

The Quantum Adversary method and Classical Formula Size Lower Bounds

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Circuit Complexity

- A million dollar question: Show an explicit function which requires superpolynomial size circuits!
- For functions in NP the best circuit lower bound we know is $5n - o(n)$
[LR01, IM02]
- The smallest complexity class we know to contain a function requiring superpolynomial size circuits is **MAEXP**! [BFT98]

Formula Size

- Weakening of the circuit model—a formula is a binary tree with internal nodes labelled by AND, OR and leaves labelled by literals. The size of a formula is its number of leaves.
- **PARITY** has formula size $\theta(n^2)$ [Khr71].
- Showing superpolynomial formula size lower bounds for a function in NP would imply $\text{NP} \neq \text{NC}^1$.
- The best lower bound for a function in NP is $n^{3-o(1)}$ [Hås98].

An Aside: Lower Bound Philosophy

- Let's look at our job as computer scientists from the point of view of computer scientists.
- How difficult is the problem of proving lower bounds?
- We will consider a lower bound technique efficient if it can be computed in time polynomial in the size of the truth table of f .

Karchmer–Wigderson Game [KW88]

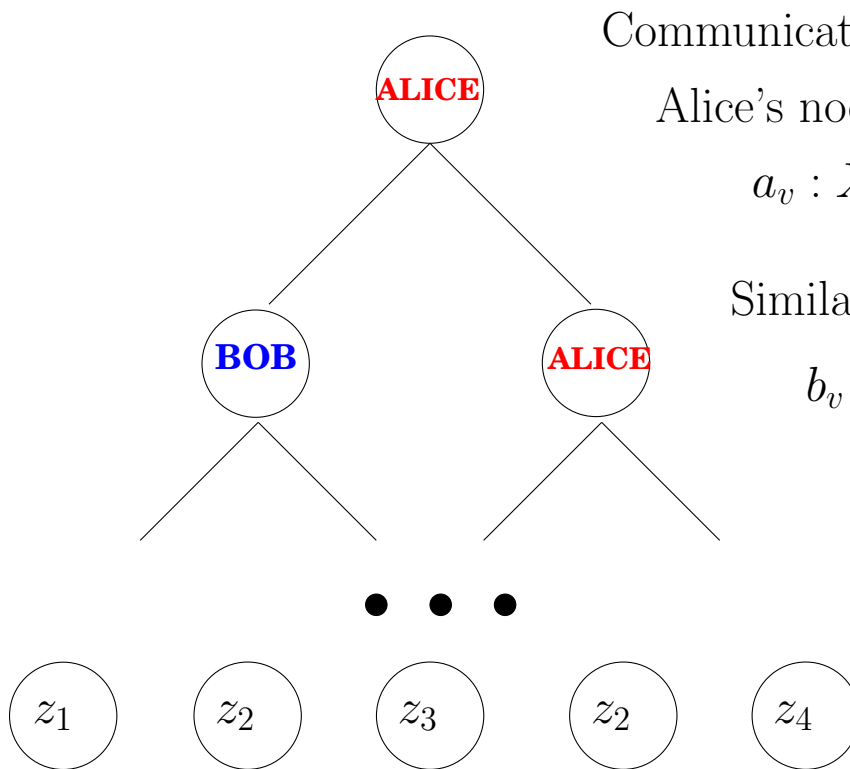
- Elegant characterization of formula size in terms of a communication game.
- For a Boolean function f , let $X = f^{-1}(0)$ and $Y = f^{-1}(1)$. Consider

$$R_f = \{(x, y, i) : x \in X, y \in Y, x_i \neq y_i\}$$

- The game is then the following: Alice is given $x \in X$, Bob is given $y \in Y$ and they wish to find i such that $(x, y, i) \in R_f$.
- Karchmer–Wigderson Thm: The number of leaves in a best communication protocol for R_f equals the formula size of f .

Communication complexity of relations

$$R \subseteq X \times Y \times Z$$



Communication protocol is a binary tree:

Alice's nodes labelled by a function:

