

Exponential Lower Bounds for Monotone Span Programs

Stephen A. Cook

Toniann Pitassi

Robert Robere

Benjamin Rossman

University of Toronto

FOCS 2016

Familiar Picture

$$\text{NC}^1 \subseteq \underline{\text{L}} \subseteq \underline{\text{NL}} \subseteq \underline{\text{NC}} \subseteq \underline{\text{P}}$$

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Formulas



Familiar Picture

Switching Networks
(Branching Programs)

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Formulas

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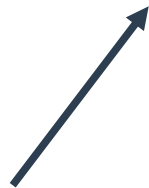
Switching Networks
(Branching Programs)



$$NC^1 \subseteq L \subseteq NL \subseteq NC \subseteq P$$

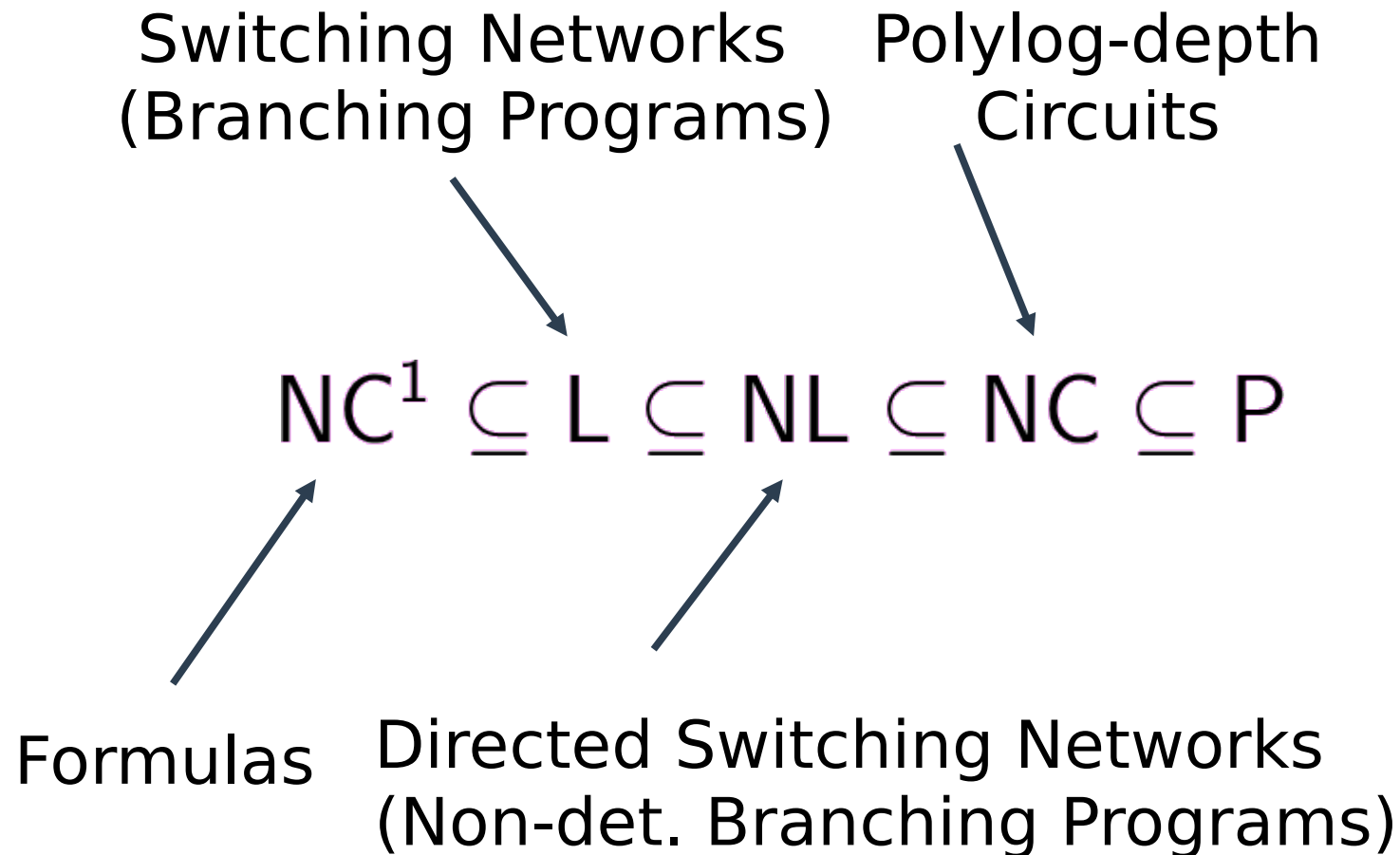


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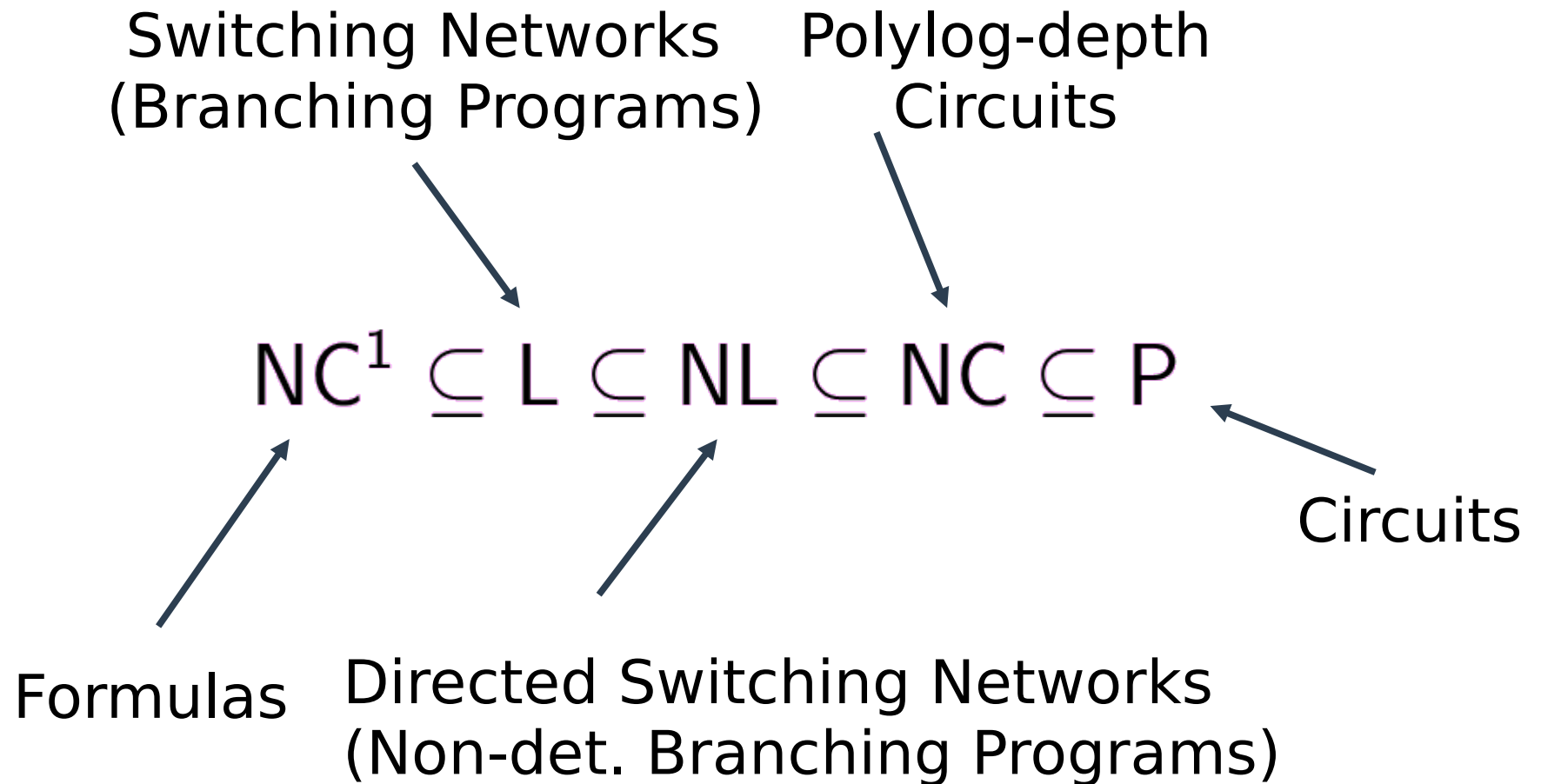


