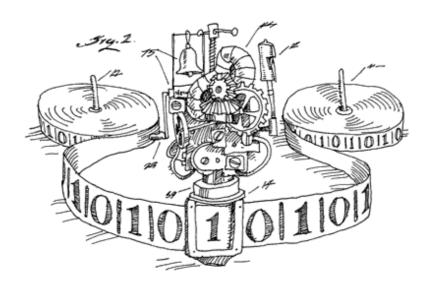
SHANNON MEETS TURING

Pei Wu

April. 2023

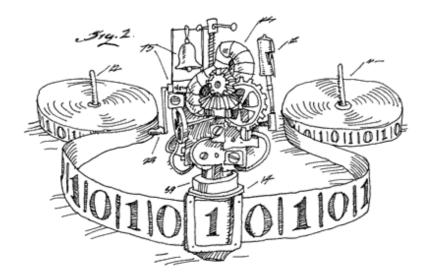


A.Turing





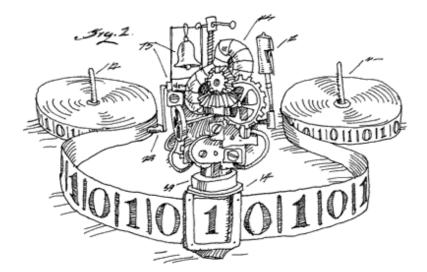




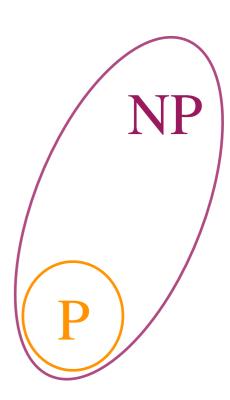
deterministic polynomial-time non-determinism



A.Turing

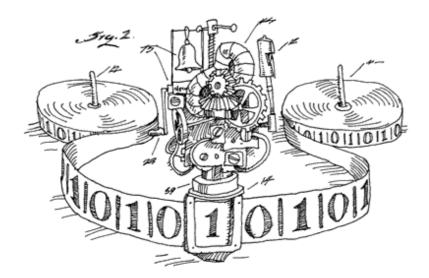


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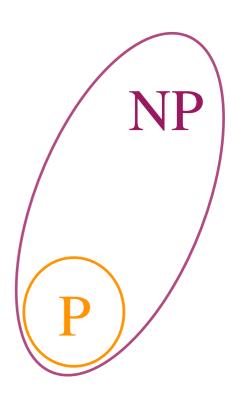






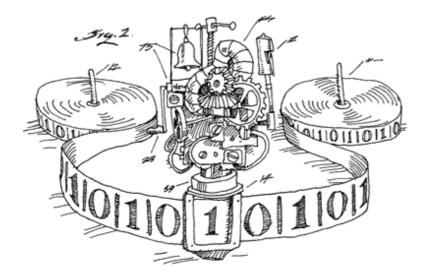


deterministic polynomial-time non-determinism randomness

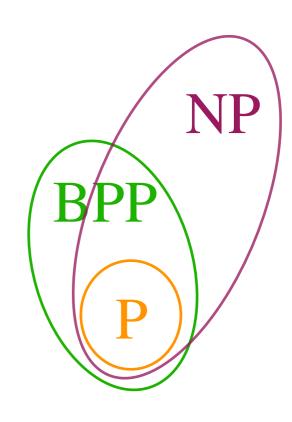




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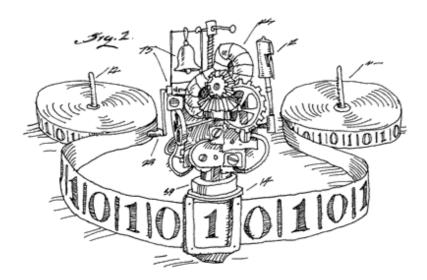


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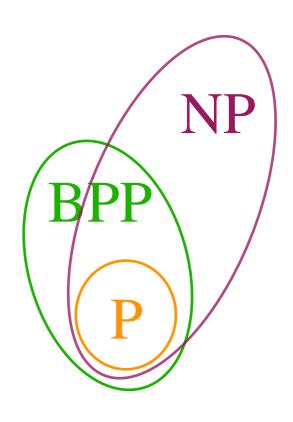




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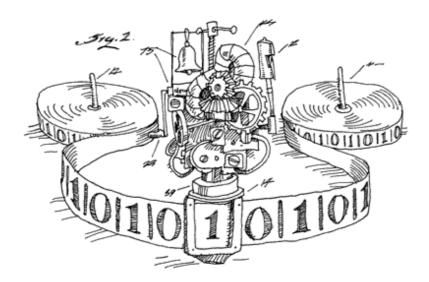


deterministic polynomial-time non-determinism randomness quantum

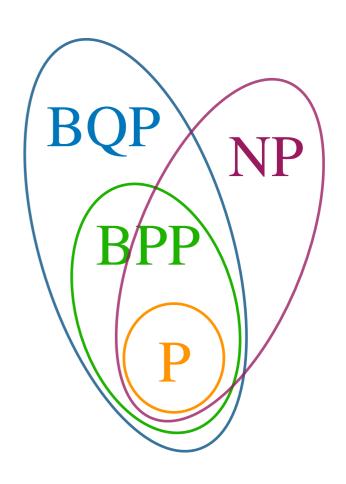




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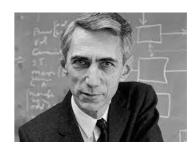


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Theory of Communication (one-way)

Reprinted with corrections from *The Bell System Technical Journal*, Vol. 27, pp. 379–423, 623–656, July, October, 1948.



A Mathematical Theory of Communication

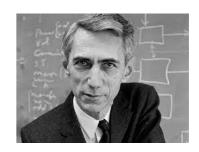
By C. E. SHANNON

INTRODUCTION

THE recent development of various methods of modulation such as PCM and PPM which exchange bandwidth for signal-to-noise ratio has intensified the interest in a general theory of communication. A

Theory of Communication (one-way)

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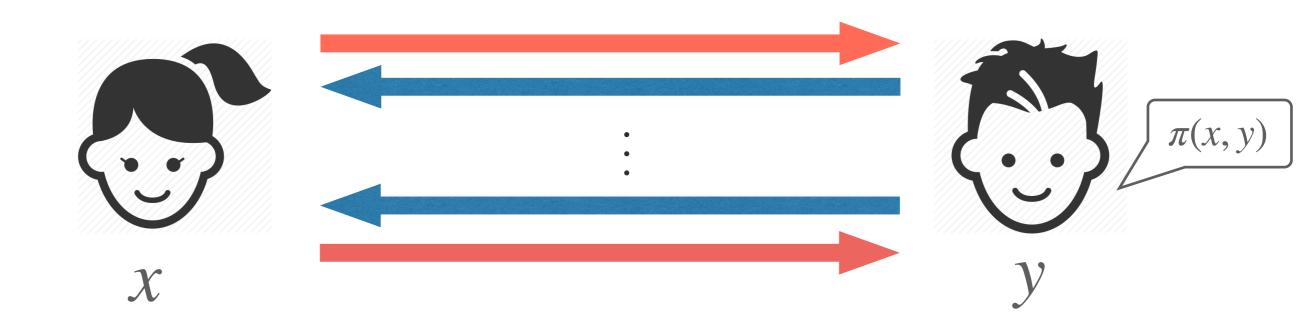
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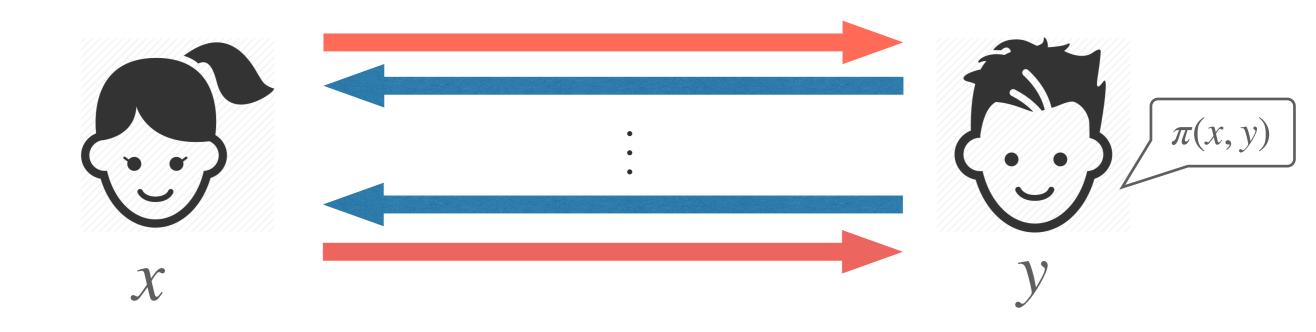






A. Yao '79

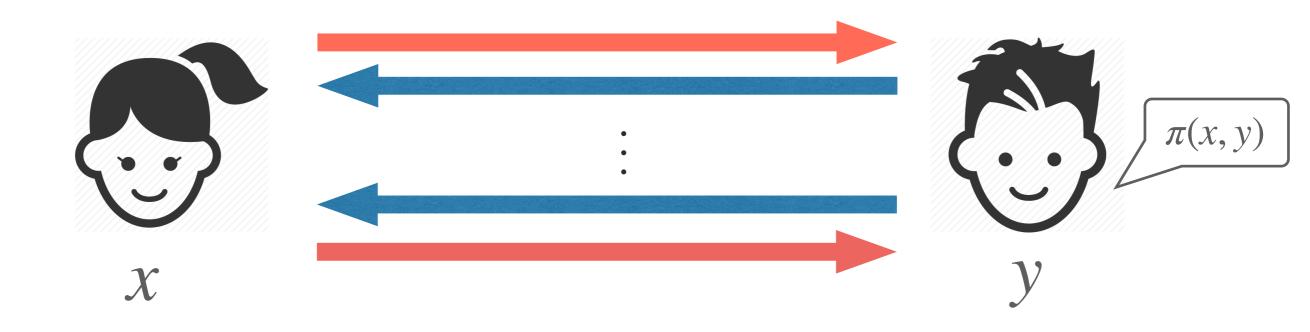
 $f: \{0,1\}^n \times \{0,1\}^n \to \{0,1\}$





A. Yao '79

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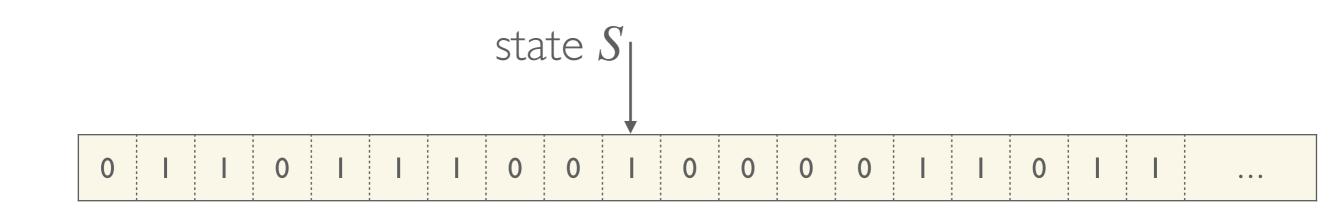


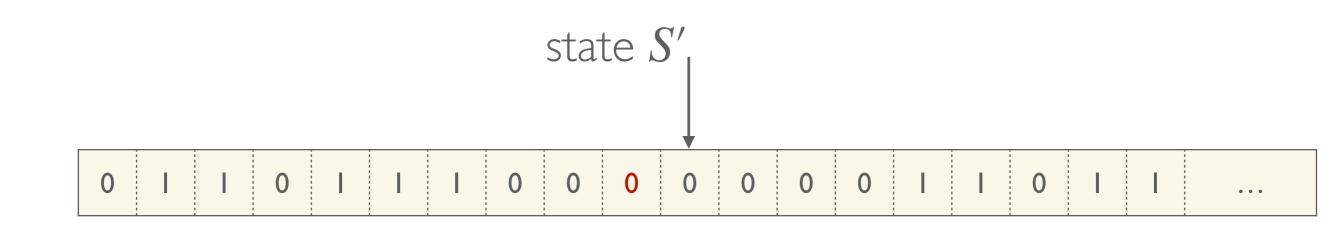
A trivial, O(n)-communication solution

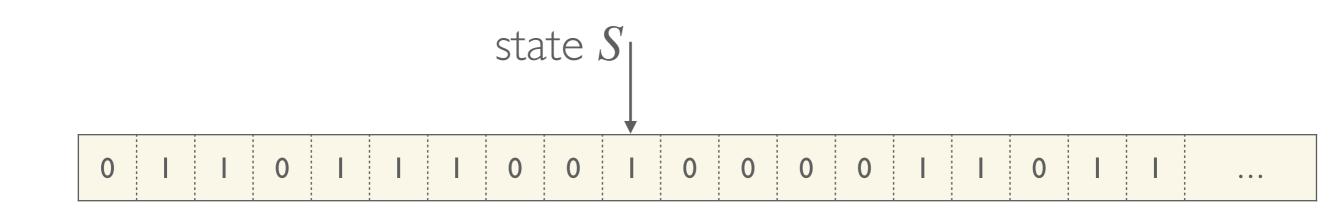
Central in cs:

