

SURVEY ON ALGEBRAIC COMPLEXITY

SRIKANTH SRINIVASAN

AARHUS UNIVERSITY

Talk Outline

- ① Introduction to Algebraic Complexity
- ② Lower bound Techniques
- ③ Polynomial Identity Testing
- ④ Proof Complexity
- ⑤ Possible Barriers to Lower Bounds

Talk Outline

① Introduction to Algebraic Complexity

Algebraic Complexity Theory

$(P_N(x_1, \dots, x_N))_N$ - sequence of polynomials
 $\deg(P_N) \leq N^{O(1)}$

Input: $a \in \mathbb{C}^N$ [or \mathbb{F}^N]

Output: $P_N(a)$

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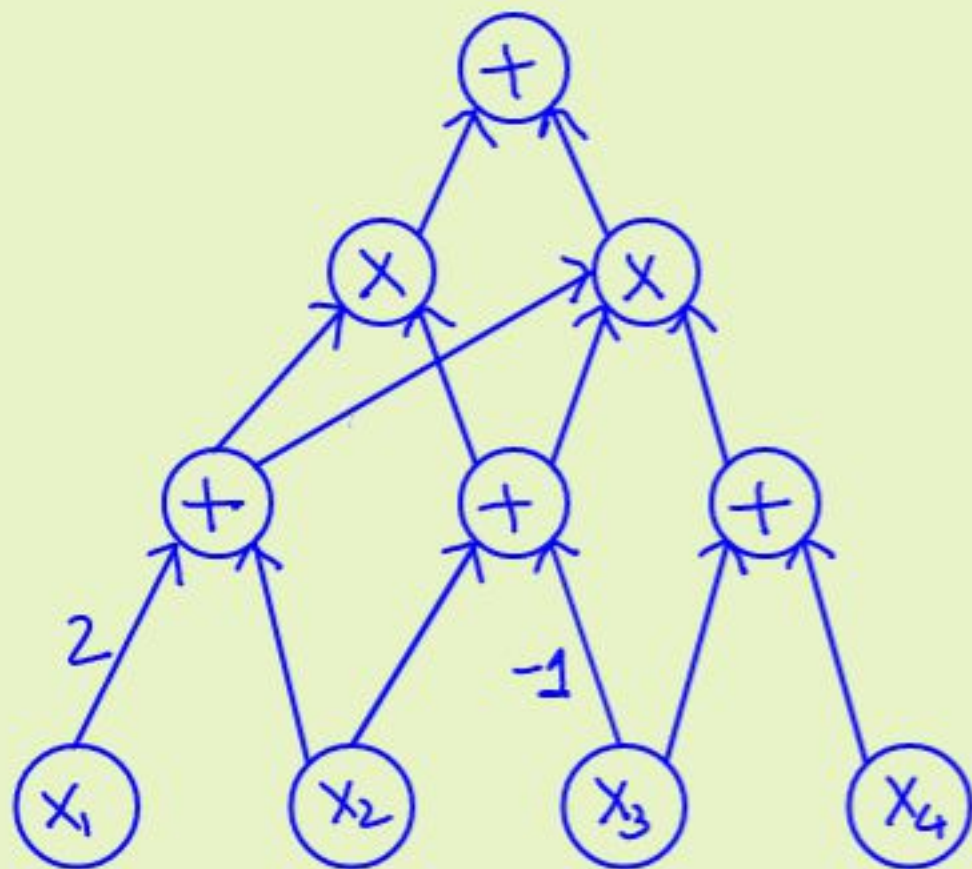
Output: $P_N(a)$

Examples: ① $\det_n(x_{i,j})_{i,j} = \sum_{\sigma \in S_n} \text{sgn}(\sigma) x_{1,\sigma(1)} \cdots x_{n,\sigma(n)}$

② $\text{per}_n(x_{i,j})_{i,j}$ $N = n^2, \deg = n$

③ $\text{IMM}_{n,d} = \begin{array}{c} \boxed{} \\ \hline \end{array} \begin{array}{c} \boxed{n \times n} \\ \hline \end{array} \cdots \begin{array}{c} \boxed{n \times n} \\ \hline \end{array} \begin{array}{c} \boxed{} \\ \hline \end{array} \quad N \approx d \cdot n^2$
 $\deg = d$