Directed Switching Networks
(Non-det. Branching Programs)

Familiar Picture



Familiar Picture



Familiar Picture

$$\text{NC}^1 \subseteq \underline{\text{L}} \subseteq \underline{\text{NL}} \subseteq \underline{\text{NC}} \subseteq \underline{\text{P}}$$

(Less) Familiar Picture

$$\begin{array}{ccccccc} & & & & \text{CC} & & \\ & & & & \cup & & \\ \text{NC}^1 & \subseteq & \text{L} & \subseteq & \text{NL} & \subseteq & \text{NC} \subseteq \text{P} \\ & & \cap & & & & \\ & & \text{SPAN}_{\mathbf{F}} & & & & \end{array}$$

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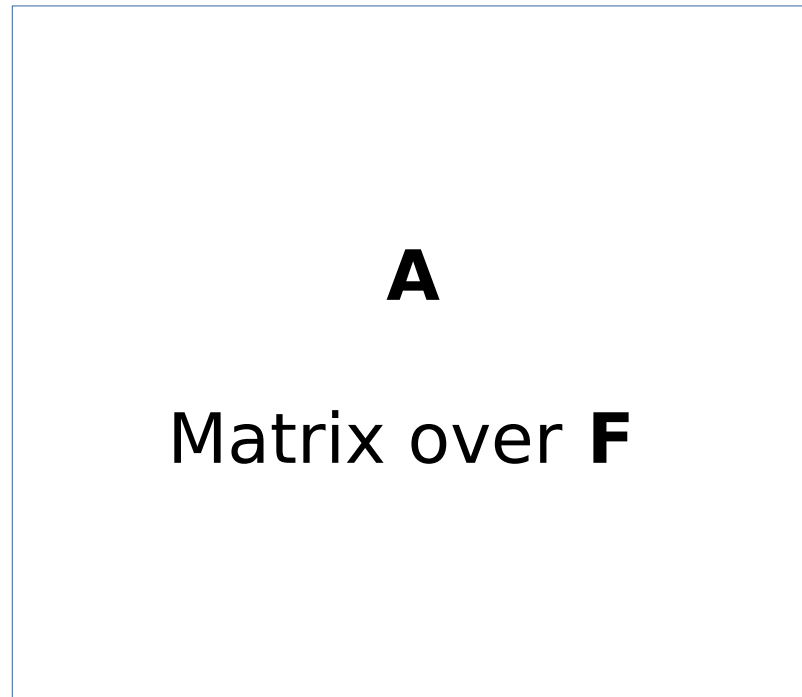
Span Programs over field **F** [KW '90]

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What is a **Span Program** over a field **F**?

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What is a **Span Program** over a field \mathbf{F} ?

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Rows labelled with input literals.

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Accept assignment if the consistent rows span all-1s vector

Span Programs [KW '90]

What is a **Span Program** over a field **F**?

x_1	1	0	0	1	$x_1 = \text{True}$ $x_2 = \text{True}$ $x_3 = \text{True}$
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What is a **Span Program** over a field **F**?

REJECT!

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Accept assignment if the consistent rows span all-1s vector

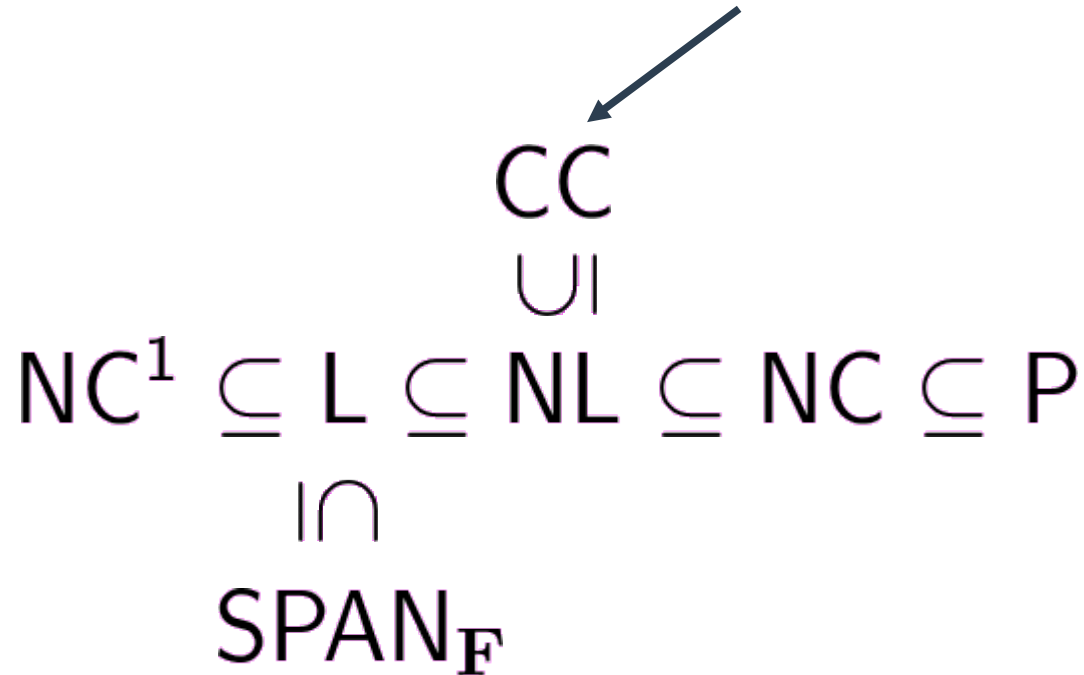
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Span Programs over field **F** [KW '90]
Capture logspace counting classes.

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Comparator Circuits



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Capture logspace counting classes.

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Comparator Circuits

~ Sorting networks.

CC
UI

$NC^1 \subseteq L \subseteq NL \subseteq NC \subseteq P$

\cap

$SPAN_F$

Span Programs over field **F** [KW '90]

Capture logspace counting classes.

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How many separations do we have?

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Fortunately, this is easy to fix.

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How many separations do we have?

$$\begin{array}{c} \text{mCC} \\ \cup \\ \text{mNC}^1 \subsetneq \text{mL} \subsetneq \text{mNL} \subsetneq \text{mNC} \subsetneq \text{mP} \\ \cap \\ \text{mSPAN}_{\mathbf{F}} \not\subseteq \text{mP} \end{array}$$

Fortunately, this is easy to fix.