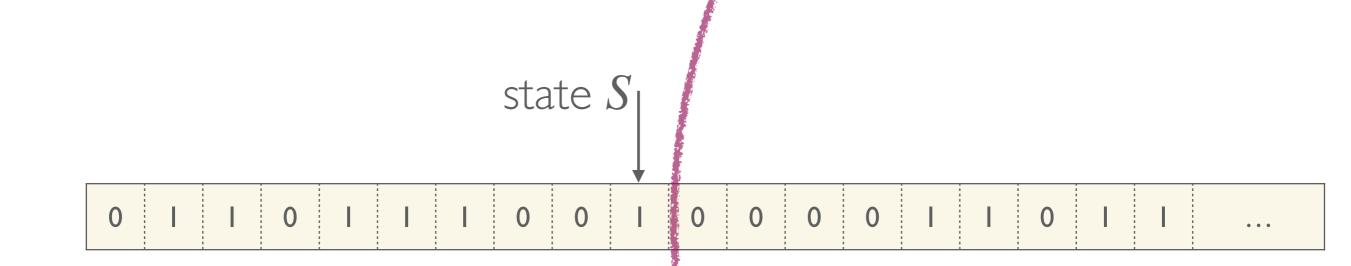
circuits complexity,
streaming algorithm,
learning theory,
differential privacy,
computational economics

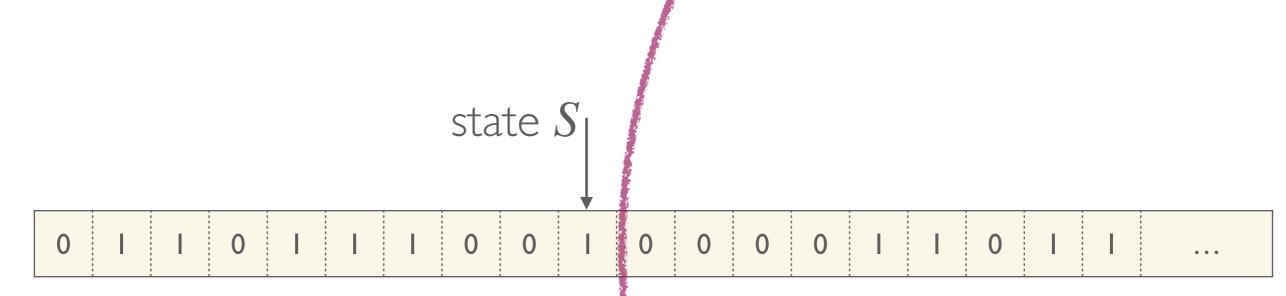
. . .





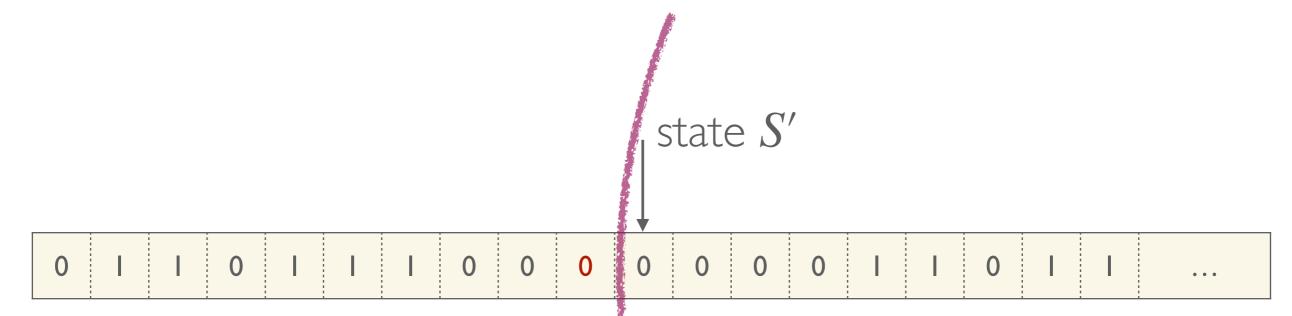






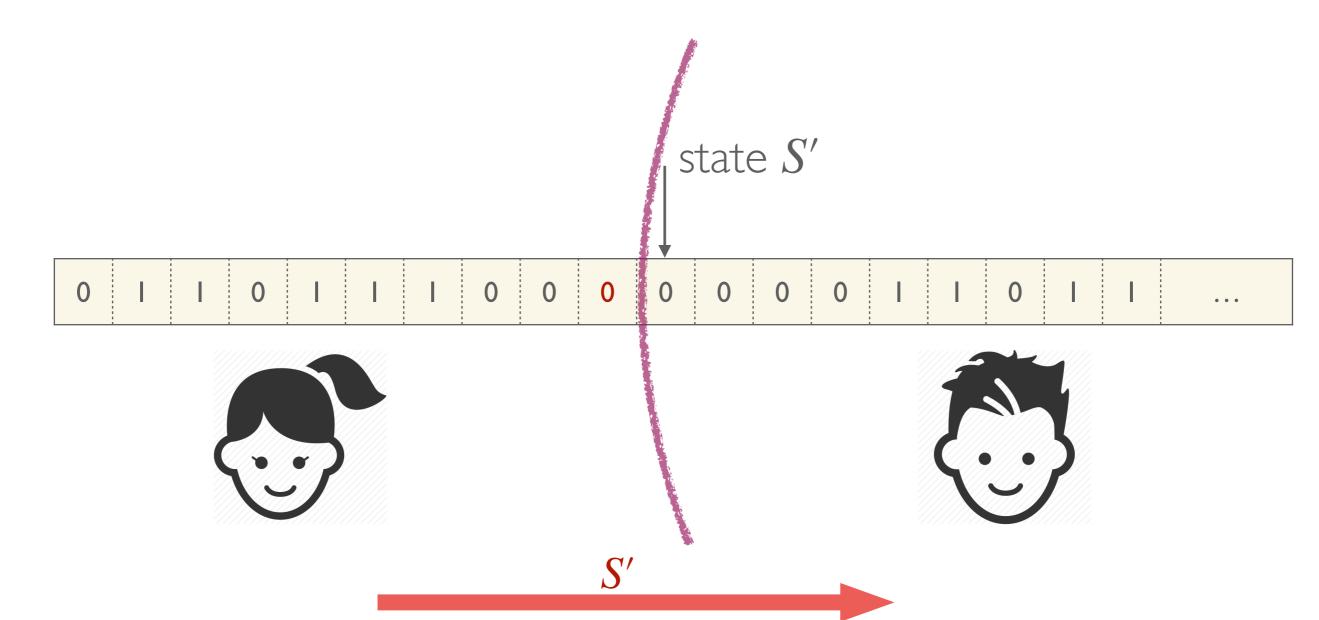


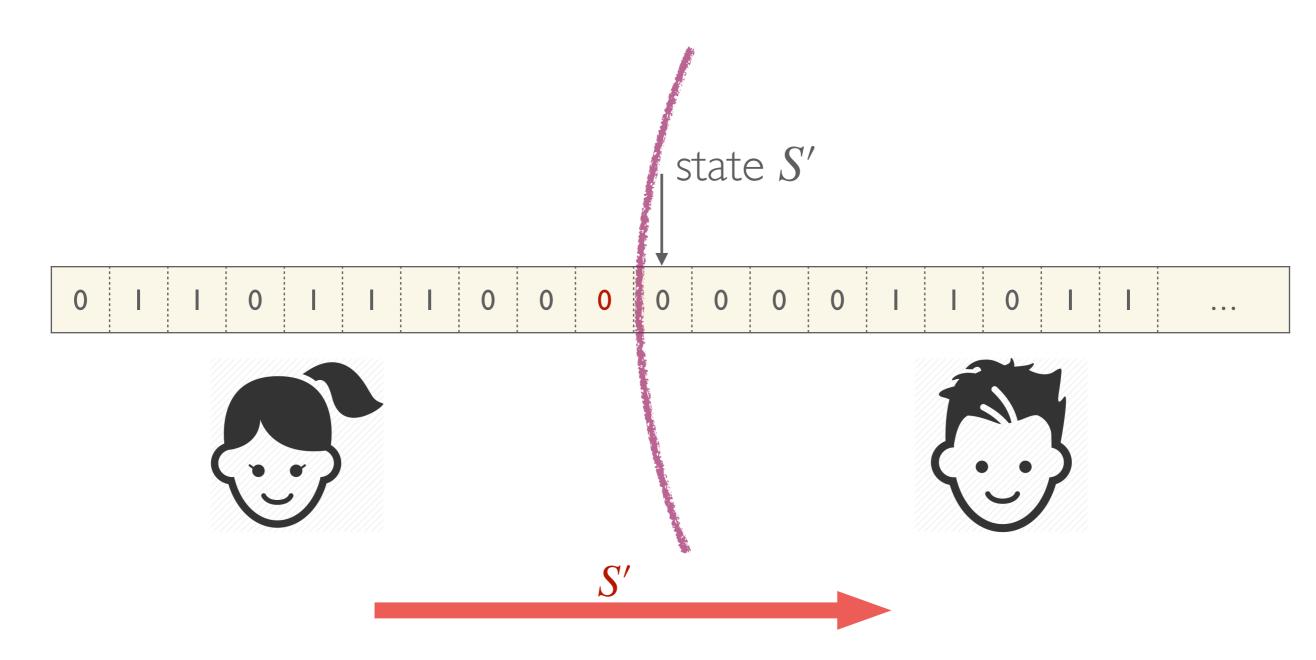












communication ≈ running time

Communication Complexity

[Babai-Frankl-Simon '86]

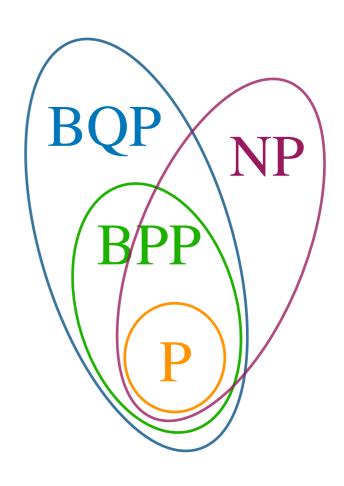
P: deterministic communication

NP: non-deterministic communication

BPP: randomized communication (bounded-error)

BQP: quantum communication

PP: randomized communication (unbounded-error)



Communication Complexity

[Babai-Frankl-Simon '86]

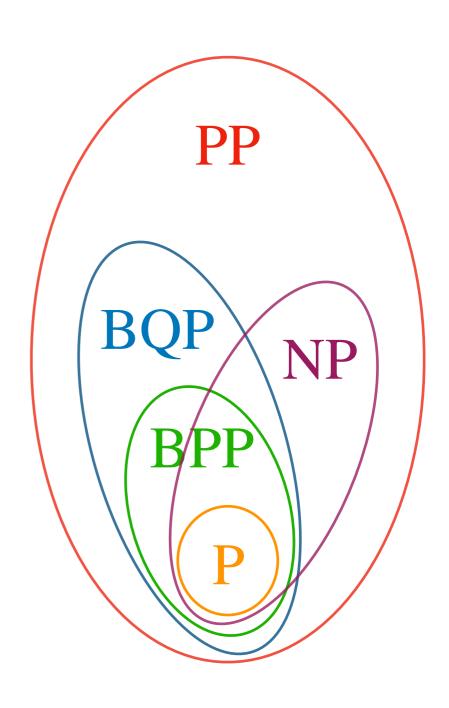
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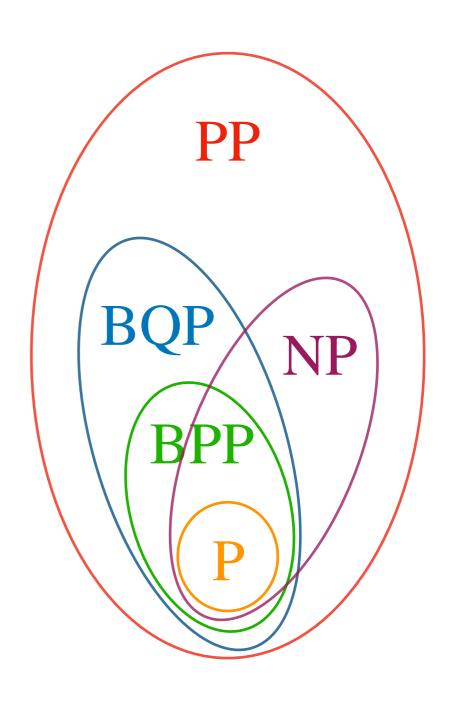
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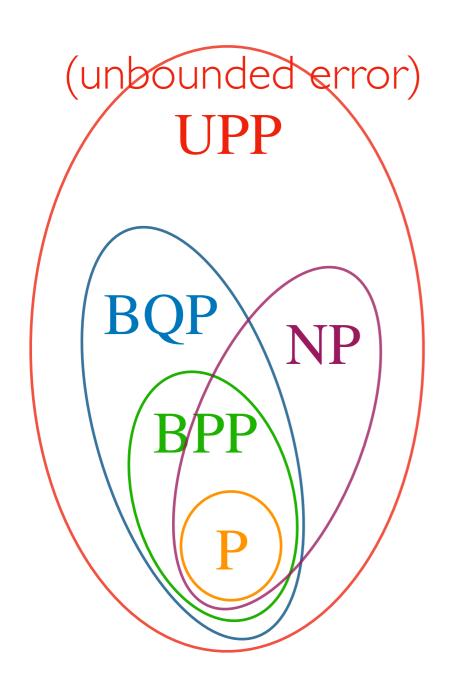
BPP: randomized communication (bounded-error)

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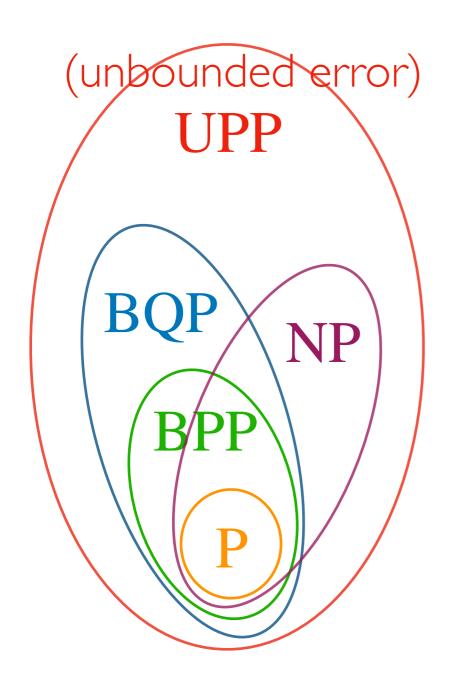
[Babai-Frankl-Simon '86]



In communication world,

 $P \subsetneq BPP \subseteq BQP \subsetneq UPP$, $P \subsetneq NP \subsetneq UPP$.