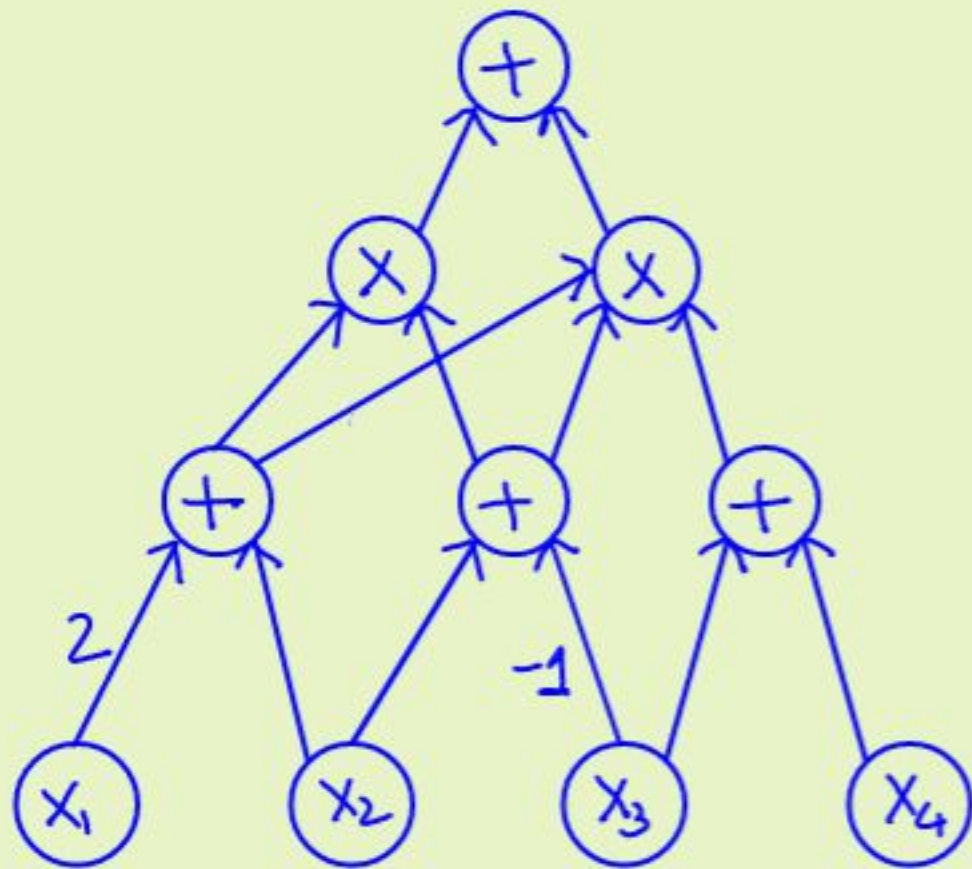
Algebraic Circuits



Size = # of gates = 6

Depth = length of longest path
= 3

Algebraic Circuits



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VP = sequences of polynomials with circuits of polynomial size.

Eg: $\text{IMM}_{n,d} \in \text{VP}$
 $\text{det}_n \in \text{VP}$

$\text{per}_n \notin \text{VP}?$

[VP vs. VNP]

VP vs. VNP

→ Special (syntactic) case of P/poly vs. NP
[Bür]

→ Concrete approaches

→ Syntactic simplification

→ Depth-reduction

Other Syntactic Restrictions

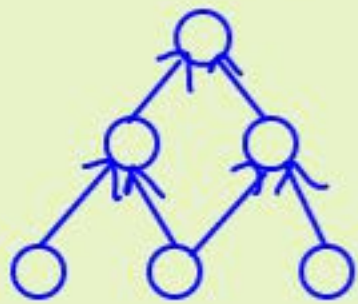
Other Syntactic Restrictions

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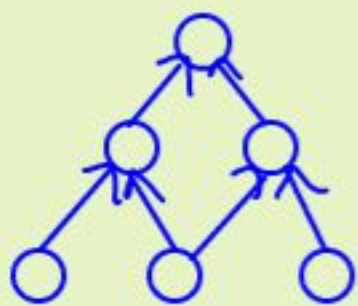
Homogeneous circuits: Each intermediate
computation is homogeneous.



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→ Sometimes, restricted circuits \approx general circuits. [Good for lbd's!]