Monotone = No Negations in Circuit Models

Familiar Picture

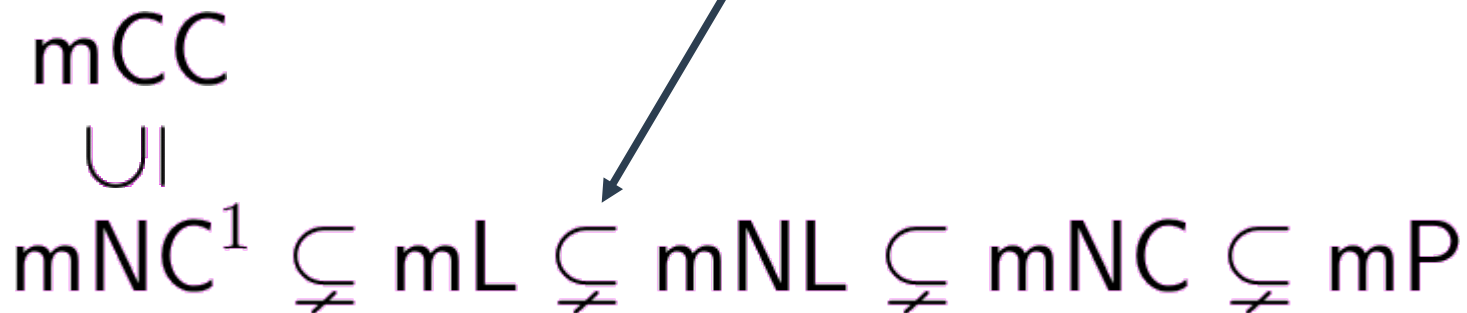
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Familiar Picture

[Potechin '10]

(Directed st-connectivity)

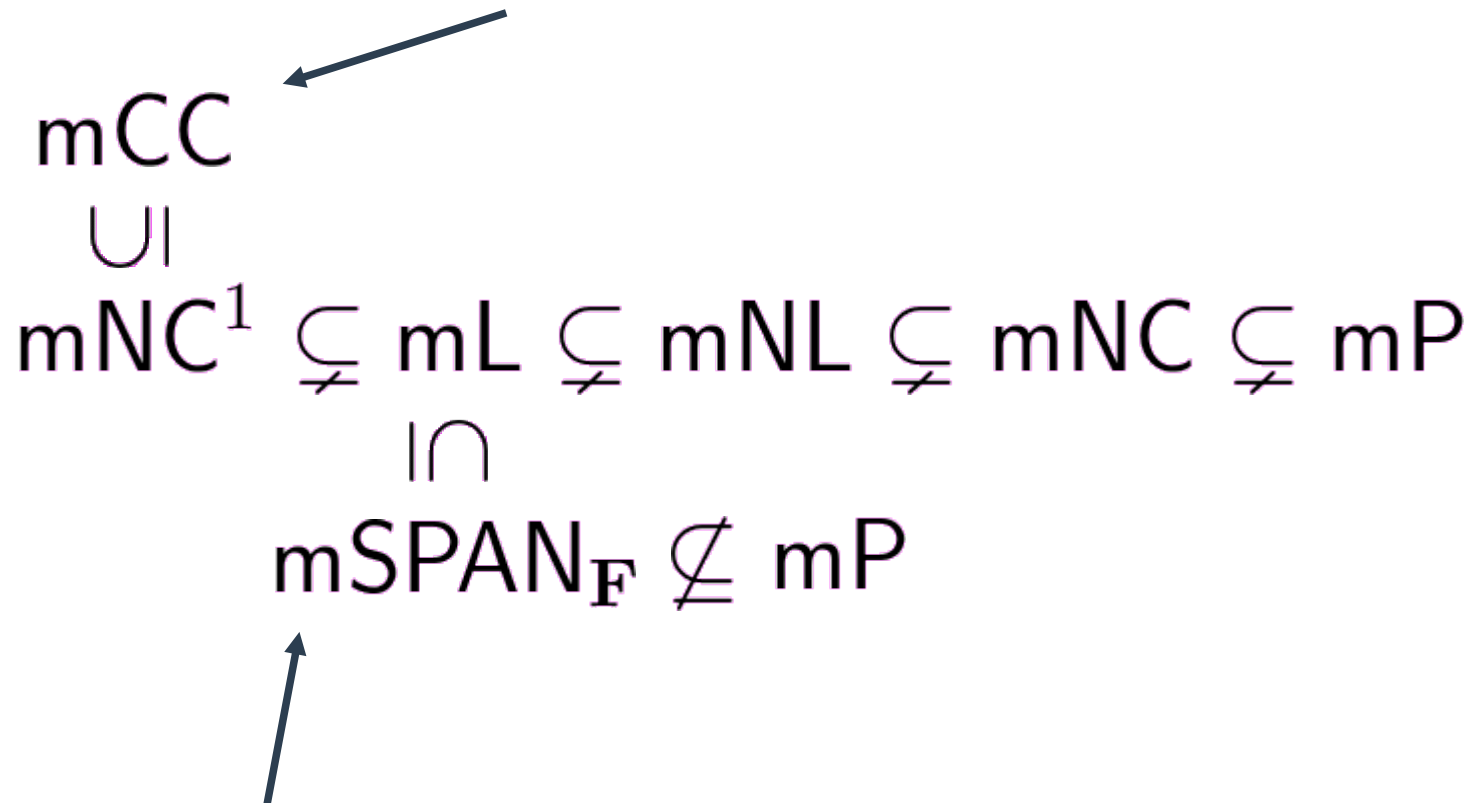


[Karchmer-Wigderson '88]
(Undirected st-connectivity)

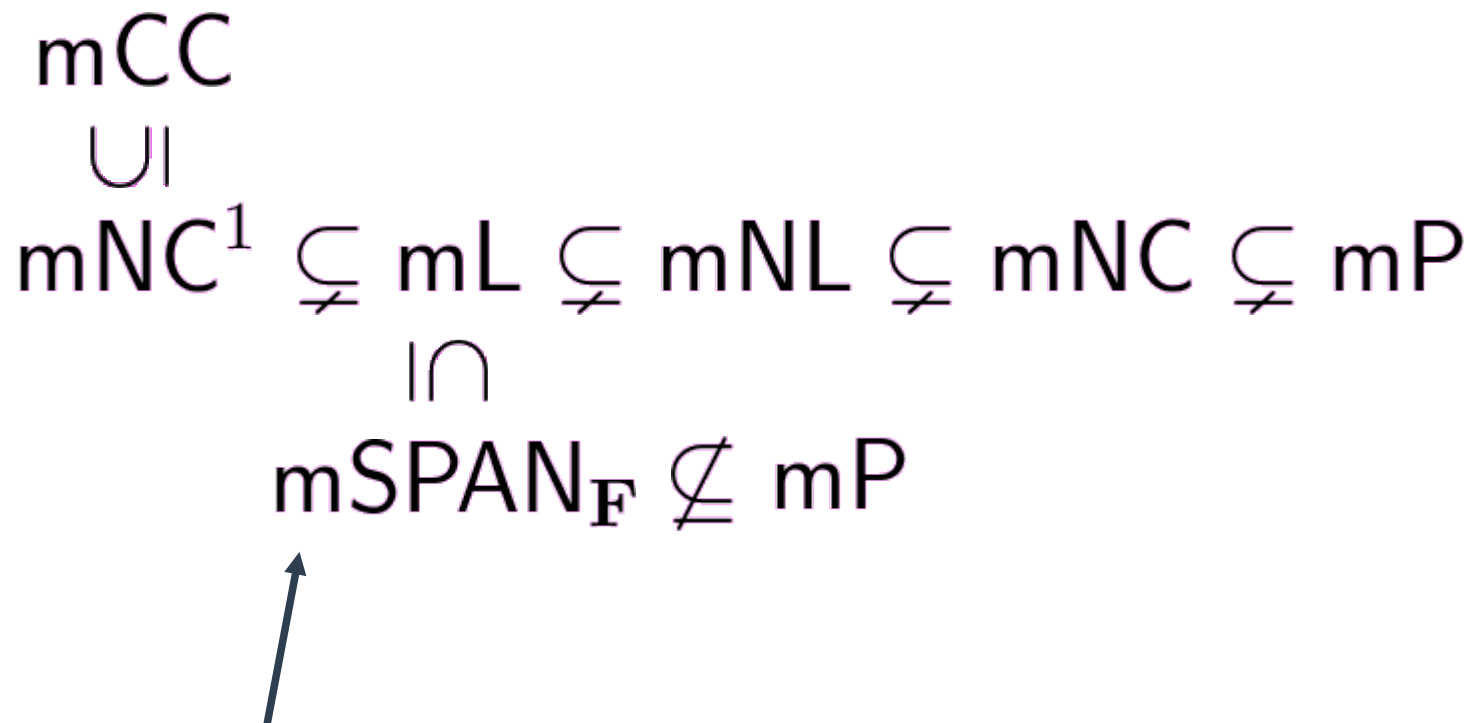
[Raz-Mckenzie '97]
(GEN)