[Babai-Frankl-Simon '86]



In communication world, $P \subsetneq BPP \subseteq BQP \subsetneq UPP$, $P \subsetneq NP \subsetneq UPP$.

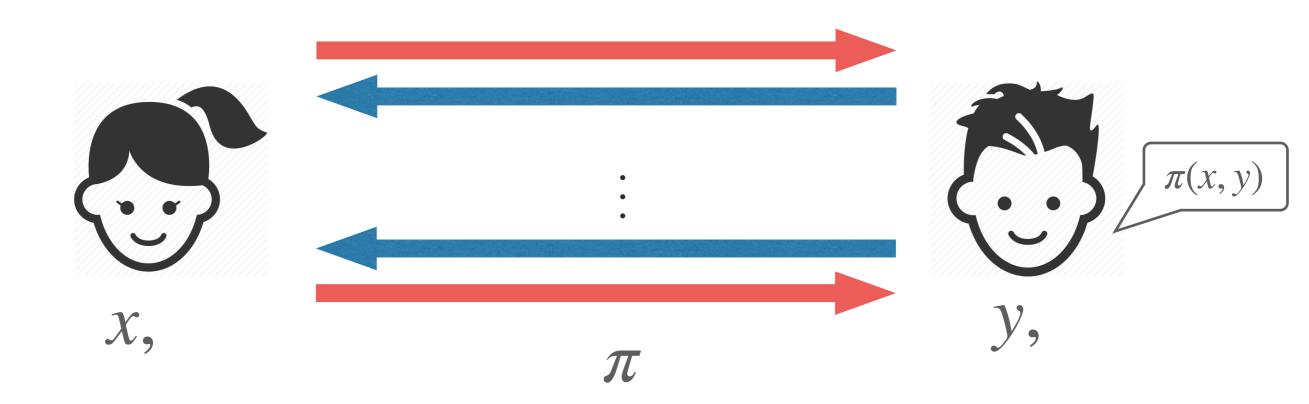
Roadmap

- Unbounded-error communication
- BQP vs. BPP communication

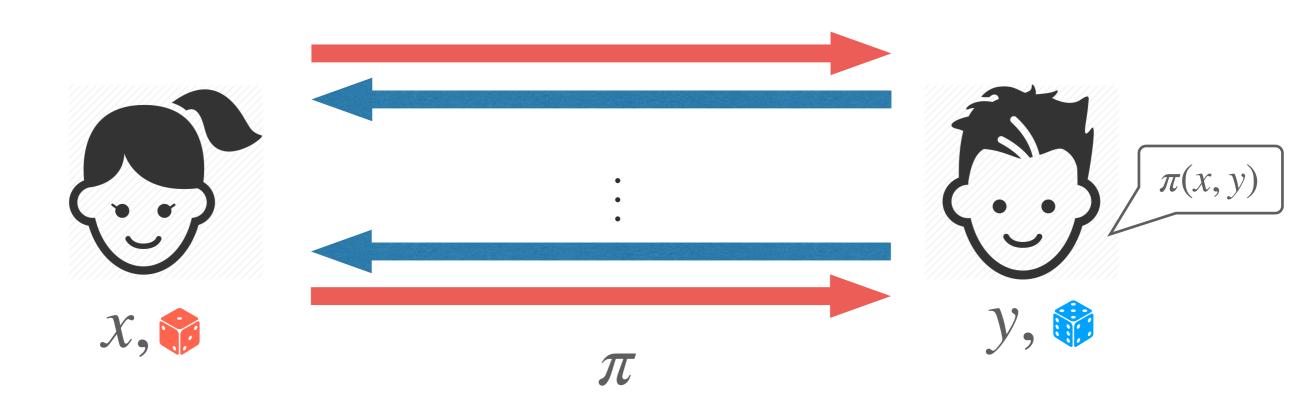
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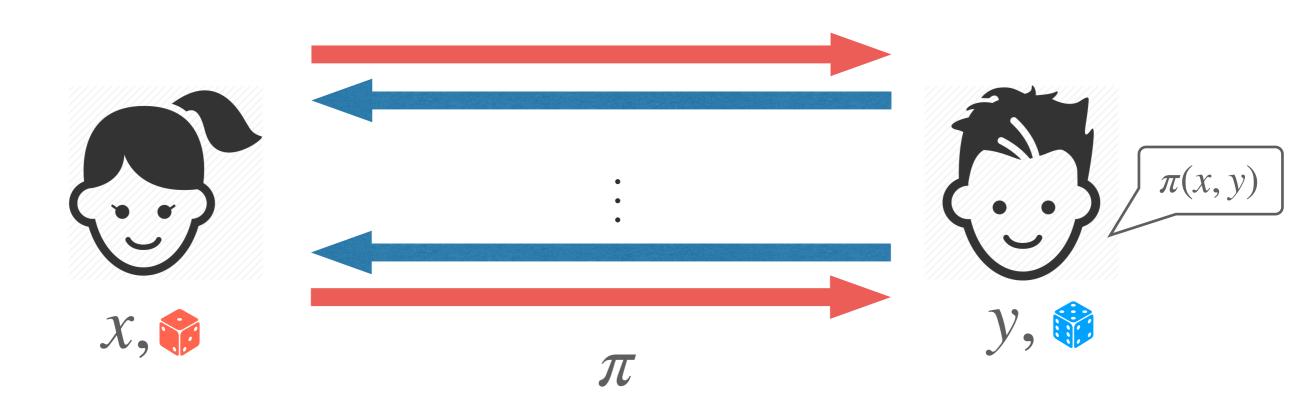
$$f: X \times Y \rightarrow \{0,1\}$$



$$f: X \times Y \to \{0,1\}$$

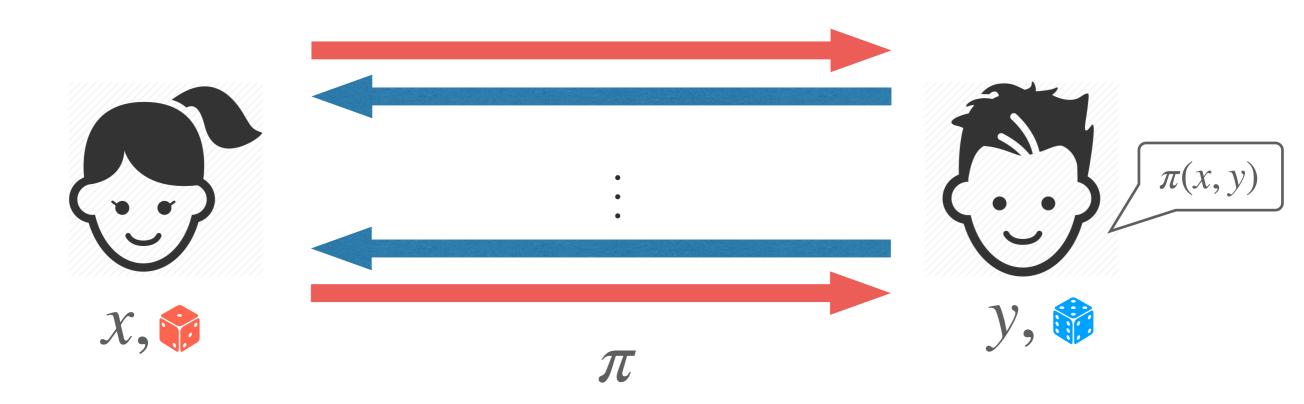


$$f: X \times Y \rightarrow \{0,1\}$$



Correctness:
$$\Pr[\pi(x, y) = f(x, y)] > \frac{1}{2}, \forall x, y$$
.

$$f: X \times Y \rightarrow \{0,1\}$$

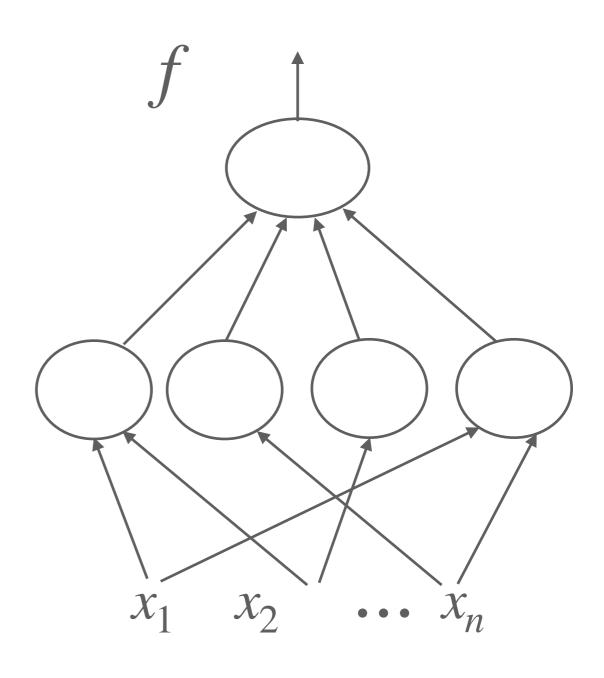


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Barely larger than guess

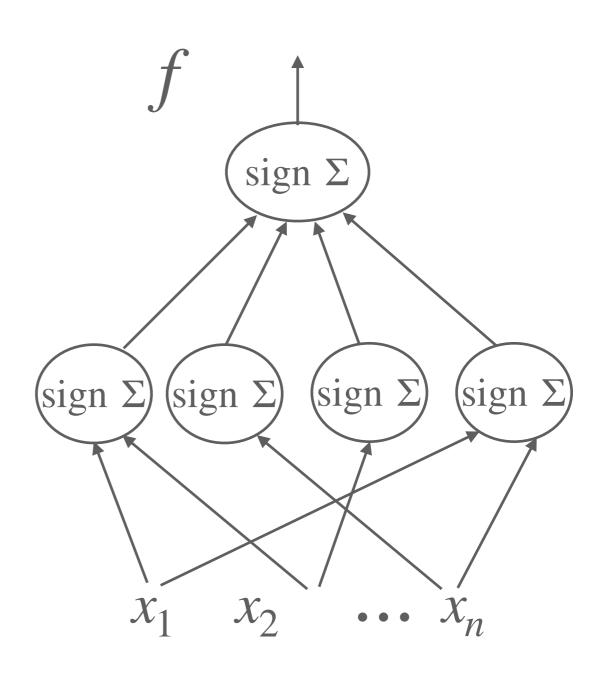
 $f: \{0,1\}^n \to \{0,1\}$

A simple neural network

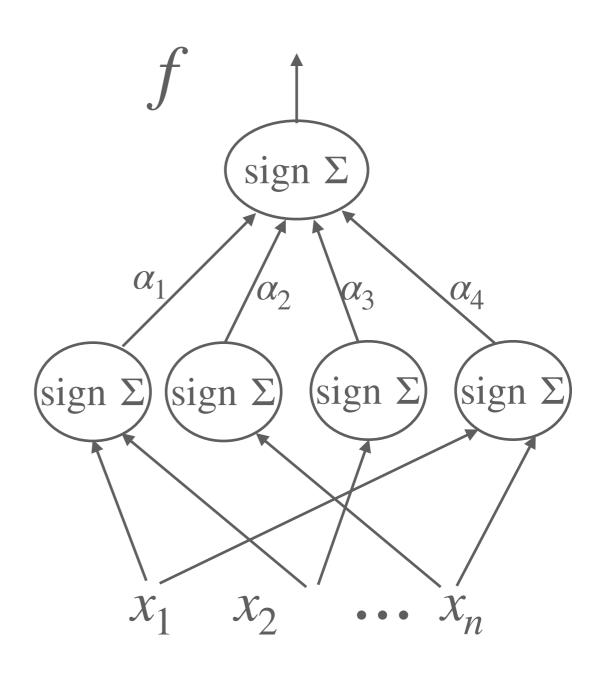


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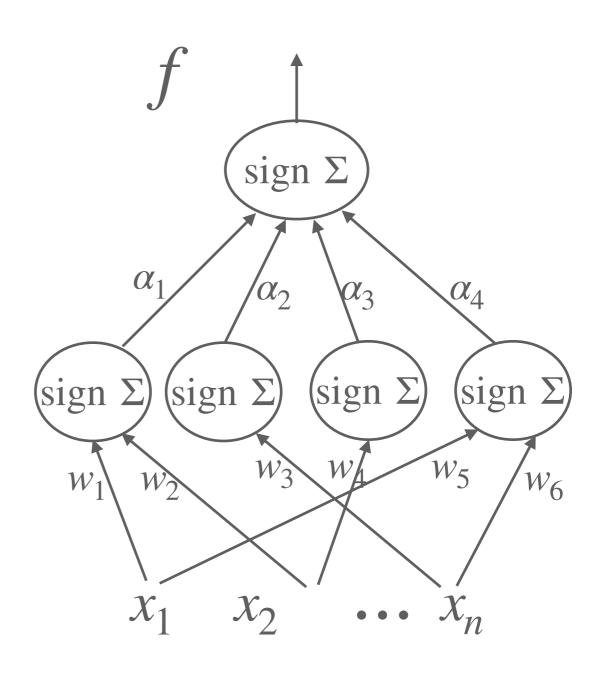
A simple neural network