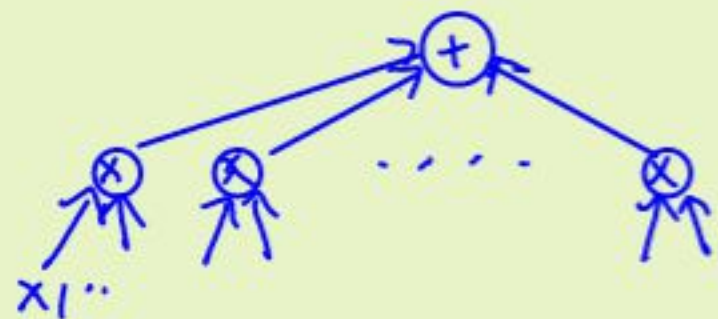
→ Interesting situations where this may not be true.

Constant-depth Algebraic circuits

$$P(x_1, \dots, x_N) = \sum_{e_1, \dots, e_N} \alpha_{e_1, \dots, e_N} x_1^{e_1} \dots x_N^{e_N}$$

$\deg(P) = d$

$e_i \geq 0 : \sum_i e_i \leq d$



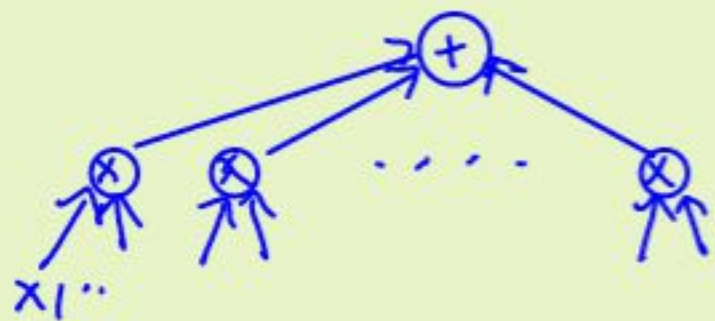
→

$\Sigma \Pi$ circuit for P

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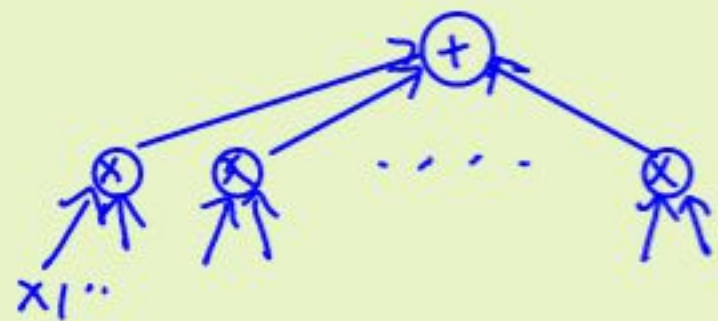


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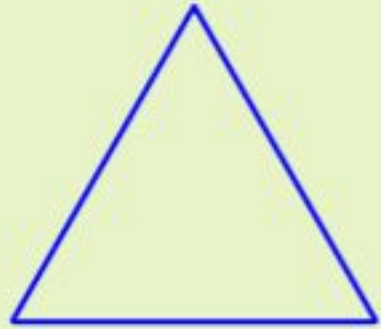


$\rightarrow \Sigma \Pi$ circuit for P
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$$\Sigma \Pi \Sigma, \Sigma \Pi \Sigma \Pi, \dots$$

\hookrightarrow much harder to reason about!

Depth-Reduction [Brent, VSBR]



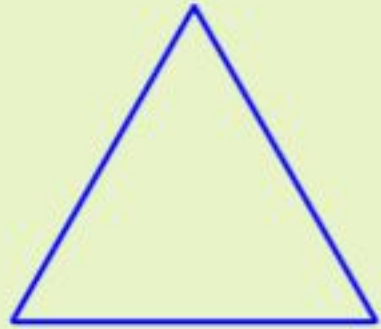
General circuit \Rightarrow
poly-size

Const. depth circuit
subexponential size

Superpoly. lbd
for general ckt \Leftarrow

Exponential const.
depth lower bounds

Depth-Reduction [Brent, VSBR]



General circuit
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Exponential const.
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$\Sigma\Pi\Sigma\Pi$

size $N^{O(\sqrt{d})}$

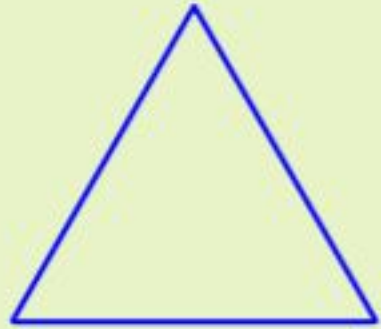
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ckt. for



homogeneous [AV, Koi, Tav]