[Babai, Gal, Wigderson '99]
(Odd Factor)

Familiar Picture



Familiar Picture



Familiar Picture

$mSPAN_F$

[Babai et al '96] Quasipolynomial lower bounds
against mNP.

Familiar Picture

$mSPAN_{\mathbb{F}}$

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[BW '05] Quasipolynomial against nonmonotone NC

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Extra Motivation:

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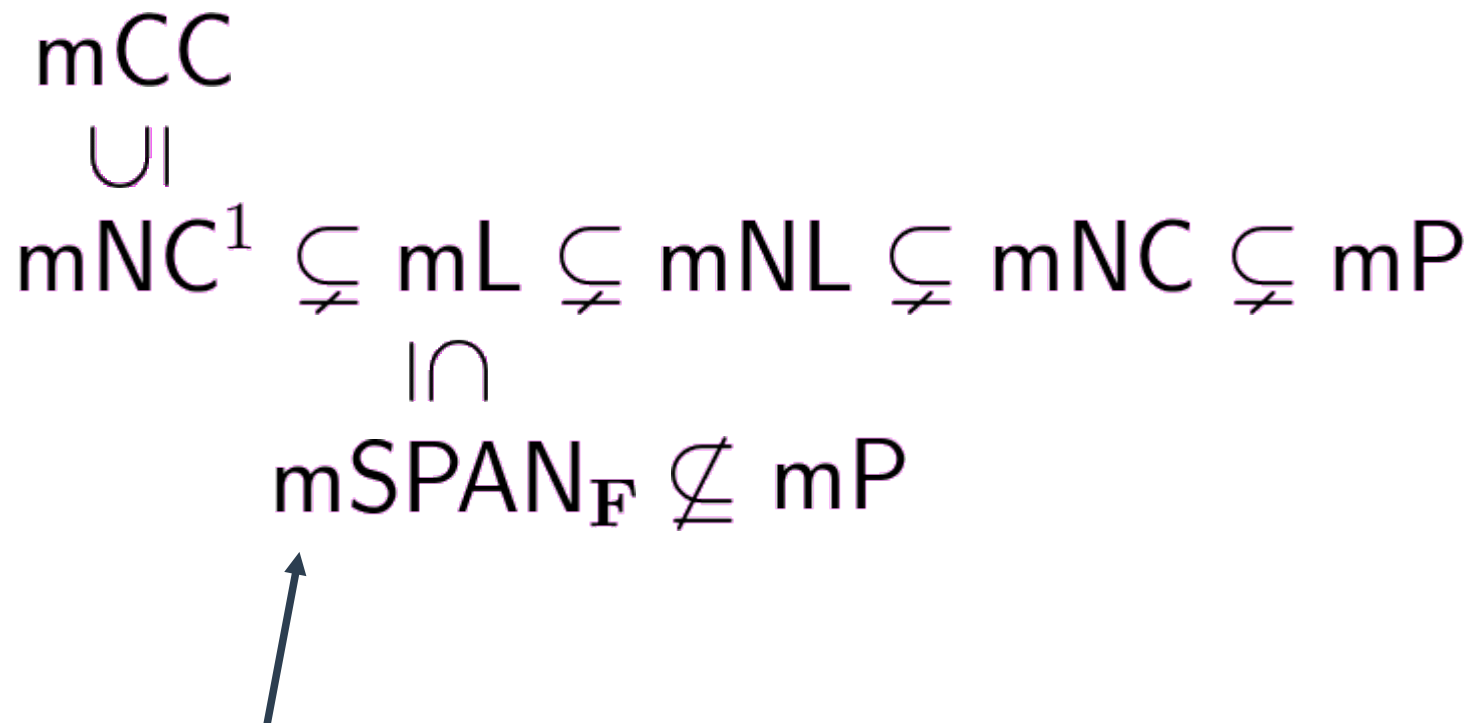
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Extra Motivation:

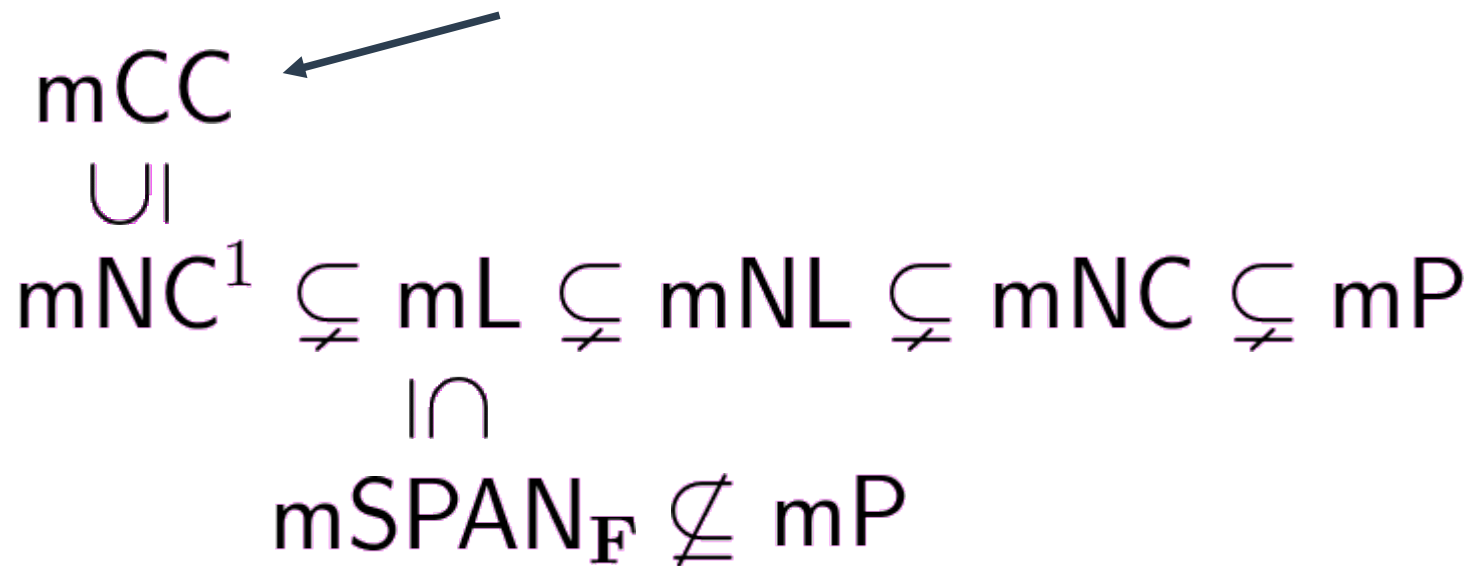
Equivalent to Linear Secret Sharing Schemes (!)

