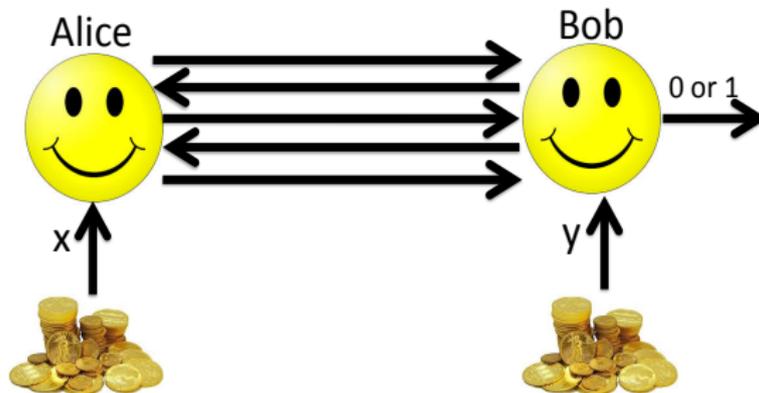
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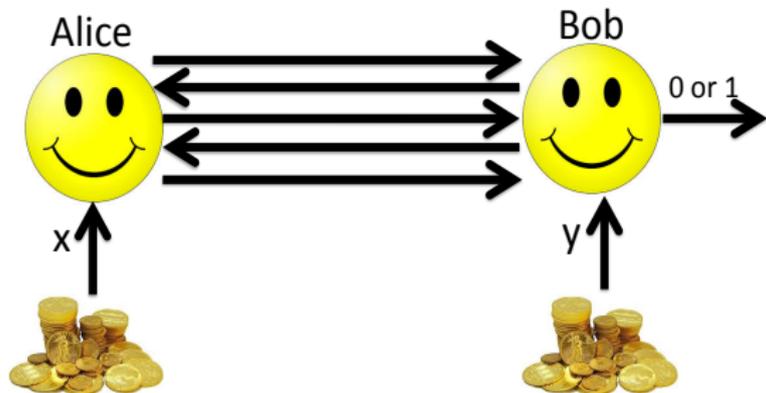
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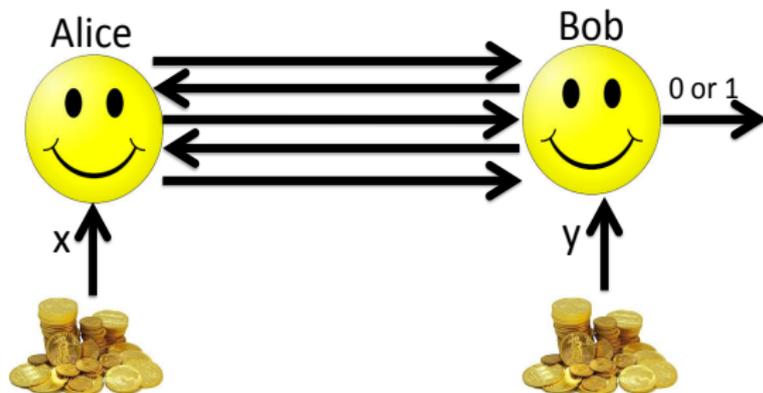


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- Protocol computes F if on every input (x, y) , the output is correct with probability greater than $1/2$.
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- Protocol computes F if on every input (x, y) , the output is correct with probability greater than $1/2$.
- The cost of a protocol is the worst-case number of bits exchanged on any input (x, y) .
- $UPP^{cc}(F)$ is the least cost of a protocol that computes F .
- UPP^{cc} is the class of all F computed by UPP^{cc} protocols of polylogarithmic cost.