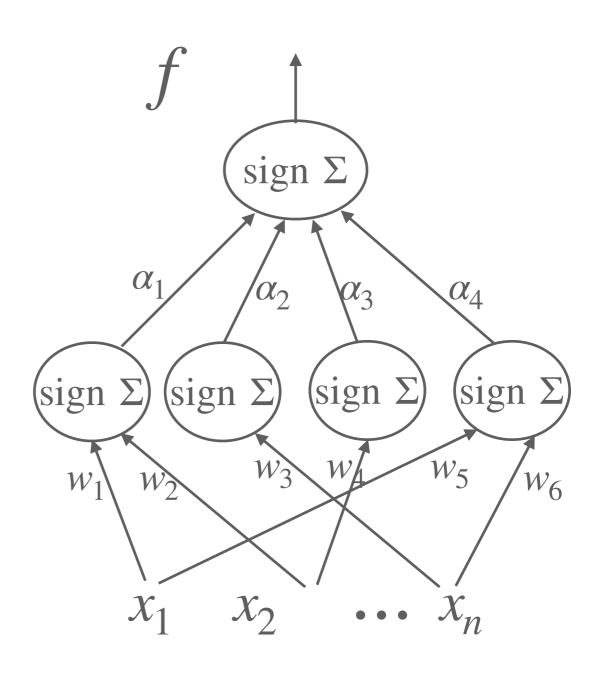
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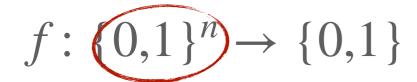


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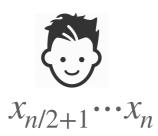


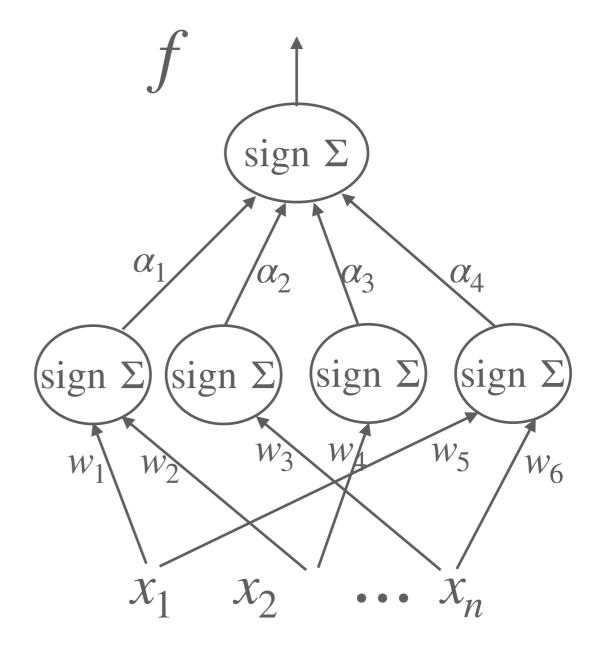
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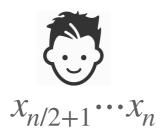






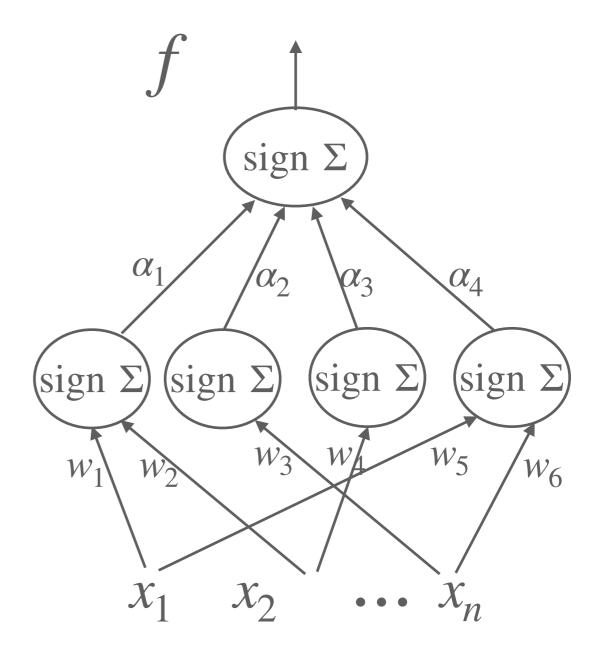
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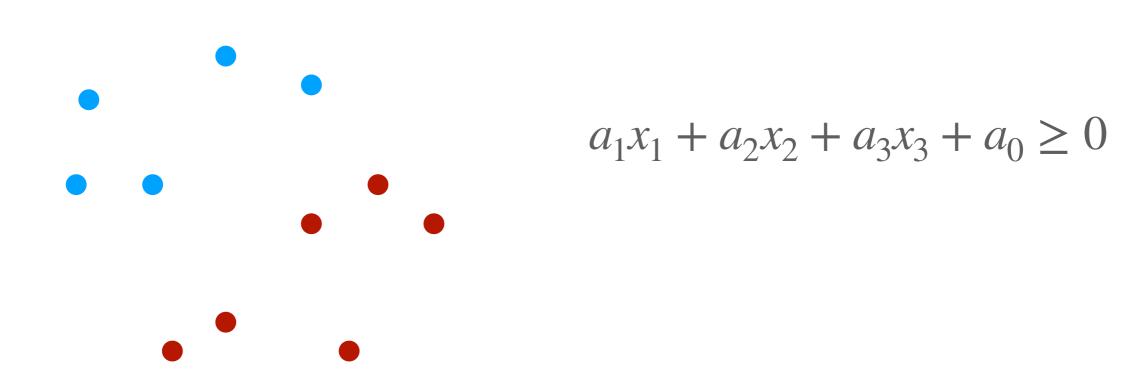


Theorem * (Forster et al. '01).