[KW '90]

Familiar Picture



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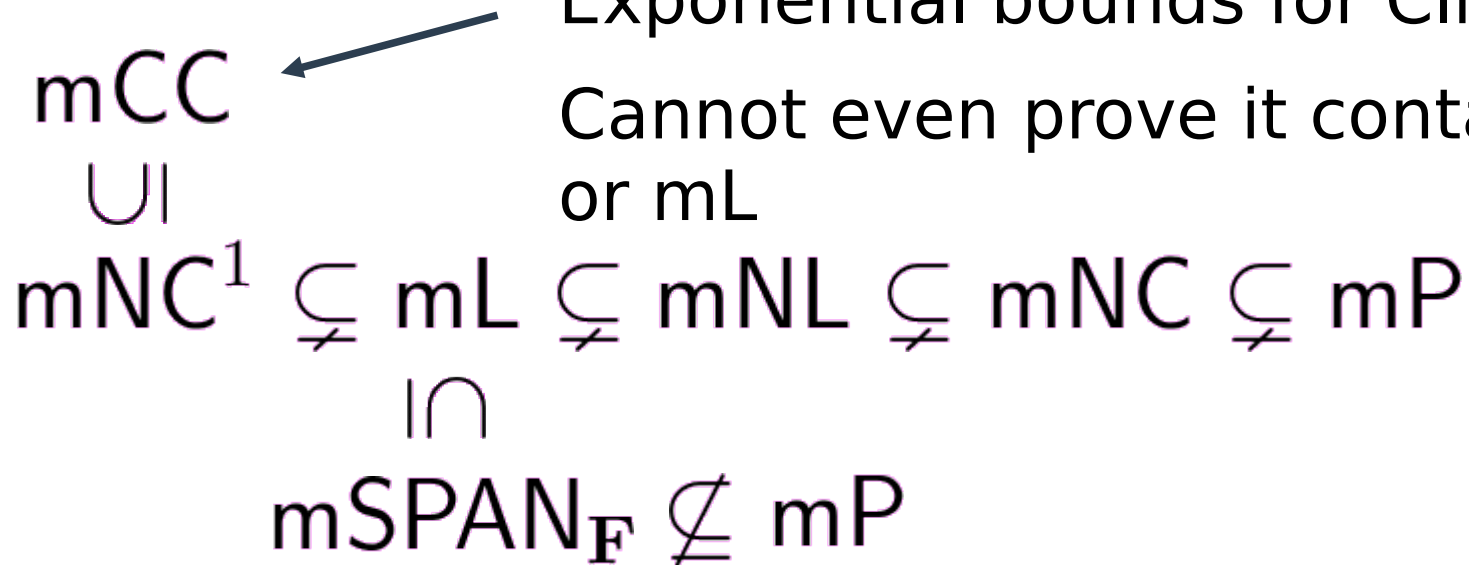


Familiar Picture

Essentially nothing known!

Exponential bounds for Clique

Cannot even prove it contains mNL or mL



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Natural Questions:

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Natural Questions:

Can we separate mSPAN from mP ? mNL ?

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Natural Questions:

Can we separate mSPAN from mP? mNL?

Can we separate mCC from mP? mNL?

Yes --- also unify nearly all lower bounds in mP.

Rank Measure

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

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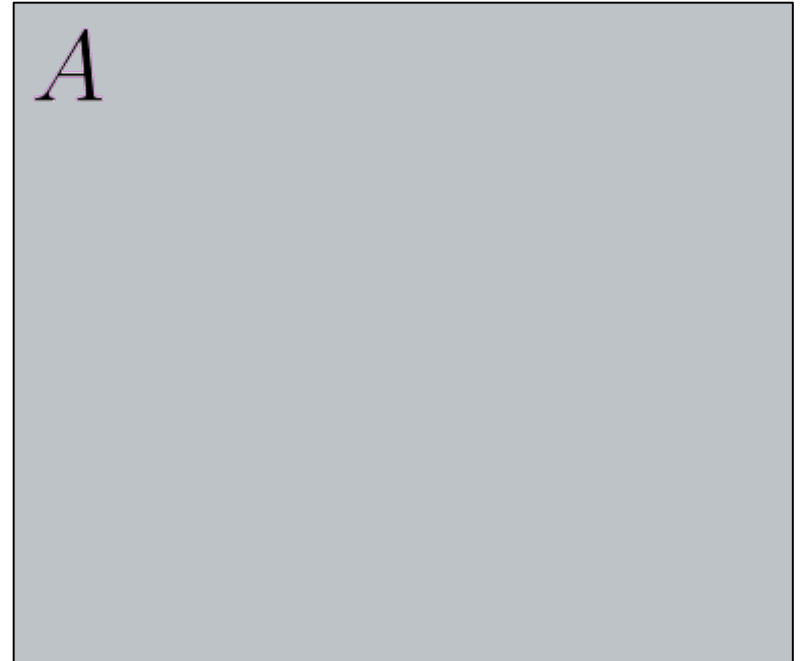
monotone

Rank Measure

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

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$$f^{-1}(0)$$



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A

Matrix

Not the
0-1 Communication
Matrix

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For any input index i ,
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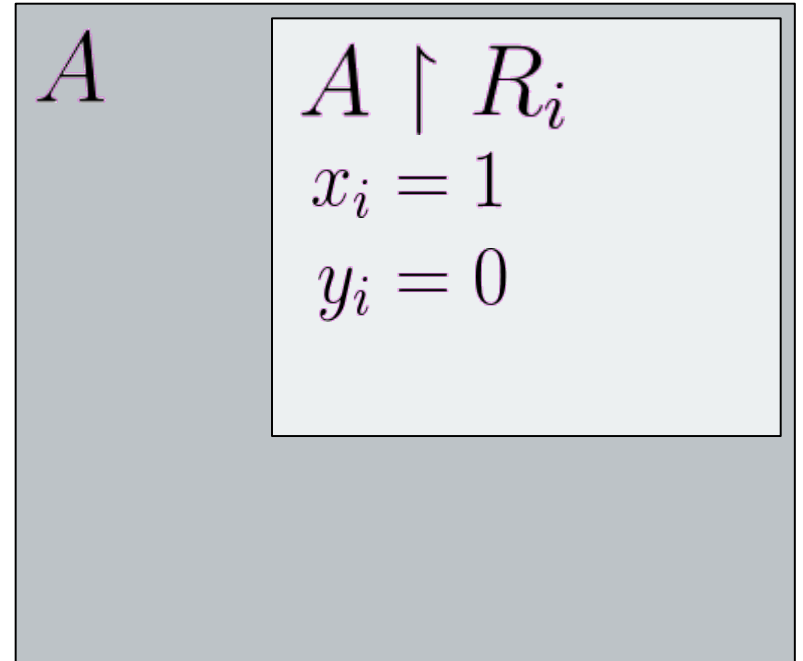
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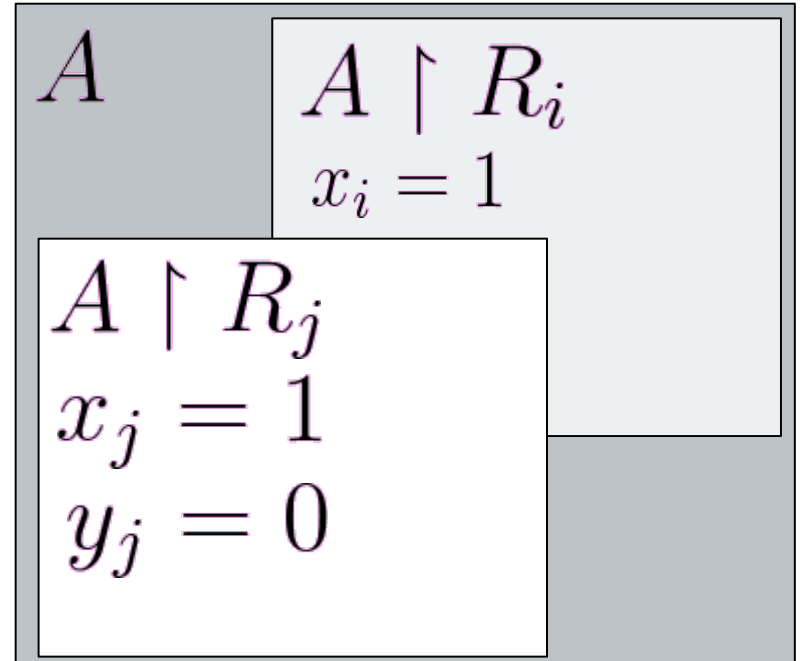
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Ranging over inputs...