$$a_v : X \rightarrow \{0, 1\}$$

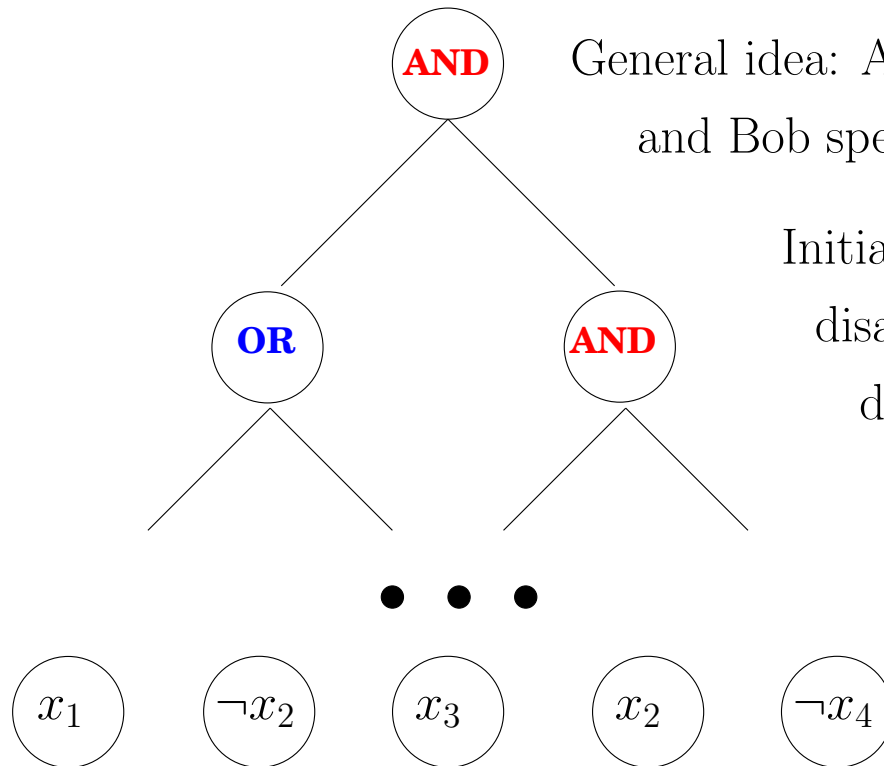
Similarly, Bob's nodes labelled

$$b_v : Y \rightarrow \{0, 1\}$$

Leaves labelled by elements $z \in Z$.

Denote by $C^P(R)$ the number of leaves in a best protocol for R .

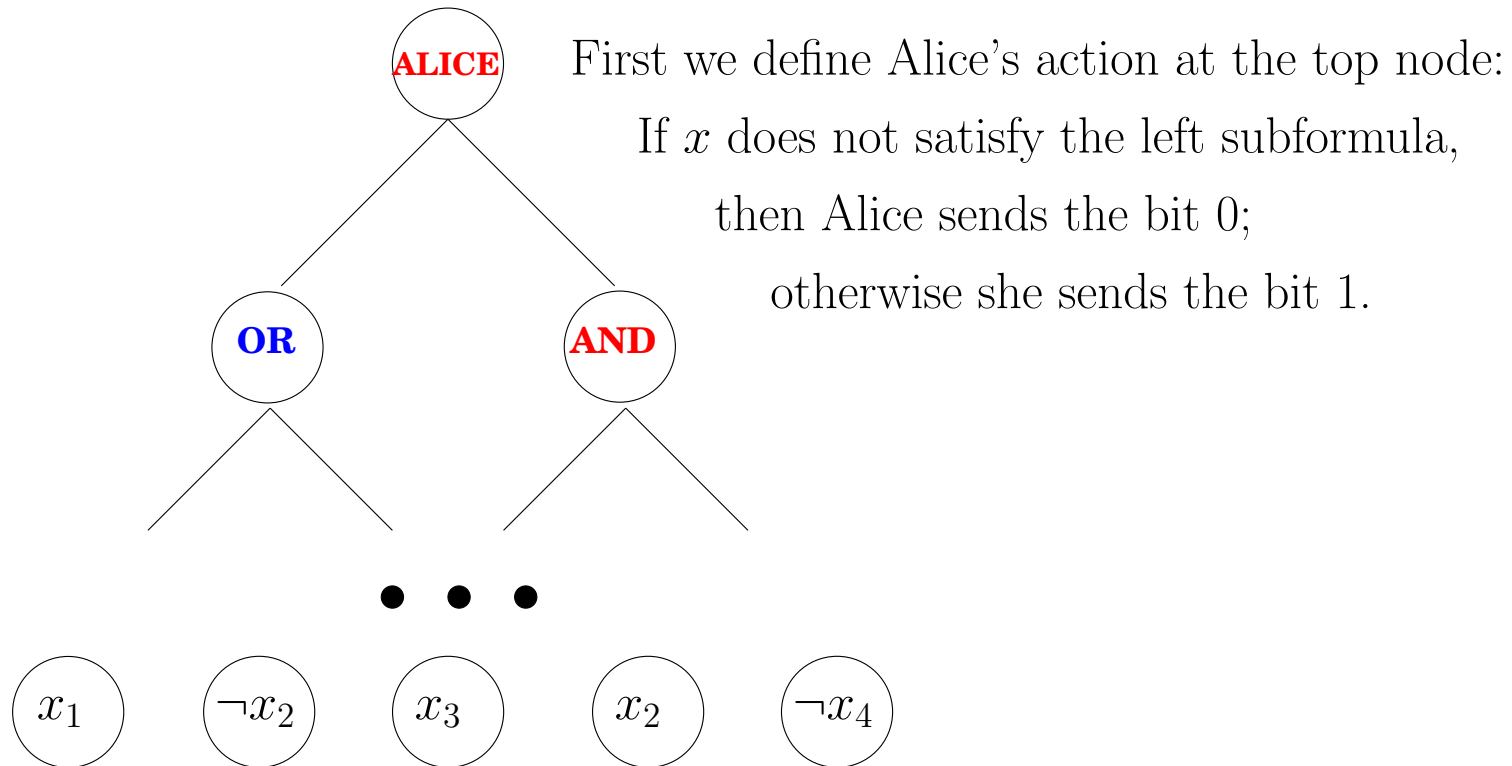
Proof by picture: $C^P(R_f) \leq L(f)$.