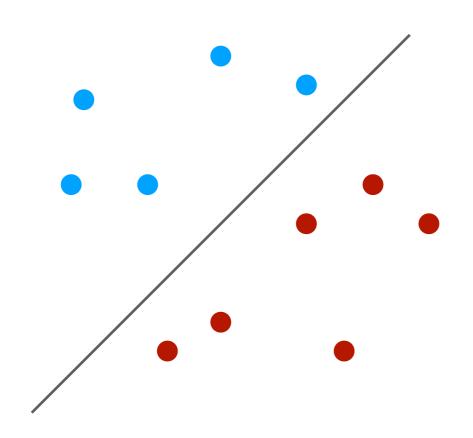
$$size(f) \gtrsim 2^{\Omega(U(f))}$$



Learn halfspaces

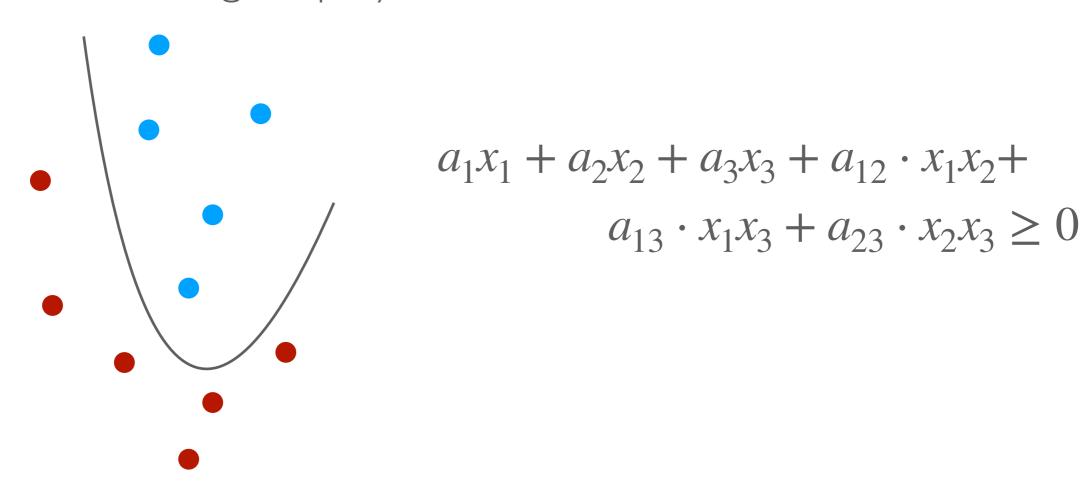


Learn halfspaces

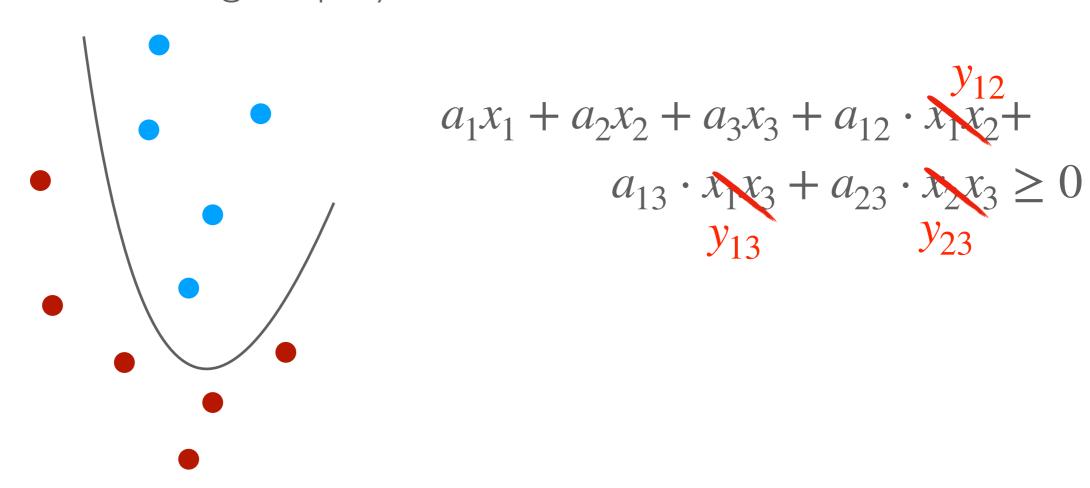


$$a_1x_1 + a_2x_2 + a_3x_3 + a_0 \ge 0$$

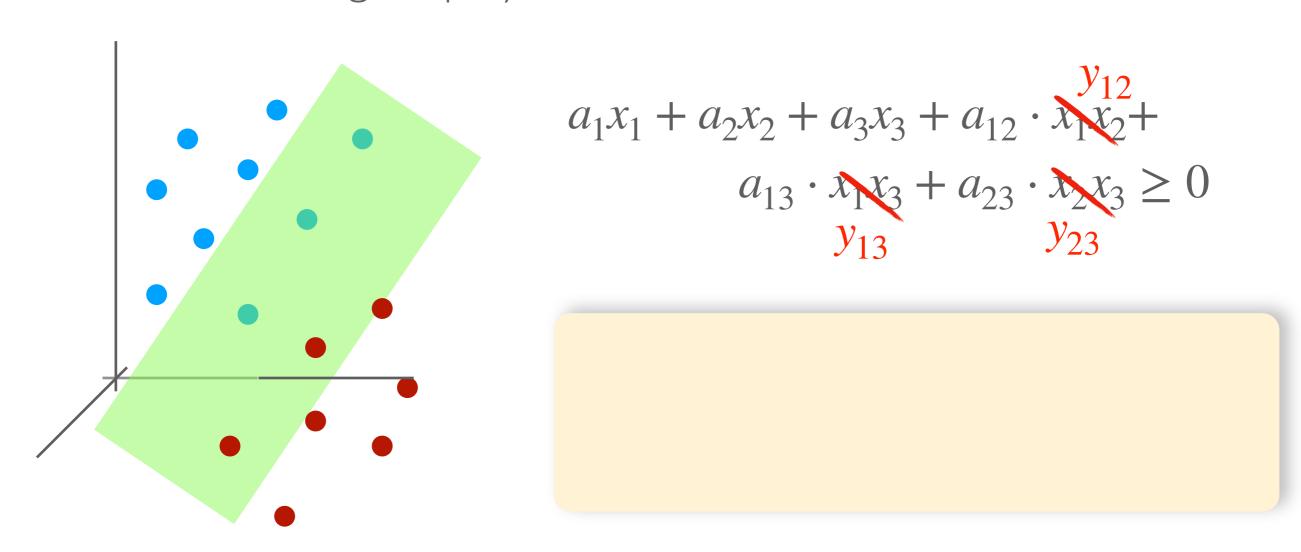
Learn low degree polynomials



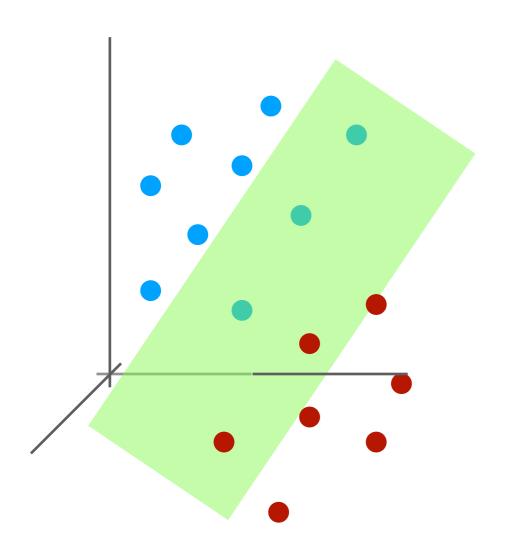
Learn low degree polynomials



Learn low degree polynomials



Learn low degree polynomials

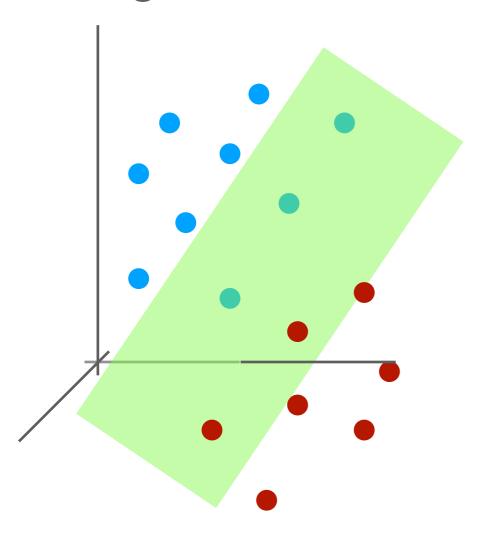


$$a_{1}x_{1} + a_{2}x_{2} + a_{3}x_{3} + a_{12} \cdot x_{1}x_{2} + a_{13} \cdot x_{1}x_{3} + a_{23} \cdot x_{2}x_{3} \ge 0$$

$$y_{13} \qquad y_{23}$$

Def.
$$f: \{0,1\}^n \to \{0,1\},$$
 $\deg_{\pm}(f)$: min degree of a separating curve

Embedding into spaces with larger dimension



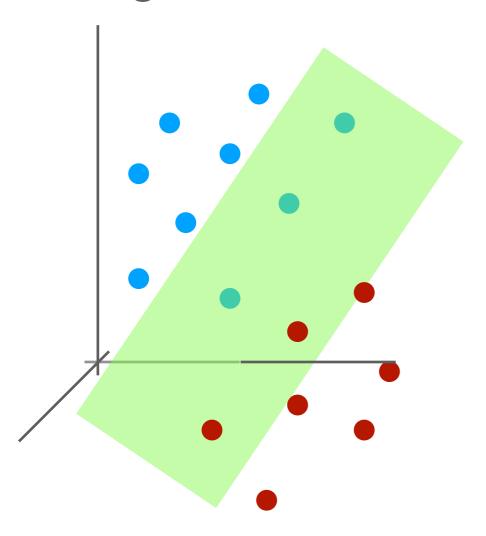
Dimension complexity

& concept class,

dc(&) minimum dimension

for such embedding

Embedding into spaces with larger dimension



Dimension complexity

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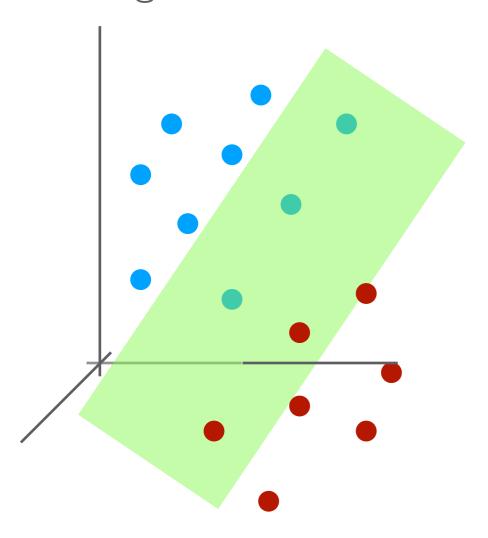
dc(&) minimum dimension

for such embedding

Surprisingly powerful!

Captures many results in PAC learning model.

Embedding into spaces with larger dimension



Dimension complexity

& concept class,

dc(&) minimum dimension

for such embedding

Fact (folklore).

$$\label{eq:dcap} \begin{split} \operatorname{dc}(\mathscr{C}) &= 2^{\Theta(U(M_{\mathscr{C}}))},\\ \text{where } M_{\mathscr{C}}(f,x) &= f(x) \;. \end{split}$$

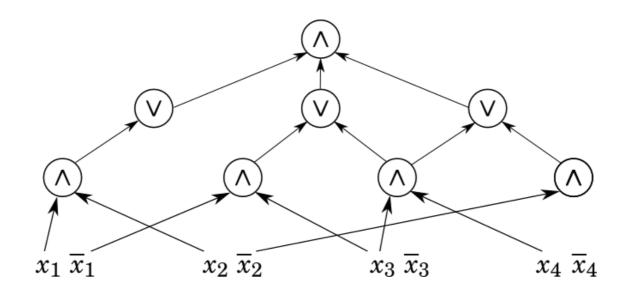


Theorem (Sherstov-W. 19)

$$U(AC^0) \ge \Omega(n^{1-\epsilon})$$
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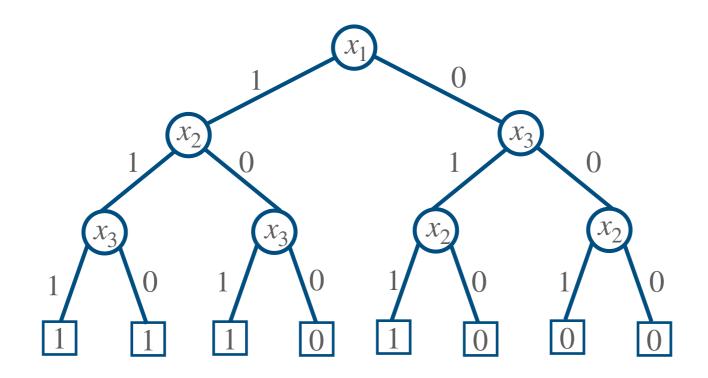
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 AC^0 : constant depth, polynomial #gates (Λ , V, \neg)

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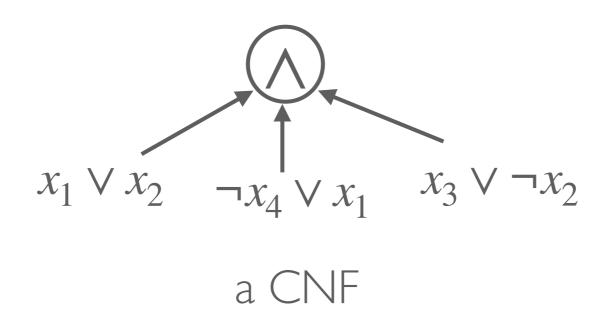
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.



a decision tree

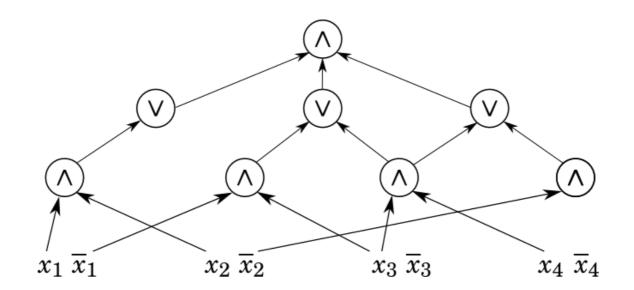
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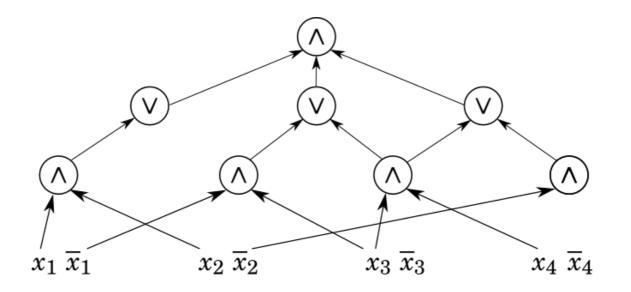


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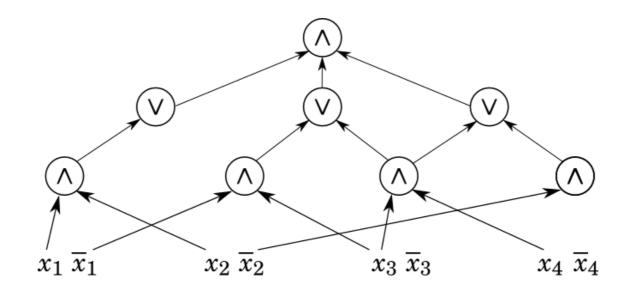


 AC^0 : constant depth, polynomial #gates (Λ , V, \neg)



Circuits
lower bound
"P vs NP"

[FSS84, Ajt83, Yao85, Has86, Aar10, RS10, LV11, BIL12, IMP12, Has14, AA15, LRR17, Ros18, Vio18]

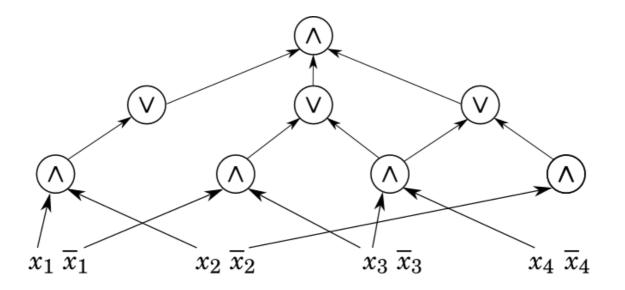


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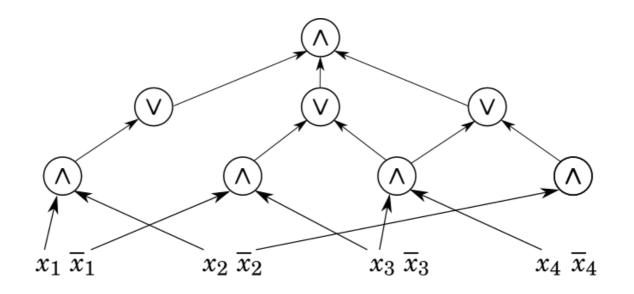
"P vs BPP"

[LN90, Nis91, Baz07, Raz08, Bra09, ETT10, GMR13, TX13, Tal14, CSV15, HS16, Tal17, ST18, DHH18, Lyu22]



Quantum supremacy?

[AS04, Amb07, ACR+10, BM10, Rei10, Bel12, BS13, RT19]



Quantum supremacy?

[AS04, Amb07, ACR+10, BM10, Rei10, Bel12, BS13, RT19]

Learning

[LMN93, Jac02, BES03, OS03, KOS04, KS04, LMSS07, AMY I 6, DRG I 7, AGS20]

.

Theorem (Sherstov-W. 19).

$$\deg_{\pm}(AC^0) = \Omega(n^{1-\epsilon})$$
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Theorem (Sherstov-W. 19).

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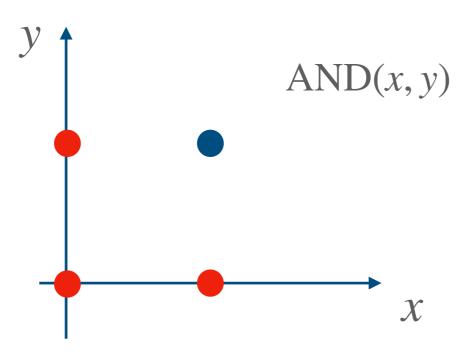
Definition.