Importance of UPP^{cc}

- UPP^{cc} is the strongest two-party communication model against which we can prove lower bounds.
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- Progress on UPP^{cc} has been slow.
 - Paturi and Simon (1984) showed that

$$UPP^{cc}(F) \approx \log(\text{sign-rank}([F(x, y)]_{x, y})).$$

- Forster (2001) nearly-optimal lower bounds on the UPP^{cc} complexity of Hadamard matrices.
- Razborov and Sherstov (2008) proved polynomial UPP^{cc} lower bounds for a function in PH^{cc} (more context to follow).

Rest of the Talk: How Much of PH^{CC} is Contained
In UPP^{CC} ?

Background

- An important question in complexity theory is to determine the relative power of alternation (as captured by the polynomial-hierarchy PH), and counting (as captured by $\#P$ and its decisional variant PP).
- Both PH and PP generalize NP in natural ways.
- Toda famously showed that their power is related: $PH \subseteq P^{PP}$.
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- Toda famously showed that their power is related: $PH \subseteq P^{PP}$.
- But it is open how much of PH is contained in PP itself.
- Babai, Frankl, and Simon (1986) introduced communication analogues of Turing Machine complexity classes.
- Main question they left open was the relationship between PH^{cc} and UPP^{cc} .
 - Is $PH^{cc} \subseteq UPP^{cc}$?
 - Is $UPP^{cc} \subseteq PH^{cc}$?

Prior Work By Razborov and Sherstov (2008)

- Razborov and Sherstov (2008) resolved the first question left open by Babai, Frankl, and Simon!
- They gave a function F in PH^{cc} (actually, in Σ_2^{cc}) such that $\text{UPP}^{\text{cc}}(F) = \Omega(n^{1/3})$.

Remainder of the Talk

- Goal: show that even lower levels of PH^{cc} are not in UPP^{cc} .
- Outline:
 - Proof sketch for Razborov and Sherstov (2008).
 - Threshold degree and its relation to UPP^{cc} .
 - The Pattern Matrix Method (PMM).
 - Combining PMM with “smooth dual witnesses” to prove UPP^{cc} lower bounds.
 - Improving on Razborov and Sherstov.

Communication Upper Bounds from Threshold Degree Upper Bounds

- Let $F: \{-1, 1\}^n \times \{-1, 1\}^n \rightarrow \{-1, 1\}$.
- Claim: Let $d = \deg_{\pm}(F)$. There is a UPP^{cc} protocol of cost $O(d \log n)$ computing $F(x, y)$.

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- Alice chooses a parity T with probability proportional to $|c_T|$, and sends to Bob T and $\chi_{T \cap [n]}(y)$.
- From this, Bob can compute and output $\text{sgn}(c_T) \cdot \chi_T(x, y)$.

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- From this, Bob can compute and output $\text{sgn}(c_T) \cdot \chi_T(x, y)$.
- Since p sign-represents F , the output is correct with probability strictly greater than $1/2$.
- Communication cost is $O(d \log n)$.

Communication Lower Bounds from Threshold Degree Lower Bounds

- The previous slide showed that threshold degree upper bounds for $F(x, y)$ imply communication upper bounds for $F(x, y)$.
- Can we use threshold degree lower bounds for $F(x, y)$ to establish communication lower bounds for $F(x, y)$?

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- Can we use threshold degree lower bounds for $F(x, y)$ to establish communication lower bounds for $F(x, y)$?
- Answer: No. Bad Example: The parity function has linear threshold degree, but constant communication complexity.
- Next Slide: Something almost as good.
 - A way to turn threshold degree lower bounds for f into communication lower bounds for a related function $F(x, y)$.

The Pattern Matrix Method (Sherstov, 2008)

- Let $f: \{-1, 1\}^n \rightarrow \{-1, 1\}$ satisfy $\deg_{\pm}(f) \geq d$.
- Turn f into a $2^{2n} \times 2^{2n}$ matrix F with $\text{UPP}^{\text{cc}}(F) \geq d$.

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- (Sherstov, 2008) **almost** achieves this.
 - Sherstov turns f into a matrix F , called the “pattern matrix” of f , such that:
 - Any randomized communication protocol that computes F correctly with probability $p = 1/2 + 2^{-d}$ has cost at least d .