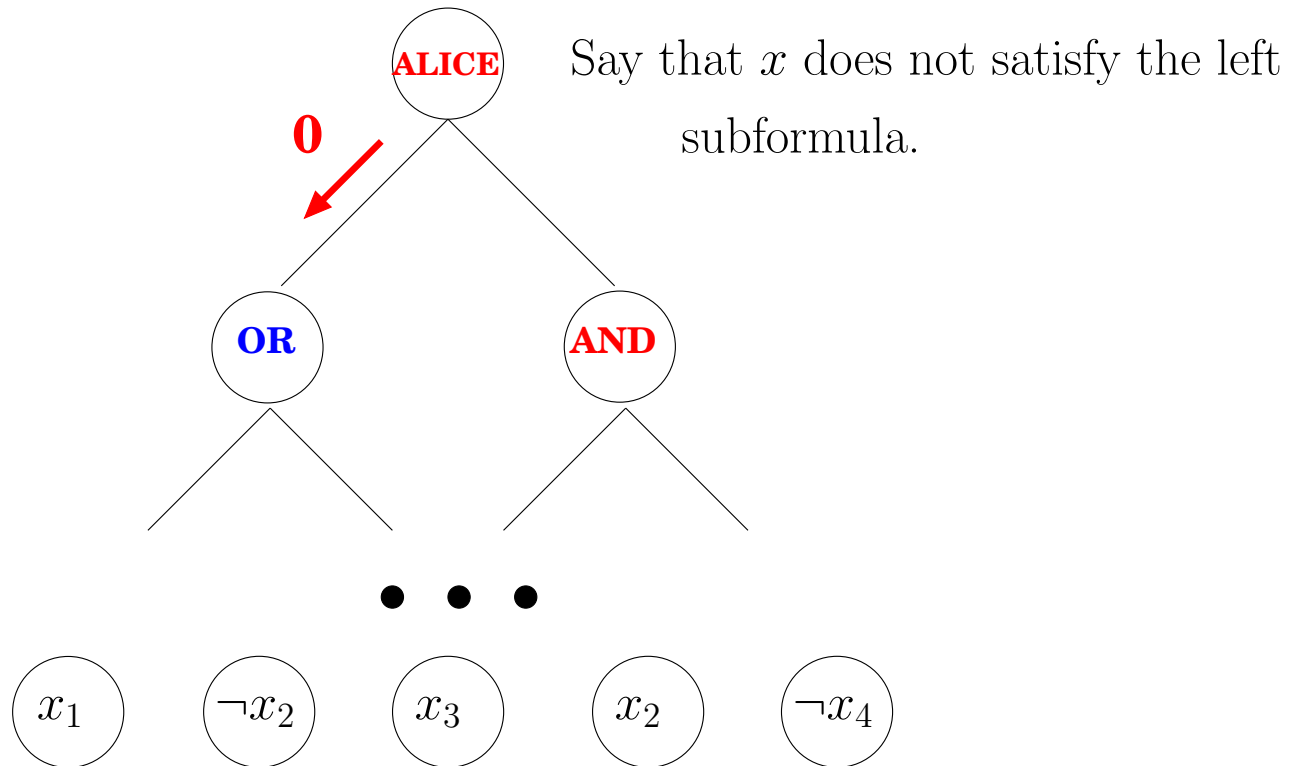
General idea: Alice speaks at AND nodes
and Bob speaks at OR nodes.

Initially, $f(x) \neq f(y)$ and we maintain this
disagreement on subformulas as we move
down the tree.