$$f^{-1}(0)$$



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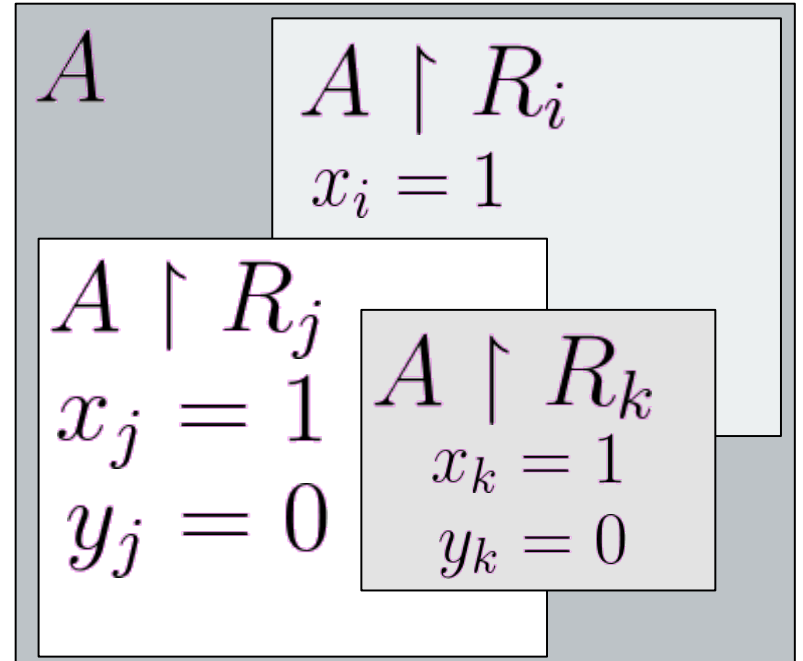
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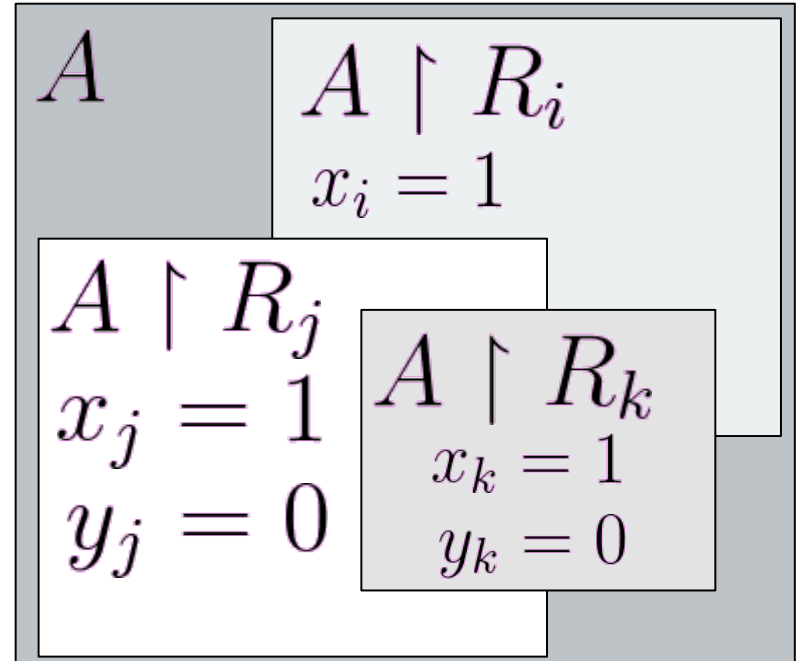
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Ranging over inputs...

All rectangles cover A!

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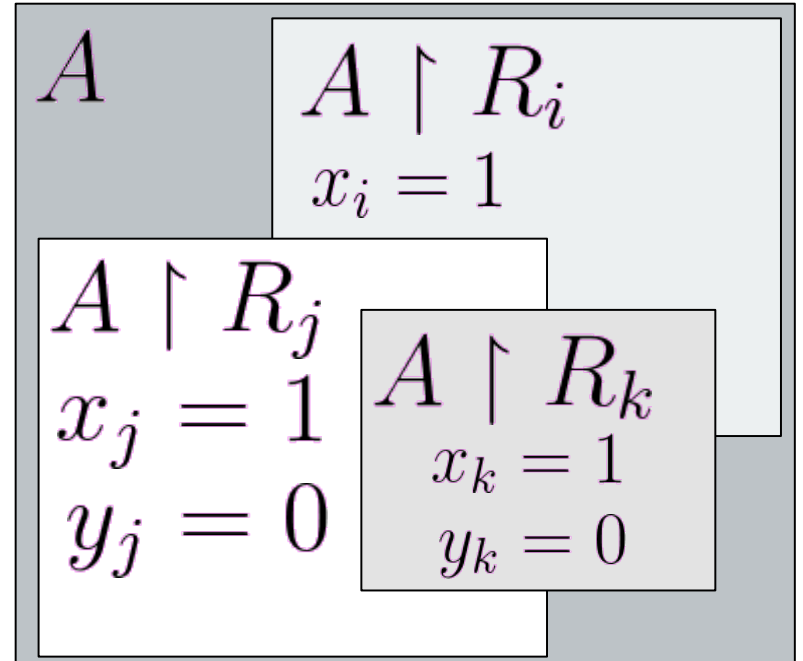
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Theorem [R '90, KW '90, G '98, **CPRR '16**]:

For any field \mathbf{F} , any boolean function f ,
and any matrix A over \mathbf{F} ,

$$\mu_A(f) \leq \text{mSPAN}_{\mathbf{F}}(f) \leq \text{mL}(f) \leq \text{mNC}^1(f)$$

$$\mu_A(f) \leq \text{mCC}(f)$$

Rank Measure

Rank Measure [Razborov '90]:

$$\text{rank}(A)$$

Best prior lower bounds:

$$\mu_A(f) \geq n^{\Omega(\log n)}$$

f in NP!

$$\mu_A(f) \geq \text{MISTAKE}(f) \geq \text{MLE}(f) \geq \text{TIME}(f)$$

$$\mu_A(f) \leq \text{mCC}(f)$$

Main Theorem

Theorem: There is a function f (GEN) in **mP** and a **real** matrix A such that $\mu_A(f) \geq 2^{\Omega(N^\epsilon)}$

There is a function g (STCONN) in **mNL** and a **real** matrix B such that $\mu_B(g) \geq N^{\Omega(\log N)}$

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Prior Work:

Unified proof of many previous monotone separations between classes within P.

Simplification of $mL \not\subseteq mNL$ [Potechin '10]

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Span Programs:

First exponential lower bounds for monotone **span programs** and linear secret sharing schemes.