 $\deg_{\pm}(f) = \min\{\deg p : p(x) \cdot (-1)^{f(x)} > 0, \ \forall x \in X\}.$

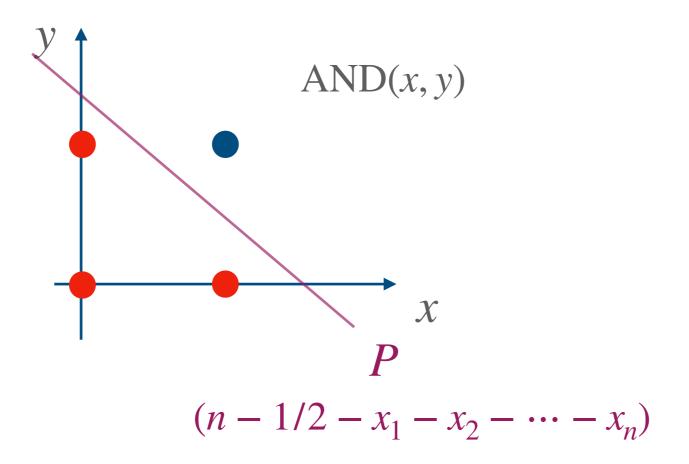
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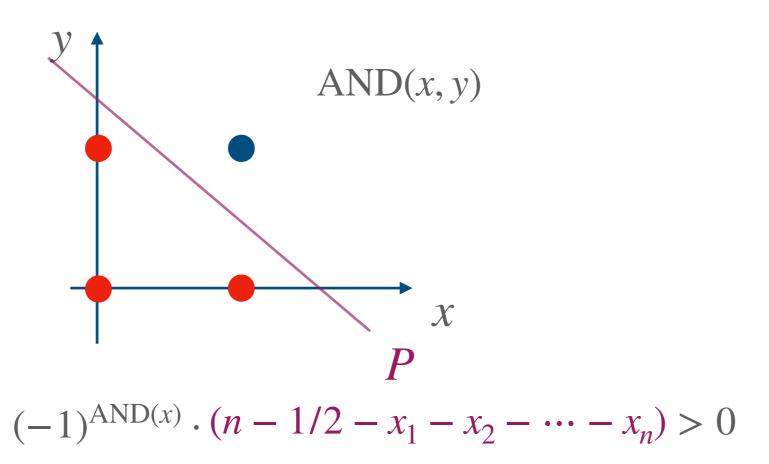
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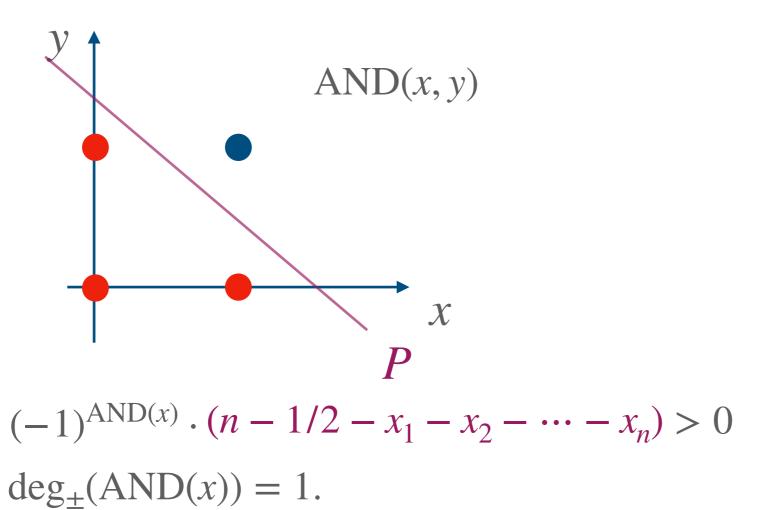
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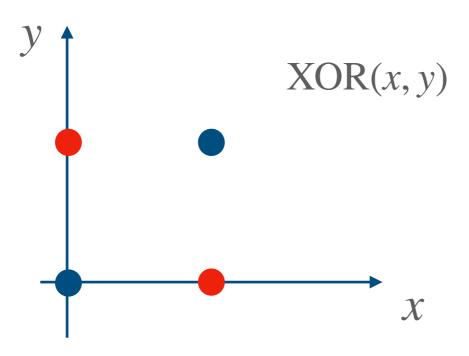
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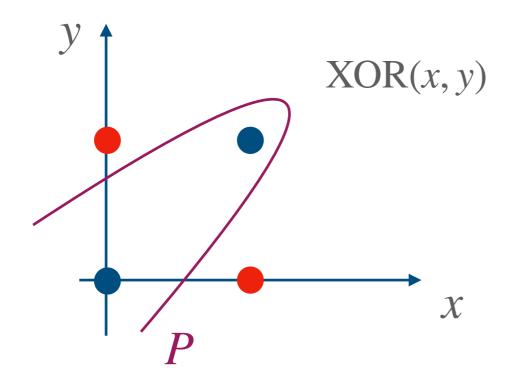
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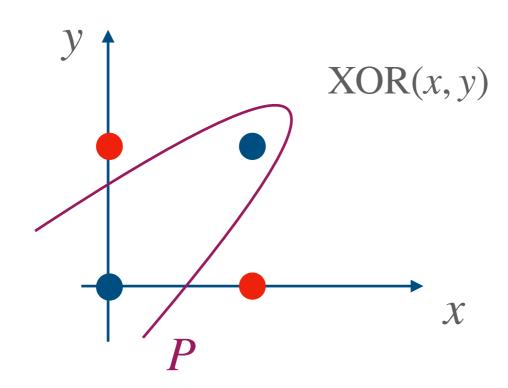
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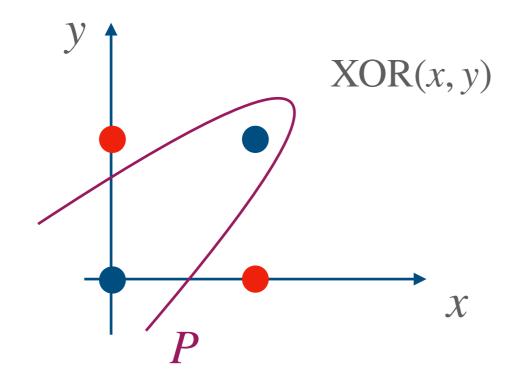
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$$\deg_{\pm}(XOR(x)) = n.$$

Definition.

 $\deg_{\pm}(f) = \min\{\deg p : p(x) \cdot (-1)^{f(x)} > 0, \ \forall x \in X\}.$



Prob. Minsky-Papert 69

Max threshold degree of AC^0 ?

$$\deg_{\pm}(XOR(x)) = n.$$

Theorem (Sherstov-W. 19).

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Theorem (Sherstov-W. 19).

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reference	threshold degree	depth
Minsky-Papert 69	$\Omega(n^{1/3})$	2
O'Donnell-Servedio 03	$\Omega(n^{1/3}\log^{\frac{2(k-2)}{3}}n)$	k
Sherstov 14	$\Omega(n^{\frac{k-1}{2k-1}})$	k
Sherstov 15	$\Omega(\sqrt{n})$	4
Bun-Thaler 18	$\tilde{\Omega}(\sqrt{n})$	3
Sherstov-W. 19	$\tilde{\Omega}(n^{1-\frac{2}{k+1}})$	k

Threshold degree of AC⁰

Theorem (Sherstov-W. 19).

$$\deg_{\pm}(AC^0) = \Omega(n^{1-\epsilon}).$$

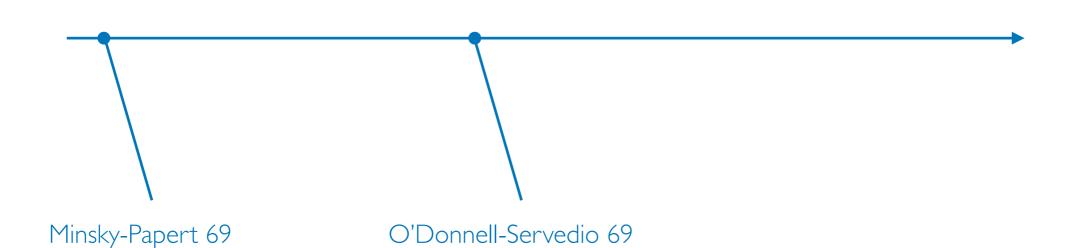
Trivial bound: $\deg_+(f) \leq n$.

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Threshold degree of AC⁰

Theorem (Sherstov-W. 19).

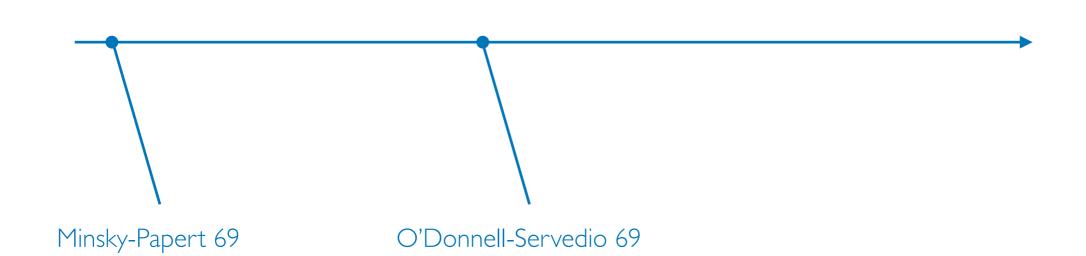
$$\deg_{\pm}(AC^0) = \Omega(n^{1-\epsilon})$$
.



Threshold degree of AC⁰

$$\deg_{\pm}(AC^0) = \Omega(n^{1-\epsilon})$$
.

Trivial bound: $\deg_+(f) \leq n$.



Proof Sketch: Hardness amplification

Given
$$f: \{0,1\}^n \to \{0,1\}, \quad \deg_{\pm}(f) = n^{1-\epsilon}$$

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$$// \setminus$$

$$CNIF$$

$$| | | | | |$$

$$y \in \{0,1\}^{N}$$

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$$| | | | | |$$

$$y \in \{0,1\}^{N}$$

$$\deg_{\pm}(f \circ \mathrm{CNF}_m) \ge n^{1-\epsilon} \cdot m$$

Proof Sketch: Compression

Given
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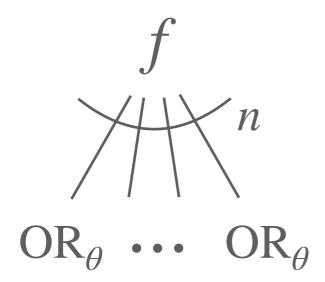
$$CNF$$

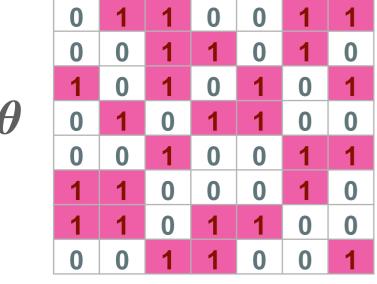
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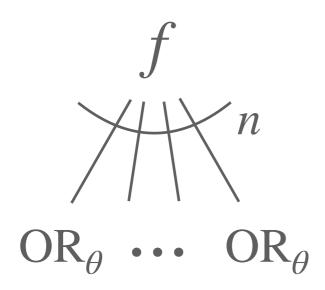
Compression: input transformation

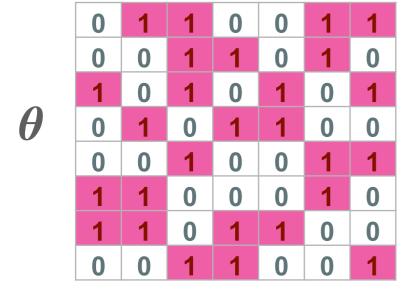


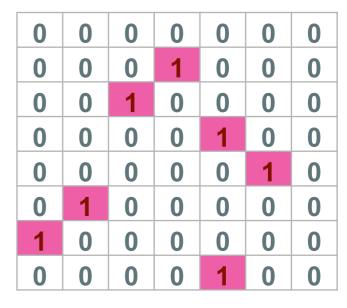


n

Compression: input transformation







n

Proof Sketch: Compression

Given
$$f: \{0,1\}^n \to \{0,1\},$$
 $\deg_{\pm}(f) = n^{1-\epsilon}$

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Then
$$F = f$$

$$// \setminus$$

$$CNF|_{\leq \theta}$$

$$| | | | | |$$

$$y \in \{0,1\}^{N}$$

$$(f \circ \text{CNF}_{\text{m}}) |_{\leq \theta}$$

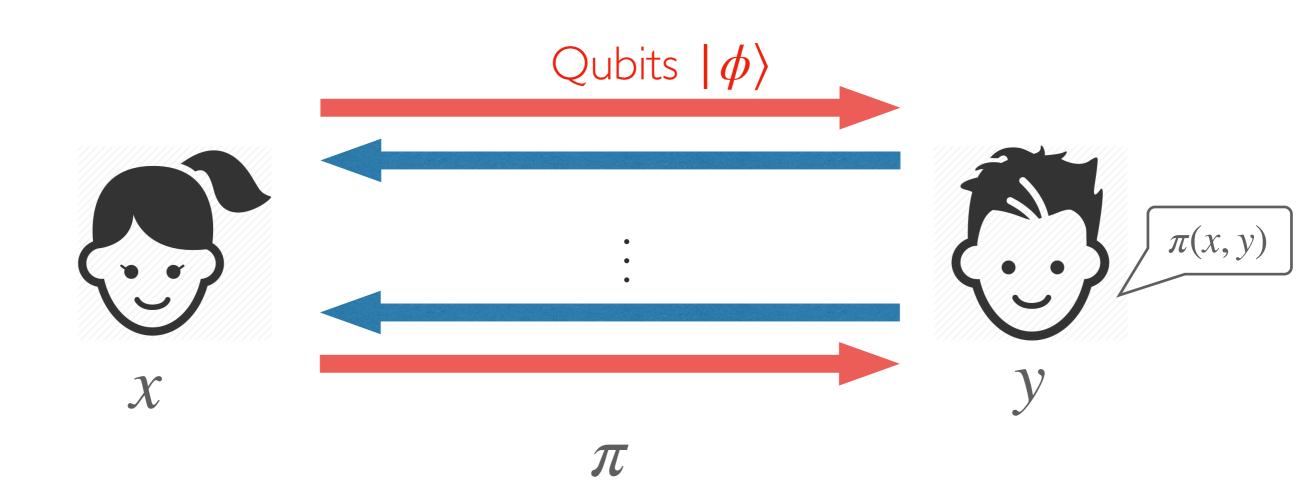
 $\deg_{\pm}(f \circ \text{CNF}_{m}) \geq n^{1-\epsilon} \cdot m$

More tools from duality.