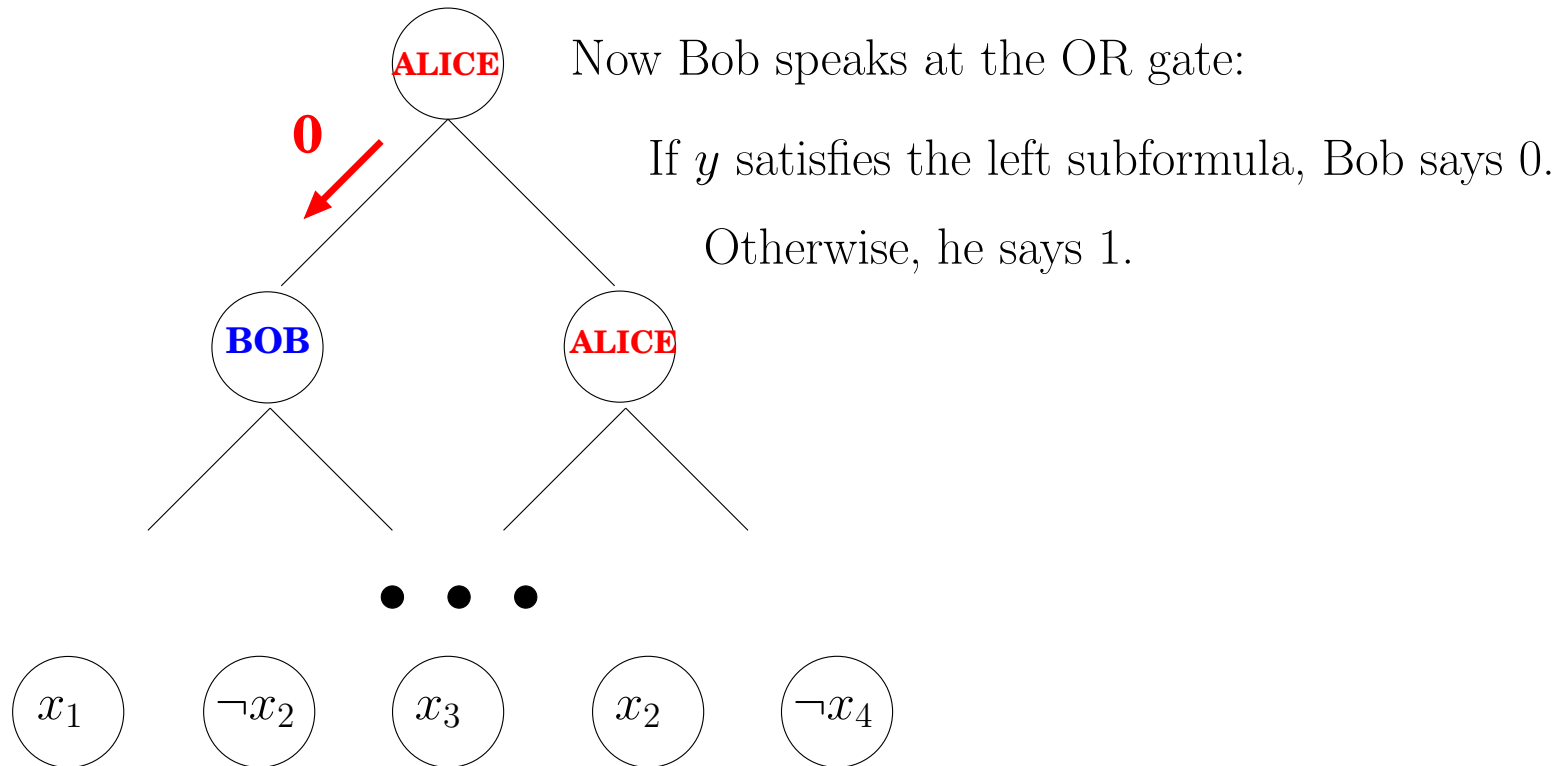
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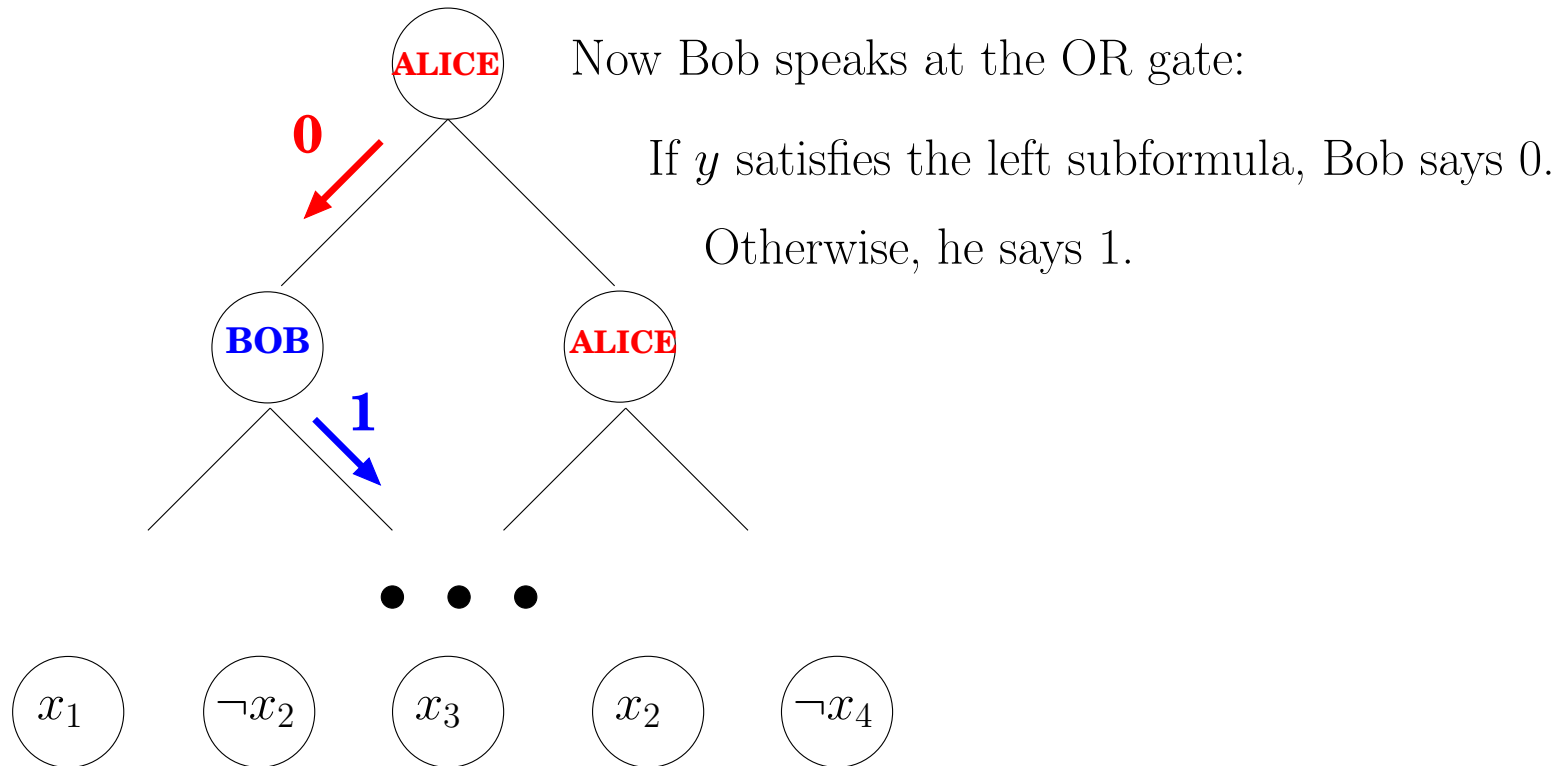
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