First separations between monotone **span programs** and monotone P, monotone NL

Example of a function computable by non-monotone **span programs over GF(2)**, not computable by **monotone span programs over reals**

Main Theorem

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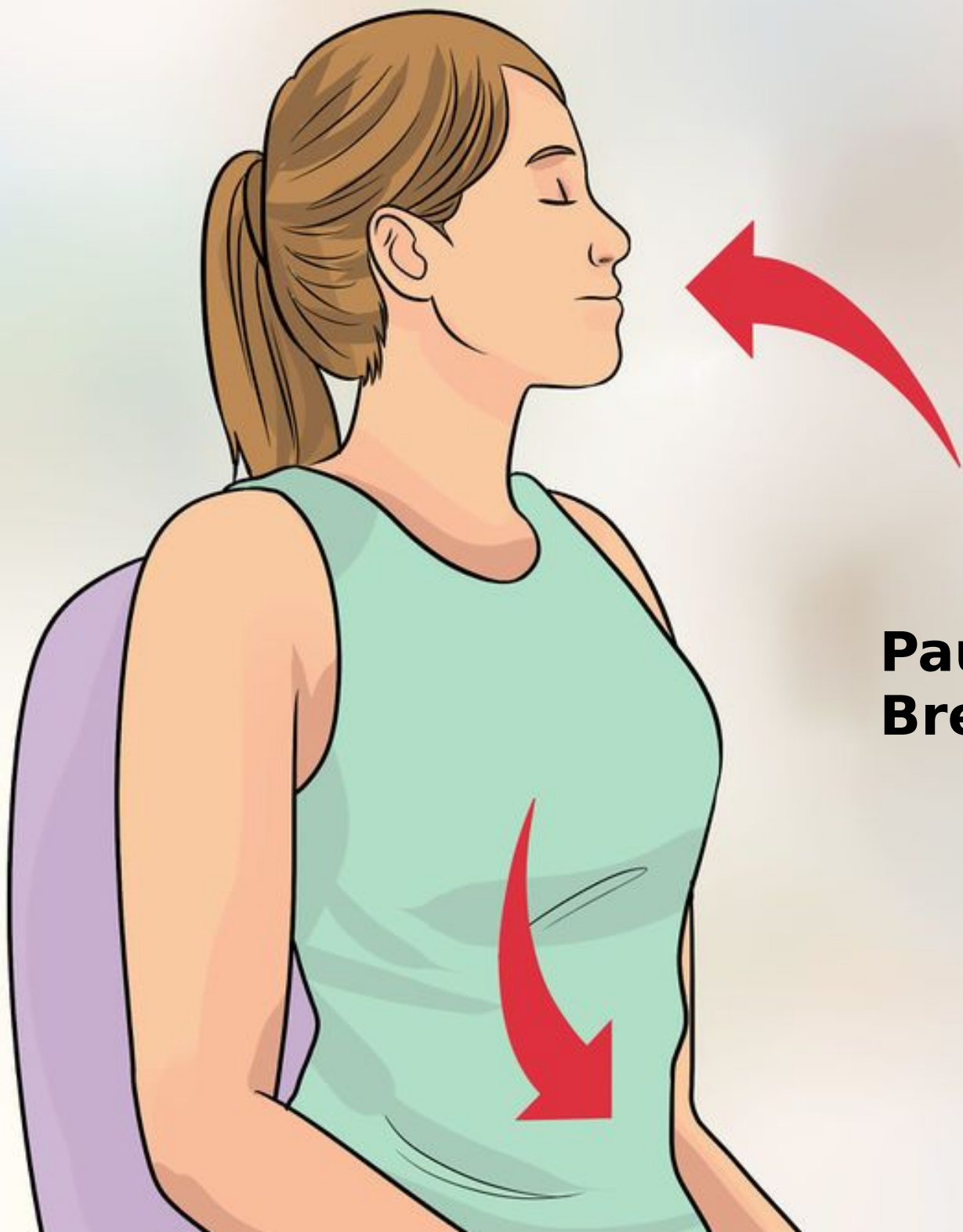
There is a function g (STCONN) in **mNL** and a **real** matrix B such that $\mu_B(g) \geq N^{\Omega(\log N)}$

Comparator Circuits:

First exponential lower bounds for **comparator circuits** computing a function in monotone P.

First separations between monotone **comparator circuits** and monotone P, monotone NL

Example of a function computable by non-monotone **comparator circuits**, not efficiently computable by monotone **comparator circuits**



**Pause!
Breathe!**

The Proof

The Proof

Previous Proofs:

The Proof

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Direct combinatorial constructions

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Resulting matrices have $\{0,1\}$ entries, for which we have quasipolynomial **upper** bounds [Razborov '90].

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Our Proof:

Prove a new **lifting theorem** to reduce the lower bound to bounding a new **algebraic query measure** on search problems.

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Our Proof:

Prove a new **lifting theorem** to reduce the lower bound to bounding a new **algebraic query measure** on search problems.

Our matrices have entries in \mathbb{R} , and so we can avoid the above obstacle.

The Proof

Overview

Rank Measure [Razborov '90]:

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- 1 Associate with certain special functions f (like GEN and ST-CONN) a search problem $\text{Search}(f)$

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- 2** (**Lift**) Reduce constructing a good matrix A for f to lower bounding a complexity measure on $\text{Search}(f)$

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- 3** Actually **prove** the query lower bounds against $\text{Search}(f)$

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Rank Measure [Razborov '90]:

Follows from
[Raz-Mckenzie '97]
[Goos-Pitassi '15]

$$\frac{\kappa(A)}{\kappa(A \upharpoonright R_i)}$$

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- 1 Associate with certain special functions f (like GEN and ST-CONN) a search problem $\text{Search}(f)$
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The Proof

Lifting Theorem

The Proof

Lifting Theorem

(Communication Setting)

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Search Problem

$$S = \text{Search}(f)$$

$$S \subseteq \{0, 1\}^n \times Q$$

The Proof

Lifting Theorem

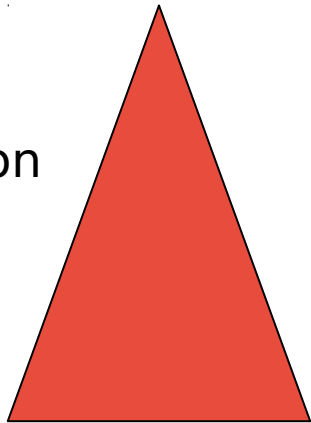
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Decision
Tree



Hard for
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Measure

The Proof

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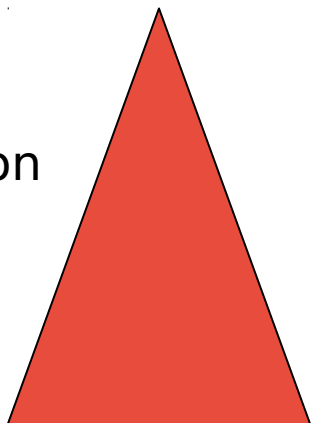
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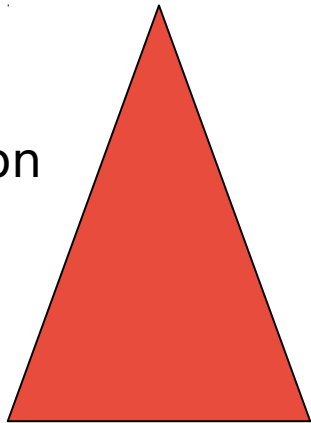
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$$S(g(x_1, y_1), \dots, g(x_n, y_n))$$