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$\Sigma\Pi\Sigma$ size $N^{O(\sqrt{d})}$

in homogeneous $[AKKS]^{(*)}$

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Constant-depth circuit lower bounds

[NW]: Partial Derivative Method

→ "Complexity of $P(x_1, \dots, x_N)$ " = rank of
matrix M_p

Constant-depth circuit lower bounds

[NW]: Partial Derivative Method

→ "Complexity of $P(x_1, \dots, x_N)$ " = rank of matrix M_p

→ Small circuit \Rightarrow small rank

→ $\text{rk}(M_1 + M_2) \leq \text{rk}(M_1) + \text{rk}(M_2)$

Example : Tensor Rank

$$\{X_1^{(1)}, \dots, X_n^{(1)}\}, \{X_1^{(2)}, \dots, X_n^{(2)}\}, \dots, \{X_1^{(d)}, \dots, X_n^{(d)}\}$$

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$$\{x_1^{(1)}, \dots, x_m^{(1)}\}, \{x_1^{(2)}, \dots, x_n^{(2)}\}, \dots, \{x_1^{(d)}, \dots, x_n^{(d)}\}$$

$$\mathcal{Q}(x^{(1)}, \dots, x^{(d)})$$

$$\sum_{i_1, \dots, i_d} \alpha_{i_1, \dots, i_d} x_{i_1}^{(1)} \dots x_{i_d}^{(d)}$$

set-multilinear poly.

Example : Tensor Rank

$$\{x_1^{(1)}, \dots, x_m^{(1)}\}, \{x_1^{(2)}, \dots, x_n^{(2)}\}, \dots, \{x_1^{(d)}, \dots, x_n^{(d)}\}$$

$$Q(\bar{x}^{(1)}, \dots, \bar{x}^{(d)}) = l_1^{(1)} \dots l_1^{(d)} + \dots + l_s^{(1)} \dots l_s^{(d)}$$

$$\sum_{i_1, \dots, i_d} \alpha_{i_1, \dots, i_d} x_{i_1}^{(1)} \dots x_{i_d}^{(d)}$$

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$$\sum \Pi \Sigma \text{ s.m. circuit}$$

$$\min s = \text{Tensor-Rank}(Q)$$

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$$\sum_{i_1, \dots, i_d} \alpha_{i_1, \dots, i_d} X_{i_1}^{(1)} \dots X_{i_d}^{(d)}$$

set-multilinear poly.

$$M_p = \begin{pmatrix} X_{i_1}^{(1)} \dots X_{i_{d/2}}^{(d/2)} & \text{coeff}(X_{i_1}^{(1)} \dots X_{i_d}^{(d)}) & X_{i_{d/2+1}}^{(d/2+1)} \dots X_{i_d}^{(d)} \end{pmatrix}_{n^{d/2} \times n^{d/2}}$$

Example: Tensor Rank

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$n^{d/2} \times n^{d/2}$

Columns are partial derivatives of p

Example : Tensor Rank

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$$Q(\vec{x}^{(1)}, \dots, \vec{x}^{(d)}) = l_1^{(1)} \dots l_1^{(d)} + \dots + \underbrace{l_s^{(1)} \dots l_s^{(d)}}_{\text{rank} \leq 1}$$

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explicit \mathcal{Q}

$$\text{s.t. } \text{rk}(\mathcal{M}_{\mathcal{Q}}) \geq n^{d/2}$$

$$\Rightarrow$$

$$s \geq n^{d/2}$$

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$$\mathcal{Q} = \langle x_1, x_{d/2+1} \rangle \langle x_2, x_{d/2+2} \rangle \dots \langle x_{d/2}, x_d \rangle$$

"Product of Inner Products"