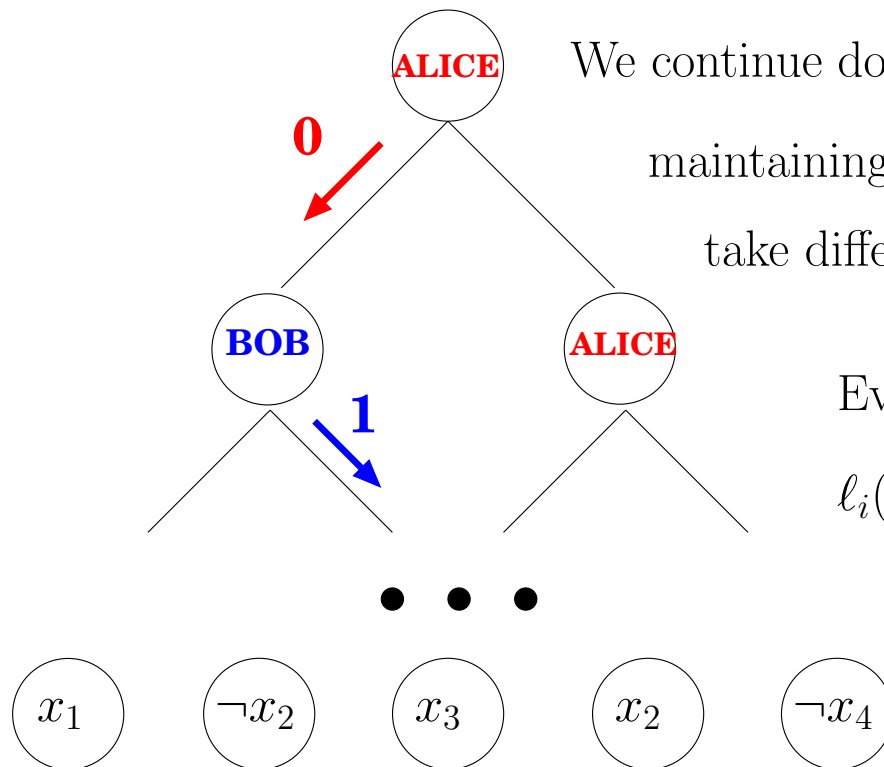
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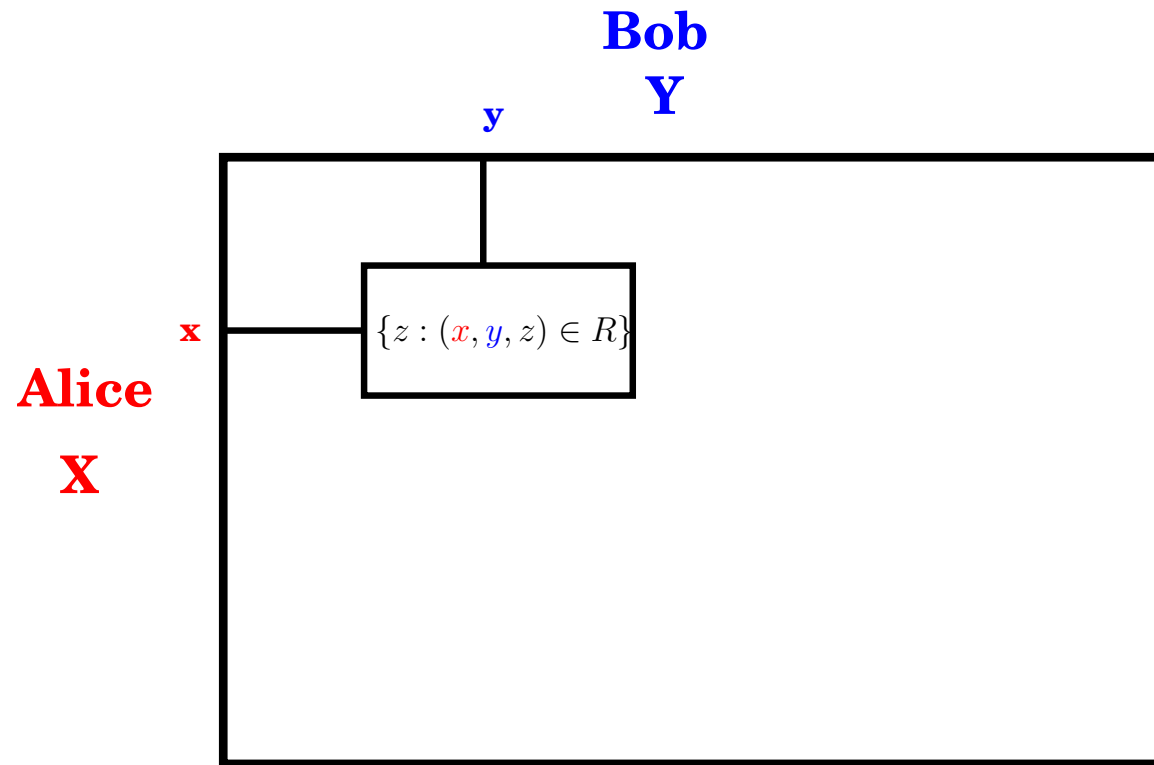