Compose S with some
two input function g

Alice gets x inputs

Bob gets y inputs

The Proof

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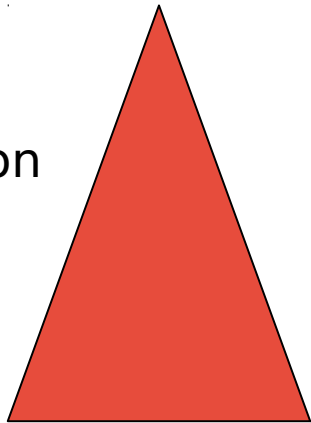
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Compose S with some
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Alice gets x inputs
Bob gets y inputs

\mathcal{A}^n



Hard for
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The Proof

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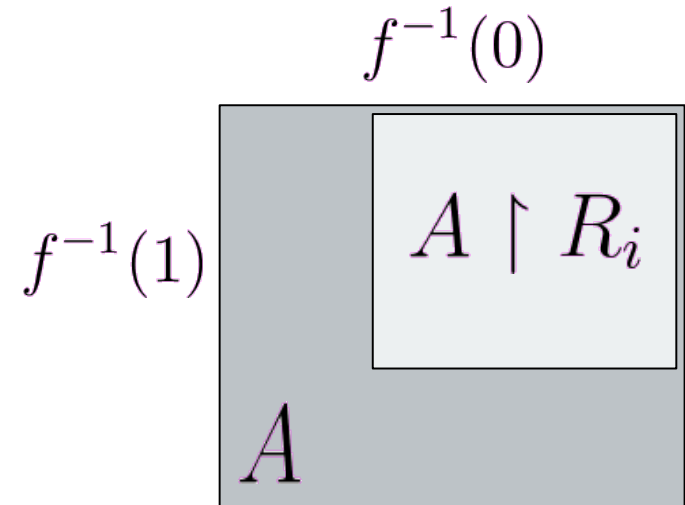
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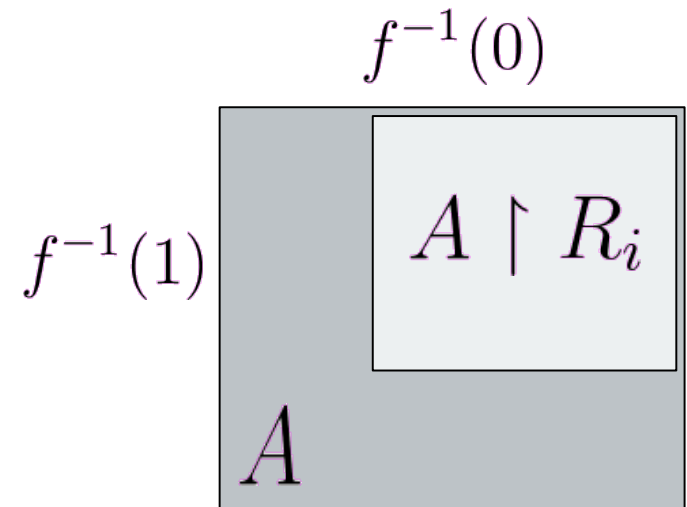
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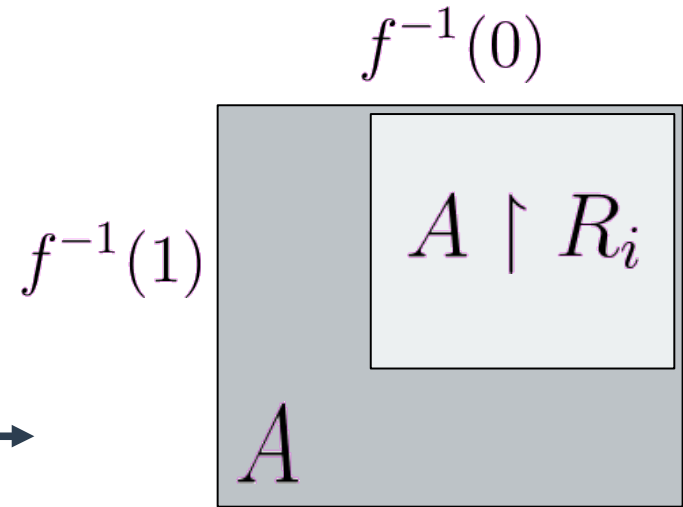
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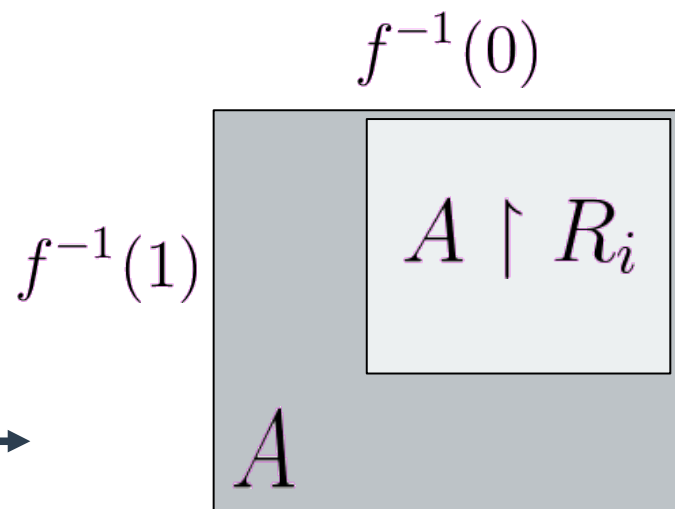
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$$p : \{0, 1\}^n \rightarrow \mathbf{R}$$

certifying a large
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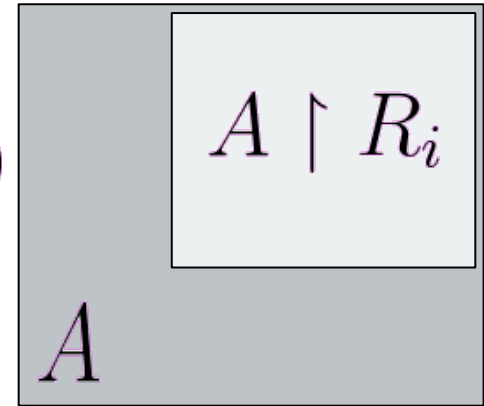
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$$f^{-1}(1)$$



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Lifting Theorem (ST-CONN)

Theorem: (Lifting Theorem for Rank Measure)

Consider layered ST-CONN on the $2m^2 \times m$ grid, and let k be the **algebraic gap complexity** of the ST-CONN search problem. There is a real matrix A such that

$$\mu_A(\text{ST-CONN}) \geq \frac{m^k}{6}$$

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Proof: Intuition on previous slide, extension of the Pattern Matrix Method [Sherstov '08].

The Proof

Overview

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Algebraic Gaps

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Lifting Theorem

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Def: Let $F = C_1 \wedge C_2 \wedge \dots \wedge C_m$ be an unsatisfiable CNF. Then $\text{Search}(F)$ is the following problem:
Given an assignment x to the variables of F ,
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Def: Let $F = C_1 \wedge C_2 \wedge \cdots \wedge C_m$ be a total search problem. The **algebraic gap complexity** of $\text{Search}(F)$ is the maximum k for which there is a polynomial $p : \{0, 1\}^n \rightarrow \mathbf{R}$ such that

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for each certificate C of $\text{Search}(F)$.

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We give lower bounds on the algebraic gap complexity for the search problems corresponding to GEN and ST-CONN by reducing to **reversible pebbling**.

The Proof

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Actually **prove** the query lower bounds against $\text{Search}(f)$

$$\text{gap}(\text{ST-CONN}) = \log n$$

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Unified lower bounds against monotone models
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Thanks for listening!

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