Roadmap

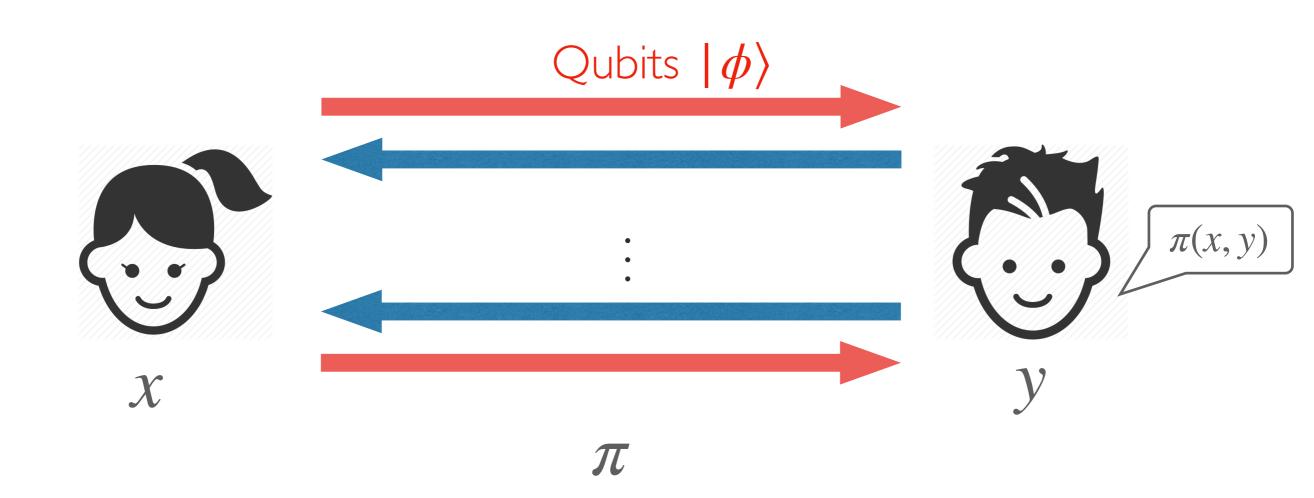
- Unbounded-error communication
- BQP vs. BPP communication

Communication complexity (Quantum)



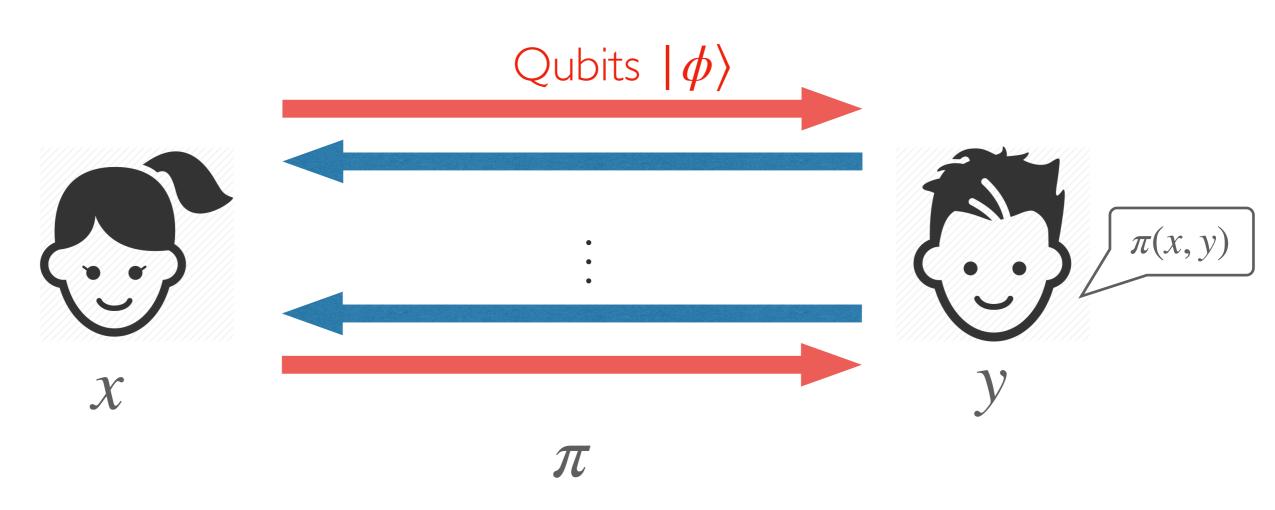
Communication complexity (Quantum)

Advantage of quantum computation?



Communication complexity (Quantum)

Advantage of quantum computation?



Correctness: $\Pr[\pi(x, y) = f(x, y)] \ge \frac{2}{3}, \ \forall x, y$.

Partial functions $f: \{0,1\}^n \times \{0,1\}^n \rightarrow \{0,1,\text{undef}\},$

	Classical	Quantum
Buhrman et al. '98	$D(f) = \Omega(n)$	$O(\log n)$

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near-optimal

Total functions $f: \{0,1\}^n \times \{0,1\}^n \to \{0,1\},$

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Buhrman et al., '98, Razborov, '02	$R(f) \ge \Omega(Q(f)^2)$
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Tal, '19	$R(f) \ge \Omega(Q(f)^{8/3 - o(1)})$
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Lifting

In short,

f, hard for query model

[Raz-McKenzie., '99]

lift
[Goos et al., '15]
[Chattopattyay et al., '19]

F, hard for communication model

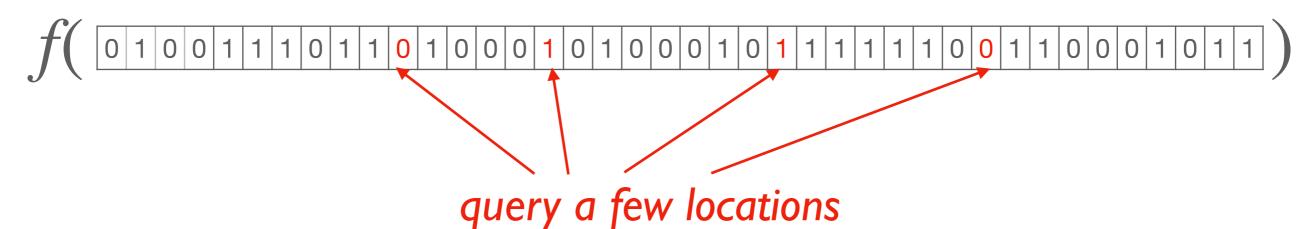
a huge unstructured database



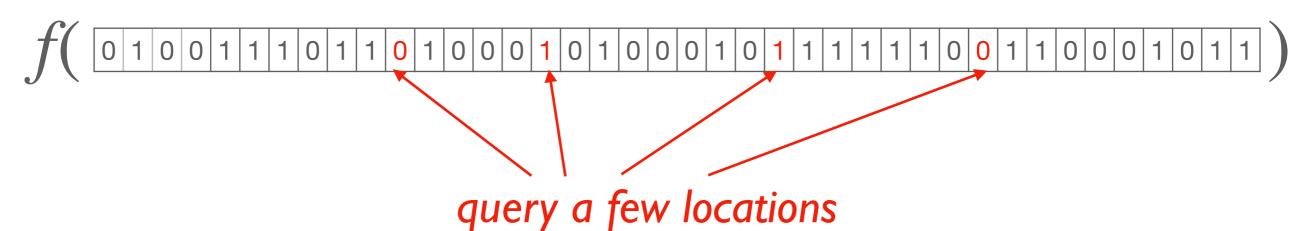
a huge unstructured database

f(0100111010100010100010111111100110001011)

a huge unstructured database



a huge unstructured database



query complexity = min queries

State any unit vector in a fixed Euclidean space

Query
$$|\phi\rangle = \sum_{i,w} a_{i,w} |i\rangle |w\rangle$$

State any unit vector in a fixed Euclidean space

Query
$$|\phi\rangle = \sum_{i,w} a_{i,w}(i)|w\rangle$$
 query index

State any unit vector in a fixed Euclidean space

Query
$$|\phi\rangle = \sum_{i,w} a_{i,w} (i) (w)$$
 query index

State

any unit vector in a fixed Euclidean space

Query

$$|\phi\rangle = \sum_{i,w} a_{i,w}(i)(w)$$
 $|\phi'\rangle = \sum_{i,w} a_{i,w}(-1)^{x_i} |i\rangle |w\rangle$

State

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Query

$$|\phi\rangle = \sum_{i,w} a_{i,w}(i)(w)$$
 $|\phi'\rangle = \sum_{i,w} a_{i,w}(-1)^{x_i} |i\rangle |w\rangle$

can access all x_i in a single query!

Quantum speedups

Query model captures nearly all quantum breakthroughs:

Deutsch-Jozsa's algorithm Bernstein-Vazirani's algorithm

Simon's algorithm Shor's factoring algorithm

Grover's search

Partial functions

	Randomized	Quantum
Simon '97	$\Omega(\sqrt{n})$	$O(\log n)$
Aaronson-Ambainis '15	$\tilde{\Omega}(\sqrt{n})$	1
AA '15, BGGS '21	$O_k(n^{1-\frac{1}{k}})$	<i>k</i> /2
Tal '19	$\tilde{\Omega}(n^{\frac{2k-2}{3k-1}})$	<i>k</i> /2
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SSW., '20	$\Omega(n^{1-\frac{1}{k}})$	k/2
	Optimal	i

Total functions

	Randomized vs. Quantum
Grover '69, BBBV '97	$R(f) = \Omega(Q(f)^2)$
Beals et al. '0 I	$R(f) = O(Q(f)^6)$
Aaronson et al. '16	$R(f) \ge \tilde{\Omega}(Q(f)^{2.5})$
Tal '19	$R(f) \ge Q(f)^{\frac{8}{3} - o(1)}$
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Total functions

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Total functions

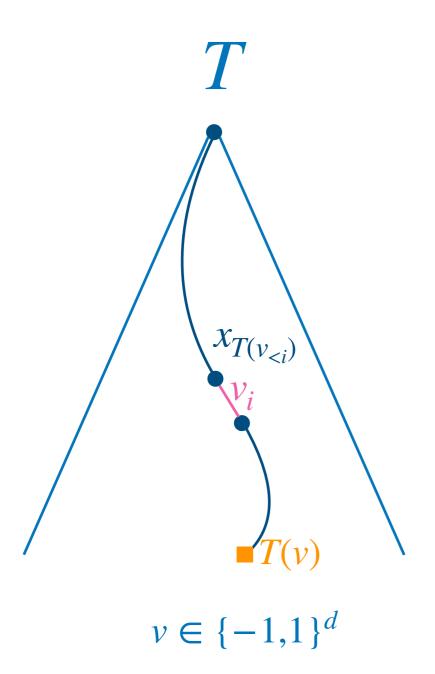
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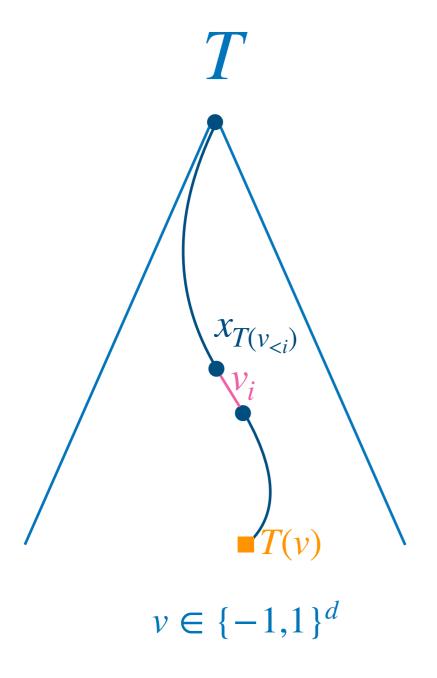
Fourier weight of decision trees

Theorem.