We continue down the tree in a similar fashion,
maintaining the property that x and y
take different values on subformulas.

Eventually, we reach a literal ℓ_i such that
 $\ell_i(x) \neq \ell_i(y)$ and so x and y differ on bit i .

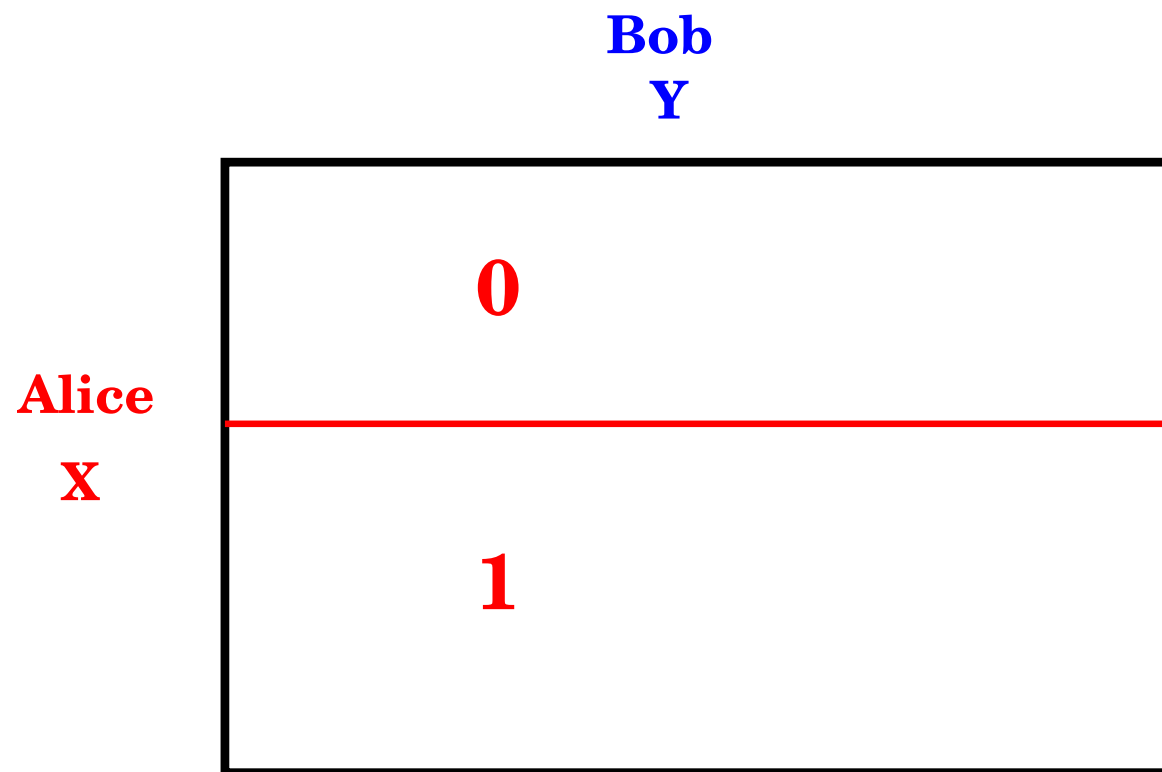
Communication Complexity and the Rectangle Bound

$$R \subseteq X \times Y \times Z$$



Communication Complexity and the Rectangle Bound

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Communication Complexity and the Rectangle Bound