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 - Specifically, $F(x, y)$ is set to $f(u)$, where $u(x, y)$ is **derived** from (x, y) in a simple way.
 - y “selects” n bits of x and flips some of them to obtain u .

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- Sherstov shows that μ can be “lifted” into a distribution over $\{-1, 1\}^{2n} \times \{-1, 1\}^{2n}$ under which $F(x, y)$ cannot be computed with probability $1/2 + 2^{-d}$, unless the communication cost is at least d .

Smooth Dual Witnesses Imply UPP^{cc} Lower Bounds

- Let $f: \{-1, 1\}^n \rightarrow \{-1, 1\}$ satisfy $\deg_{\pm}(f) \geq d$.
- Razborov and Sherstov showed that if there is a dual witness μ for f that additionally satisfies a **smoothness** condition, then the pattern matrix F of f actually has $UPP^{cc}(F) \geq d$.

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- The bulk of Razborov-Sherstov is showing that the Minsky-Papert DNF has a smooth dual witness to the fact that its threshold degree is $\Omega(n^{1/3})$.
- Since f is computed by a DNF formula, its pattern matrix is in Σ_2^{cc} .

Improving on Razborov-Sherstov (Part 1)

- Recall:

Theorem (She14)

Let f be a Boolean function with $\widetilde{\text{odeg}}_{-,1/2}(f) \geq d$. Let $F = \text{OR}_t(f, \dots, f)$. Then $\text{deg}_{\pm}(F) = \Omega(\min\{d, t\})$.

- The dual witness constructed in (Sherstov 2014) isn't smooth.
- [BT16] showed how to smooth-ify the dual witness of (Sherstov 2014) (under a mild additional restriction on f).
 - Implied more general and quantitatively stronger UPP^{cc} lower bounds for Σ_2^{cc} compared to [RS08].

Improving on Razborov-Sherstov (Part 2)

- Recall:

Theorem (BCHTV16)

Let f be a Boolean function with $\widetilde{\deg}_{1/2}(f) \geq d$. Let $F = \text{GAPMAJ}_t(f, \dots, f)$. Then $\deg_{\pm}(F) \geq \Omega(\min\{d, t\})$.

Improving on Razborov-Sherstov (Part 2)

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Theorem (BCHTV16)

Let f be a Boolean function with $\widetilde{\deg}_{1/2}(f) \geq d$. Let $F = \text{GAPMAJ}_t(f, \dots, f)$. Then $\deg_{\pm}(F) \geq \Omega(\min\{d, t\})$.

- Moreover, can use the methods of [BT16] to smooth-ify the dual witness!
- Corollary: a function in NISZK^{cc} that is not in UPP^{cc} .
 - Improves on Razborov-Sherstov because:

$$\text{NISZK}^{\text{cc}} \subseteq \text{SZK}^{\text{cc}} \subseteq \text{AM}^{\text{cc}} \cap \text{coAM}^{\text{cc}} \subseteq \text{AM}^{\text{cc}} \subseteq \Sigma_2^{\text{cc}}.$$

Open Questions and Directions

- Beyond Block-Composed Functions.
 - Challenge problem: obtain quantitatively optimal lower bounds on the approximate degree and threshold degree of AC^0 .
 - Best lower bound for approximate degree is $\Omega(n^{2/3})$ [AS04].
 - Best lower bound for threshold degree is $\Omega(n^{1/2})$ [She15].
 - Best upper bound for both is the trivial $O(n)$.
- Break the “ UPP^{cc} barrier” in communication complexity.
 - i.e., Identify any communication class that is not contained in UPP^{cc} (such as $NISZK^{cc}$), and then prove a superlogarithmic lower bound on that class for an explicit function.
- Strengthen UPP^{cc} lower bounds into lower bounds on distribution-free Statistical Query learning algorithms.

Thank you!