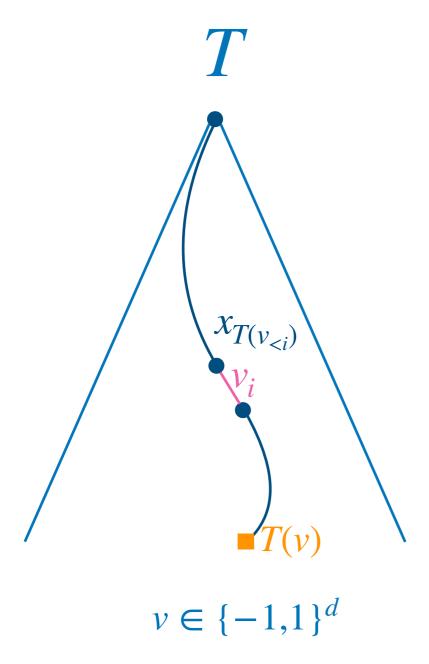
For any decision tree $T: \{-1,1\}^n \to \{0,1\}$ of depth d,

$$\sum_{\substack{S \subseteq \{1,2,\ldots,n\}:\\ |S| = \ell}} |\hat{T}(S)| \le c^{\ell} \sqrt{\binom{d}{\ell}} (1 + \log n)^{\ell-1}.$$

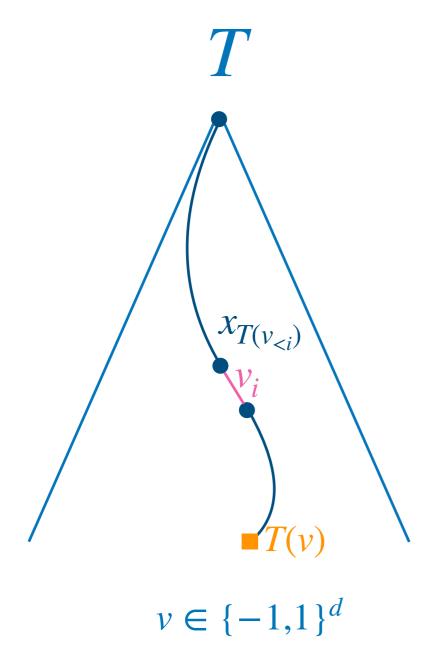




$$T(v) \prod_{i=1}^{d} \frac{1 + v_i x_{T(v_{< i})}}{2}$$

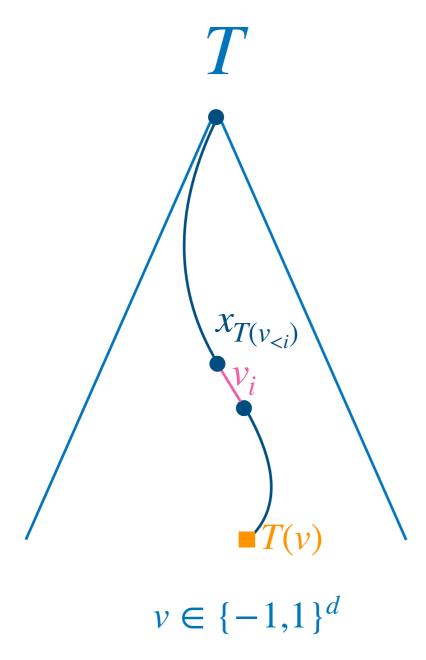


$$T = \sum_{v \in \{-1,1\}^d} T(v) \prod_{i=1}^d \frac{1 + v_i x_{T(v_{< i})}}{2}$$



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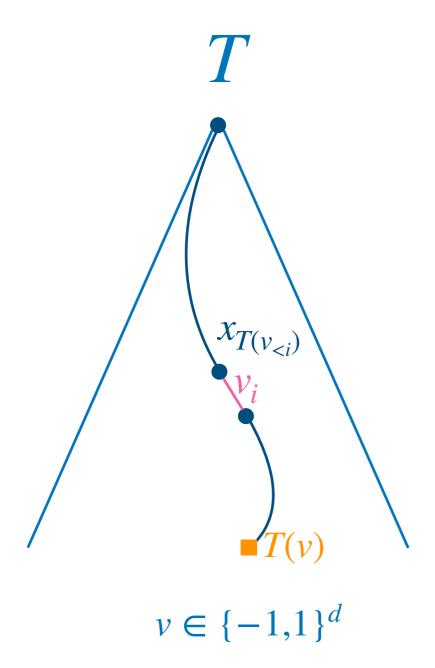
$$= \sum_{v \in \{-1,1\}^d} T(v) 2^{-d} \sum_{S \subseteq \{1,...,d\}} \prod_{i \in S} v_i x_{T(v_{< i})}$$



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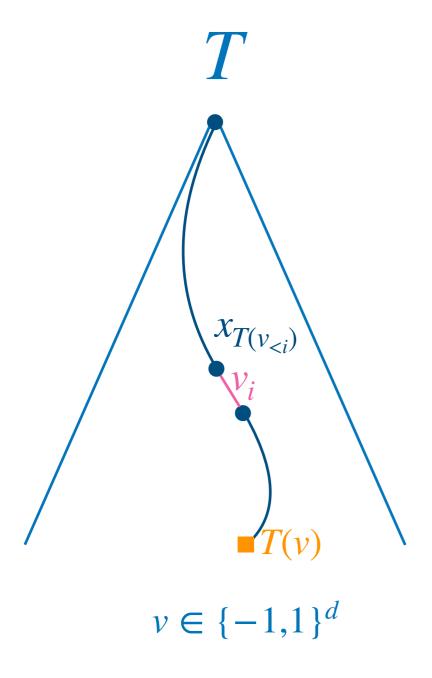


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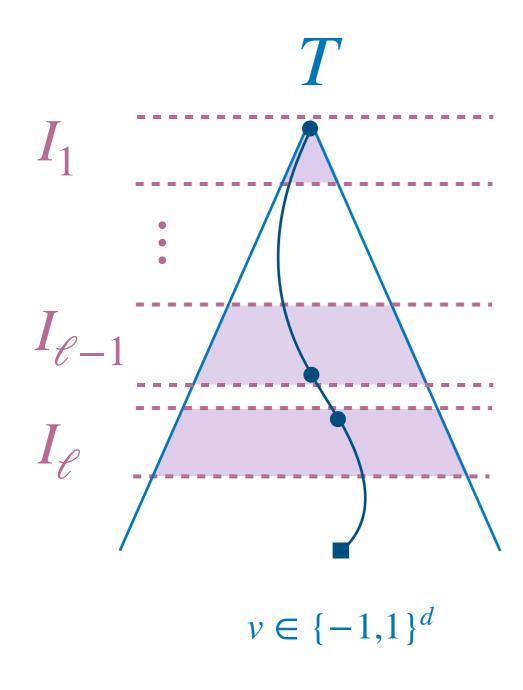
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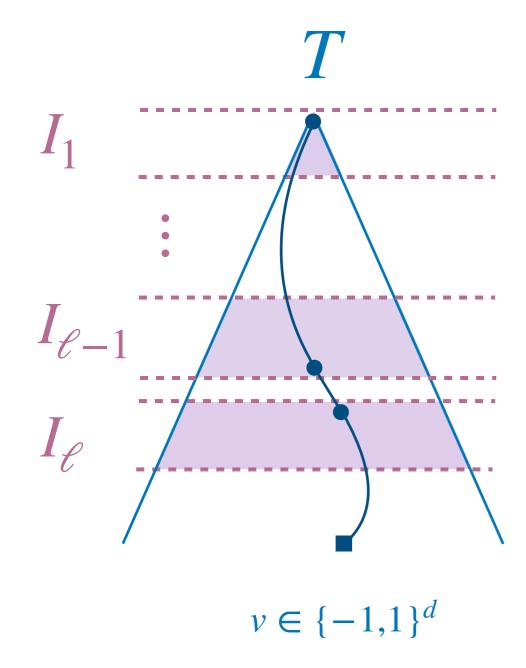
$$L_{\ell} T = \sum_{S \in \mathcal{P}_{d,\ell}} \sum_{v \in \{-1,1\}^d} T(v) 2^{-d} \prod_{i \in S} v_i x_{T(v_{< i})}.$$



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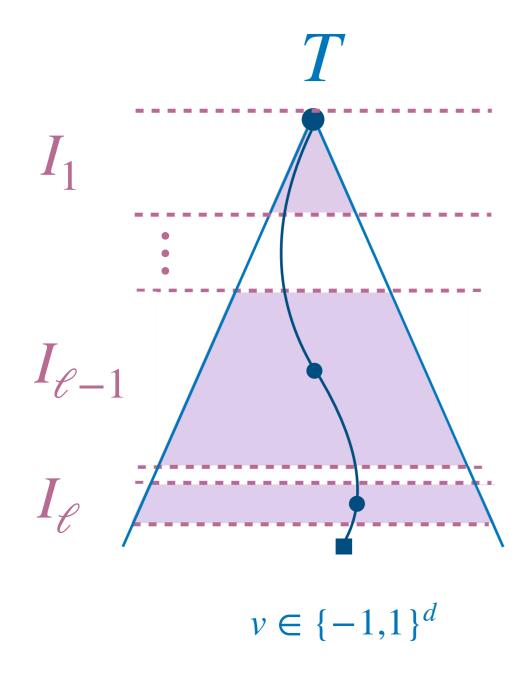
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$$T|_{I_1*I_2*...*I_{\ell}} = \sum_{S \subseteq \{1,...,d\}: \ v \in \{-1,1\}^d} T(v) 2^{-d} \prod_{i \in S} v_i x_{T(v_{< i})}.$$

$$|S \cap I_i| = 1$$



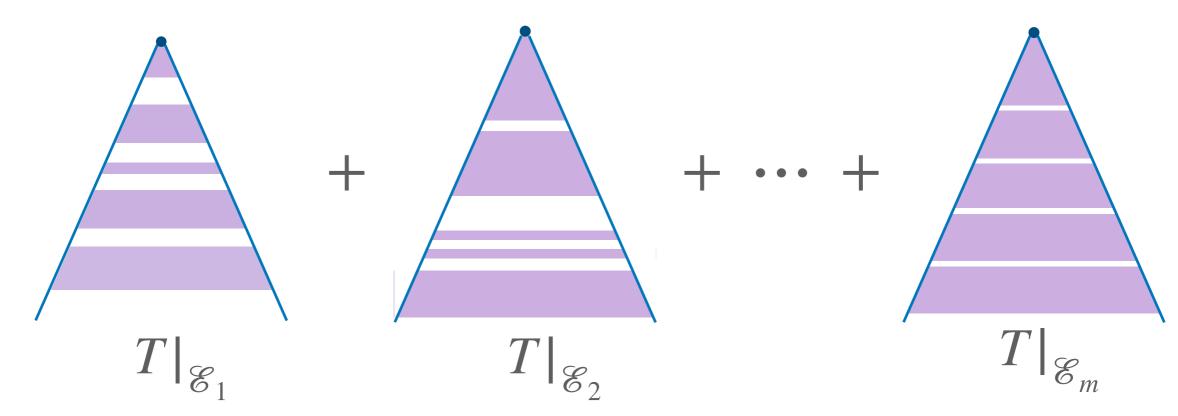
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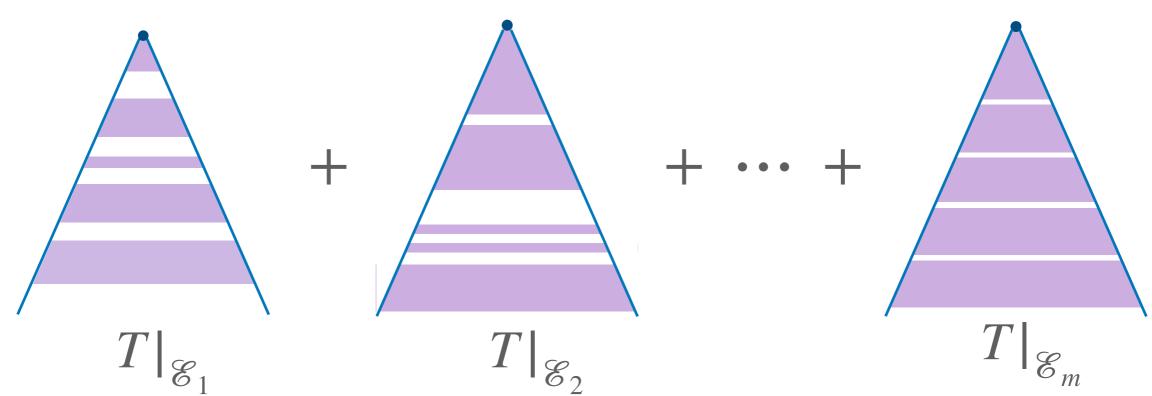
Fourier weight of decision trees

$$L_{\ell}T =$$



Fourier weight of decision trees

$$L_{\ell}T =$$



$$\|L_{\ell}T\| \leq \sum \|T|_{\mathcal{E}_i}\|$$
 . (Triangle-inequality)

Grand Challenges

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- I. Quantum v.s. Classical communication
- 2. Quantum Proof System

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Thank you!