$$R \subseteq X \times Y \times Z$$

		Bob Y	
Alice X	0	00	01
	1	11	10

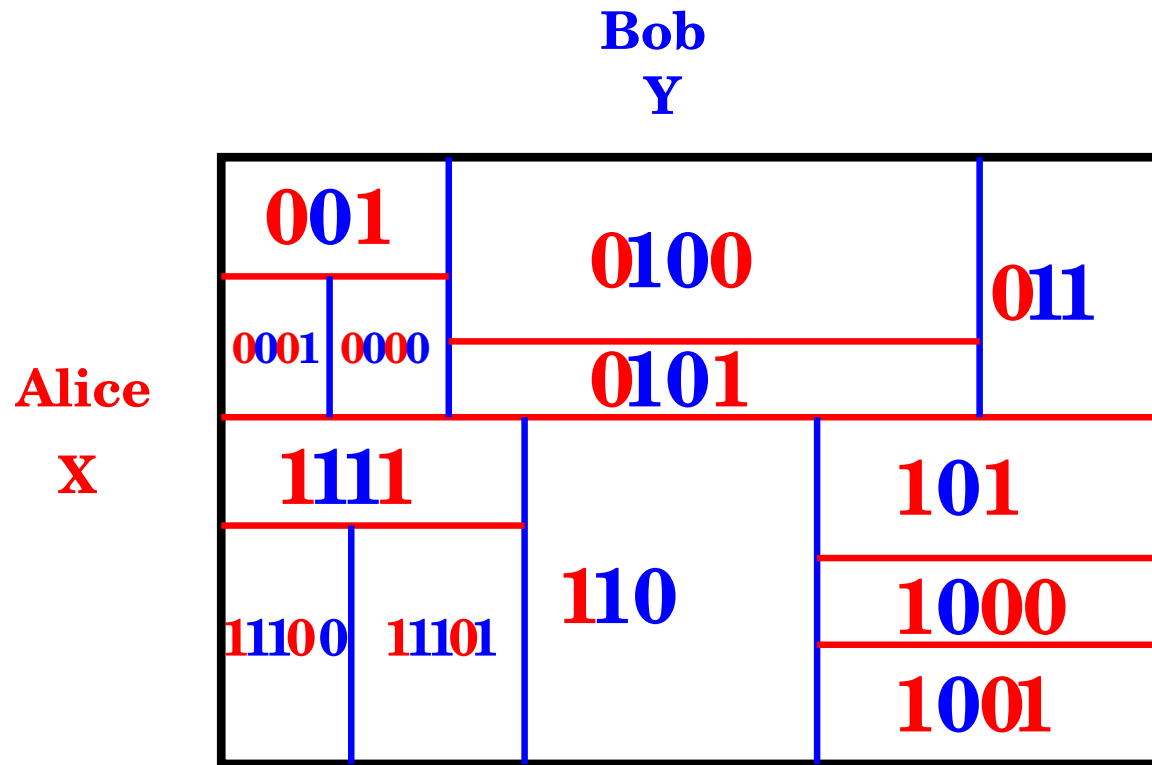
Communication Complexity and the Rectangle Bound

$$R \subseteq X \times Y \times Z$$

		Bob	
		Y	
Alice	X	001	010
		000	011
	111	110	101
			100

Communication Complexity and the Rectangle Bound

$$R \subseteq X \times Y \times Z$$



A rectangle S is monochromatic if there exists z such that $(x, y, z) \in S$ for all $(x, y) \in S$.

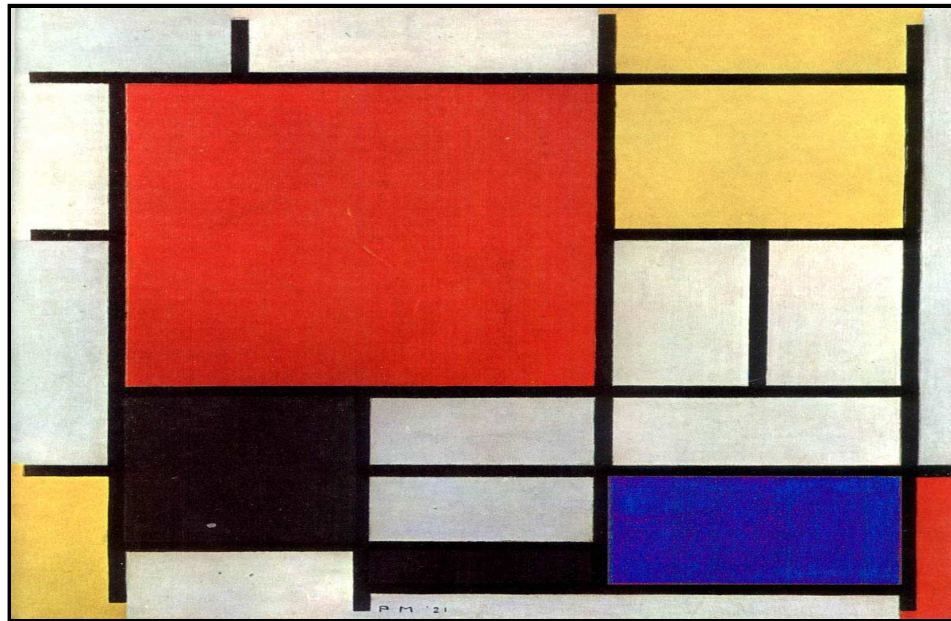
A successful protocol partitions $X \times Y$ into monochromatic rectangles.

Communication Complexity and the Rectangle Bound

$$R \subseteq X \times Y \times Z$$

Bob
Y

Alice
X



Rectangle Bound

- We denote by $C^D(R)$ the size of a smallest partition of $X \times Y$ into monochromatic (with respect to R) rectangles. By the argument above, $C^D(R) \leq C^P(R)$.
- The rectangle bound is a purely combinatorial quantity.
- We can still hope to prove larger lower bounds by focusing on the rectangle bound:

$$C^D(R) \leq C^P(R) \leq 2^{(\log C^D(R))^2}$$

- Major drawback—it is NP hard to compute.

Approximating the rectangle bound

- We will see that a measure on rectangles satisfying two properties, subadditivity and monotonicity, can be used to lower bound the rectangle bound.
- Several previous methods fit into this framework, including the rank method of Razborov [\[Raz90\]](#), and a probability on rectangles method (called B_* in Kushilevitz and Nisan).
- We add a new method within this framework based on the spectral norm.

An example: the rank method of Razborov

We know that $\text{rk}(A + B) \leq \text{rk}(A) + \text{rk}(B)$ for any two matrices A, B . Thus if \mathcal{R} is an optimal monochromatic rectangle partition of R_f , then

$$\max_A \frac{\text{rk}(A)}{\max_{R \in \mathcal{R}} \text{rk}(A_R)} \leq C^D(R_f) \leq L(f).$$

We want a method, however, that doesn't depend on knowing the optimal partition!