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"Product of Inner Products"

$$M_{\mathcal{Q}} = I_n \otimes I_n \otimes \dots$$

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explicit Q

s.t. $\text{rk}(M_Q) \geq n^{d/2}$

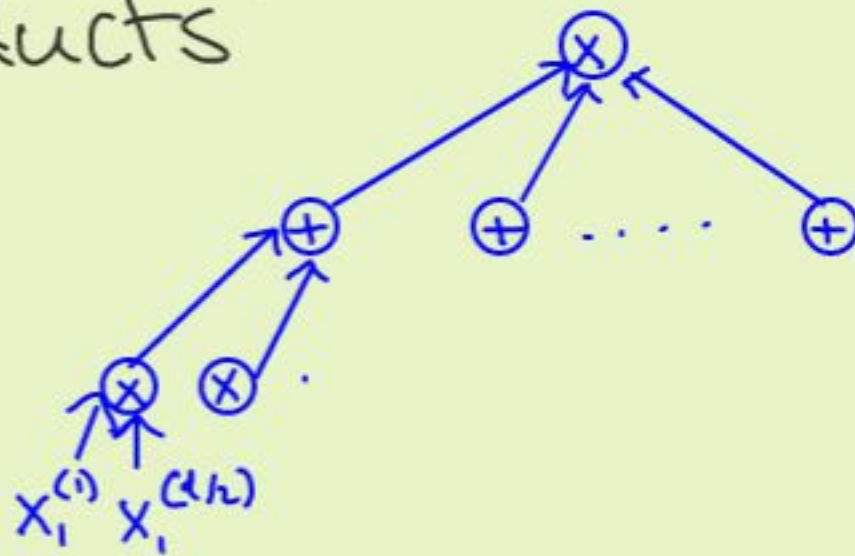
\Rightarrow

$s \geq n^{d/2}$

$$Q = \langle x_1, x_{d/2+1} \rangle \langle x_2, x_{d/2+2} \rangle \dots \langle x_{d/2}, x_d \rangle$$

"Product of Inner Products"

$$M_Q = I_n \otimes I_n \otimes \dots$$



Other applications of Partial derivative method

→ [NW]: homogeneous $\Sigma \Pi \Sigma$ circuits.

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- [NW]: homogeneous $\Sigma\Pi\Sigma$ circuits.
- [NW, Raz, RY]: Weaker "subexponential" lower bounds against higher-depth set-multilinear circuits & generalizations.
- Partial derivatives \dagger Random Restrictions.
- Necessary because Products of Inner Products is $\Sigma\Pi\Sigma\Pi$.

Shifted Partial Derivative Method [GKS]

→ lower bounds against homogeneous $\Sigma\Pi\Sigma\Pi$
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→ Partial derivatives of such circuits are "simple"

→ derivative \times monomial of degree $\leq l$

$$M_p = \left(\begin{array}{c} \\ \\ \\ \\ \end{array} \right)$$

Shifted Partial Derivative Method [GKKS]

→ lower bounds against homogeneous $\Sigma\Pi\Sigma\Pi$ circuits

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→ [FLMS, KLSS, KS]: Lower bounds of $N^{\Omega(d)}$ against homogeneous $\Sigma\Pi\Sigma\Pi$

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Hard polynomial = $IMM_{n,d}$

Lopsided Partial derivatives [LST]

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→ Product of Inner Prods $(X^{(1)}, \dots, X^{(d)})$

$$= \left(\sum_{i=1}^n X_i^{(1)} X_i^{(d/2+1)} \right) \left(\sum_{i=1}^n X_i^{(2)} X_i^{(d/2+2)} \right) \dots$$

→ Avoiding PIF: variable sets have different sizes!

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→ Avoiding PIF: variable sets have different sizes!

Ex: $|X^{(1)}| = |X^{(2)}| = \dots = |X^{(t)}| = n$

$$|X^{(t+1)}| = \dots = |X^{(d)}| = n^\alpha$$

s.t. $|p-q|$ large for "small" p, q .

Lopsided Partial derivatives [LST]

Thm: Lbd. of $N^{\Omega(d)}$ against $\Sigma\Pi\Sigma\Pi\Sigma$ set-
multilinear circuits.

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Thm [SW, CKSV]: Depth-structure tradeoff^(*).

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Cor: $d < \sqrt{\log N} \Rightarrow N^{\Omega(d)}$ lbd. against $\Sigma\Pi\Sigma$

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Lopsided Partial derivatives [LST]

Thm: Lbd. of $N^{d^{\exp(-\Delta)}}$ against depth Δ set-multilinear circuits.

Thm [LST]: Depth-structure tradeoff^(*).