An example: the rank method of Razborov

We now use the monotonicity property. As the rectangles are monochromatic, each rectangle R is a subset of $D_i = \{(x, y) : x \in X, y \in Y, x_i \neq y_i\}$, for some $i \in [n]$. For this i we have $\text{rk}(A_R) \leq \text{rk}(A \circ D_i)$. Thus

$$\max_A \frac{\text{rk}(A)}{\max_i \text{rk}(A \circ D_i)} \leq C^D(R_f) \leq L(f).$$

Razborov uses this method to show superpolynomial *monotone* formula size lower bounds. He also shows, however, it is trivial for regular formula size [\[Raz92\]](#).

Our main lemma: spectral norm squared is subadditive

- Spectral norm has several equivalent formulations. We will use:

$$\|A\|_2 = \max_{u,v: \|u\|_2=\|v\|_2=1} |u^T A v|$$

- Main Lemma: Let A be a matrix over $X \times Y$ and \mathcal{R} be a partition of $X \times Y$ into rectangles. Then

$$\|A\|_2^2 \leq \sum_{R \in \mathcal{R}} \|A_R\|_2^2.$$

- Note that it is not true in general that $\|A + B\|_2^2 \leq \|A\|_2^2 + \|B\|_2^2$.

Proof of main lemma

Fix unit vectors u, v which maximize $|u^T A v|$. By definition,

$$\|A\|_2 = |u^T A v| = |u^T (\sum_{R \in \mathcal{R}} A_R) v|$$

Proof of main lemma

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$$\begin{aligned}\|A\|_2 &= |u^T A v| = |u^T (\sum_{R \in \mathcal{R}} A_R) v| \\ &\leq \sum_{R \in \mathcal{R}} |u^T A_R v|\end{aligned}$$

Proof of main lemma

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Proof of main lemma

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Proof of main lemma

Fix unit vectors u, v which maximize $|u^T A v|$. By definition,

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Applying the lemma

From the lemma it follows that if \mathcal{R} is an optimal rectangle partition of R_f , then

$$\max_A \frac{\|A\|_2^2}{\max_{R \in \mathcal{R}} \|A_R\|_2^2} \leq C^D(R_f).$$

We want a method, however, that doesn't depend on knowing the optimal partition!

Monotonicity

- the rectangles in \mathcal{R} are monochromatic, thus each rectangle is a subset of $D_i = \{(x, y) : x \in X, y \in Y, x_i \neq y_i\}$, for some $i \in [n]$.
- If A is nonnegative, then $\|A_R\|_2 \leq \|A \circ D_i\|_2$
- Thus we obtain

$$\max_A \frac{\|A\|_2^2}{\max_i \|A \circ D_i\|_2^2} \leq C^D(R_f) \leq L(f).$$

- We now have a bound which can be computed in time polynomial in the truth table of f

The quantum adversary method emerges

Define

$$\text{sumPI}(f) = \max_A \frac{\|A\|_2}{\max_i \|A_i \circ D_i\|_2}$$

- We have shown that $\text{sumPI}^2(f) \leq C^D(R_f) \leq L(f)$
- It turns out that $\text{sumPI}(f)$ is a lower bound on the quantum query complexity of f ! [BSS03]
- The quantity $\text{sumPI}(f)$ has emerged over several years [Amb02, Amb03, BSS03, LM04] in the context of quantum query complexity, and has many nice properties and equivalent formulations [Š05].

More on the quantum adversary method

- The name sumPI comes from the following equivalent min max formulation

$$\text{sumPI}(f) = \min_p \max_{x \in X, y \in Y} \frac{1}{\sum_{i: x_i \neq y_i} \sqrt{p_x(i) p_y(i)}}$$

- Using both the max min and min max formulations appropriately makes it easy to give exact characterizations of $\text{sumPI}(f)$.
- For example, one can show $\text{sumPI}(f)$ behaves very well under composition: $\text{sumPI}(f^k) = (\text{sumPI}(f))^k$ for any Boolean function f [\[Amb03, LLS05\]](#).

Khrapchenko's Method

- Define a bipartite graph, with left hand side a subset of $f^{-1}(0)$ and right hand side $f^{-1}(1)$.
- Connect x, y with an edge if they have Hamming distance 1
- Khrapchenko's bound is the product of the average degree of the left hand side with the average degree on the right hand side.

Generalizing Khrapchenko's Method

$$\max_{p_0, p_1, q} \min_{x, y} \frac{p_0(x)p_1(y)}{q^2(x, y)} \leq C^D(R_f) \leq L(f)$$

- Define the matrix $A[x, y] = q(x, y) / \sqrt{p_0(x)p_1(y)}$.
- Then $\|A\|_2 \geq 1$.
- Each matrix $A \circ D_i$ has at most one entry in each row and column.
- Thus $\|A \circ D_i\|_2 \leq \max_{x, y} q(x, y) / \sqrt{p_0(x)p_1(y)}$.

Open problems

- Is quantum query complexity squared a lower bound on formula size?
- How about approximate polynomial degree?
- Are the rectangle bound and formula size polynomially related?
- How large is the rectangle bound for a random function?