Depth Δ , size $s \Rightarrow$ Depth $2\Delta+1$, s.m. size $s \cdot d^{O(d)}$

Cor: $d < \sqrt{\log N} \Rightarrow N^{d^{\exp(-\Delta)}}$ lbd. against depth Δ

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- ③ Polynomial Identity Testing

Polynomial Identity Testing

$$\begin{aligned} (x_1^2 + x_2^2 + x_3^2 + x_4^2) \cdot (y_1^2 + y_2^2 + y_3^2 + y_4^2) &= (x_1 y_1 - x_2 y_2 - x_3 y_3 - x_4 y_4)^2 + \\ & (x_1 y_2 + x_2 y_1 + x_3 y_4 - x_4 y_3)^2 + \\ & (x_1 y_3 - x_2 y_4 + x_3 y_1 + x_4 y_2)^2 + \\ & (x_1 y_4 + x_2 y_3 - x_3 y_2 + x_4 y_1)^2 \end{aligned}$$

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Input: $P(x_1, \dots, x_N)$ (as a circuit)

Output: Is $P=0$?

Deterministic Algorithms for PIT & Lower bounds

→ Rand algo: ① Fix $S \subseteq \mathbb{F}$. $|S| \geq 10d$.

② Pick $a \in \mathbb{F}^n$. Test if $P(a) = 0$.

Deterministic Algorithms for PIT & Lower bounds

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→ Can we get efficient non-randomized algo?

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Thm $\left[\begin{array}{l} \text{KI,} \\ \text{Agr} \end{array} \right]$ PIT algos \Rightarrow Lower bounds

→ PIT algos. for weak circuit classes

→ Hardness-randomness tradeoffs.

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Superpolynomial lbd \Rightarrow Subexponential time PIT
for general ckts

Exponential lbd \Rightarrow Quasipoly. time PIT

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[GKSS]: Lower bounds \Rightarrow Poly-time PIT.
for $O(1)$ -variable polys

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Thm [DSY, CKS]: Tradeoffs for const. depth

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Thm [DSY, CKS]: Tradeoffs for const. depth

LOW-DEGREE
Superpoly. lower bds.

against $O(1)$ -depth ckts



Subexponential time
PIT for $O(1)$ -depth
ckts.

Deterministic Algorithms for PIT & Lower bounds

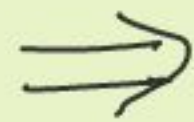
→ Rand algo: ① Fix $S \subseteq \mathbb{F}$. $|S| \geq 10d$.

② Pick $a \in \mathbb{F}^n$. Test if $P(a) = 0$.

→ Can we get efficient non-randomized algo?

Thm [DSY, CKS]: Tradeoffs for const. depth

Low-DEGREE
Superpoly-lower bds.



Subexponential time
PIT for $O(1)$ -depth
ckts.

against $O(1)$ -depth ckts

Cor: Lower bounds for $\text{IMM}_{n, \sqrt{\log n}} \Rightarrow \text{PIT}$

Talk Outline

- ① Introduction to Algebraic Complexity
- ② Lower bound Techniques
- ③ Polynomial Identity Testing
- ④ Proof Complexity

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→ Lbds for restricted ckts [ESTW]

→ Lbds for $O(1)$ -depth over char 0 [AF, GH1]

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- ⑤ Possible Barriers to Lower Bounds

Barriers to rank-based techniques

→ Rank-based technique

Linear $\mathcal{L}: \mathcal{P} \mapsto M_p$

$$\text{rk}(\mathcal{L}(\text{small ckt.})) \ll \max_{\mathcal{P}} \text{rk}(\mathcal{L}(\mathcal{P}))$$

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Thm: [EGow] No rank-based technique can prove $\gg n^{d/2}$ - lbd's on tensor rank.

[Mow]: Extensions to higher notions of rank.

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- All rank-based lower bounds are natural.
- Succinct hitting sets \Rightarrow no natural lower bound against \mathcal{VP}
- Evidence for [FSV, BIJL] & against [GKRST]

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What I didn't cover

→ Monotone Algebraic Circuits

→ GCT & Border Complexity

→ Symmetric Algebraic Circuits

→ Factorizations of Algebraic Circuits.

→ Reconstruction

⋮

Open Questions

- Stronger lower bounds.
- Lower bounds for depths $\gg \log \log d$
- $\text{char} > 0$ [AKKS, CICS, GKSS, LST, ...]
- Lower bounds for syntactic simplification
- Hierarchy theorems
- Optimal hardness-randomness tradeoffs
- Other meta-complexity questions

