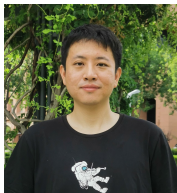
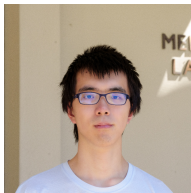


$$\text{BPL} \subseteq \text{L-AC}^1$$



Kuan Cheng
(Peking University)



Yichuan Wang
(Tsinghua University)

2024-07-23

BPL \subseteq L-AC¹

Definition (BPL, bounded-error probabilistic logspace)

M runs in space $O(\log |x|)$;

$$x \text{ (input)} \mapsto \begin{cases} \text{Yes} & \text{if } \Pr_r[M(x, r) = 1] \geq 2/3 \\ \text{No} & \text{if } \Pr_r[M(x, r) = 1] \leq 1/3 \\ \perp & \text{otherwise} \end{cases} \quad (r: \text{ random bits})$$

(Important) M only has read-once access to random tape r ;

Halt on any random tape $\implies |r| \leq \text{poly}(|x|)$.

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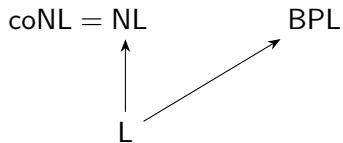
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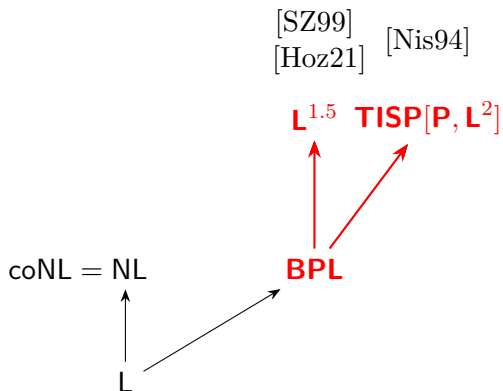
- ▶ Unbounded fan-in AND/OR gates and free NOT gates.
- ▶ $\text{poly}(n)$ -size, $O(\log n)$ -depth.
- ▶ Logspace uniform.

Relations Between Complexity Classes ($A \rightarrow B$ means $A \subseteq B$)



- ▶ **Wish to prove:** $L = \text{BPL}$.
- ▶ **Don't even know:** does $L = \text{NL}$ imply $L = \text{BPL}$?

Relations Between Complexity Classes ($A \rightarrow B$ means $A \subseteq B$)



► Progress towards $L = BPL$:

[Sav70] [BCP83] [Nis92] [Nis94]
[INW94] [NZ96] [SZ99] [KvM02]
[CH20] [Hoz21] [Pyn23]

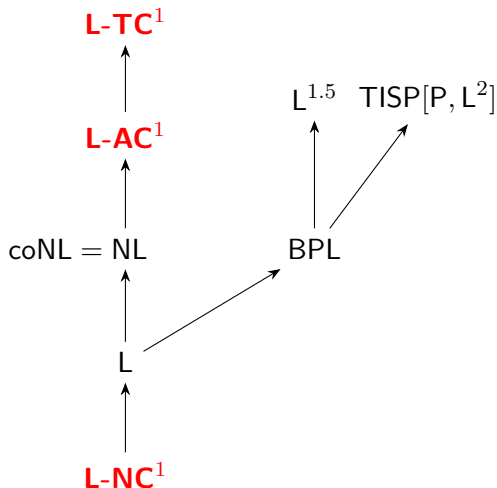
...

Black-box PRG

Richardson Iteration

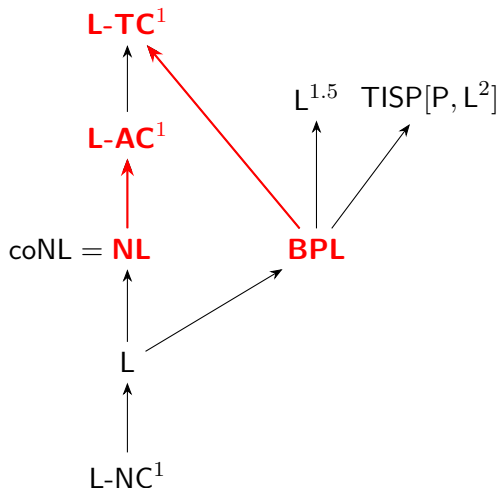
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- Hierarchy of shallow circuit classes:
 - $L-NC^1$: logspace uniform NC^1 ;
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- ▶ Hierarchy of shallow circuit classes:
 - $L-NC^1$: logspace uniform NC^1 ;
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- ▶ $NL \subseteq L-AC^1$, $BPL \subseteq L-TC^1$.
We will see why.

Preliminaries: Matrix Norm

Definition (L_1 -norm)

- ▶ For vector, $\left\| (x_1, x_2, \dots, x_n)^\top \right\| := |x_1| + |x_2| + \dots + |x_n|$.
- ▶ For matrix, $\|\mathbf{A}\| := \max_{\mathbf{x}} \frac{\|\mathbf{A}\mathbf{x}\|}{\|\mathbf{x}\|} = \max_i \left\| (i\text{-th column of } \mathbf{A}) \right\|$.

Proposition

- ▶ $\|\mathbf{A} + \mathbf{B}\| \leq \|\mathbf{A}\| + \|\mathbf{B}\|$
- ▶ $\|\mathbf{AB}\| \leq \|\mathbf{A}\| \cdot \|\mathbf{B}\|$

Definition (Stochastic vector/matrix)

A vector/matrix \mathbf{A} is stochastic if:

1. all entries of \mathbf{A} are nonnegative; and
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Definition (Substochastic vector/matrix)

A vector/matrix \mathbf{A} is **sub**stochastic if:

1. all entries of \mathbf{A} are nonnegative; and
2. sum of entries in each column is ≤ 1 . (i.e., $\|\mathbf{A}\| \leq 1$)

Stochastic Vector: represents a probability distribution.

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Matrix Multiplication View of BPL

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- ▶ Estimating powers of \mathbf{A} is BPL-complete!

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1/poly(n)-error standard MM
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 $\implies \mathbf{BPL} \subseteq \mathbf{L-TC}^1$

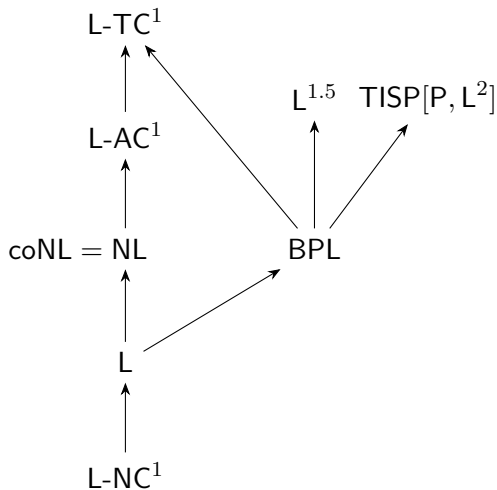
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Relations Between Complexity Classes ($A \rightarrow B$ means $A \subseteq B$)

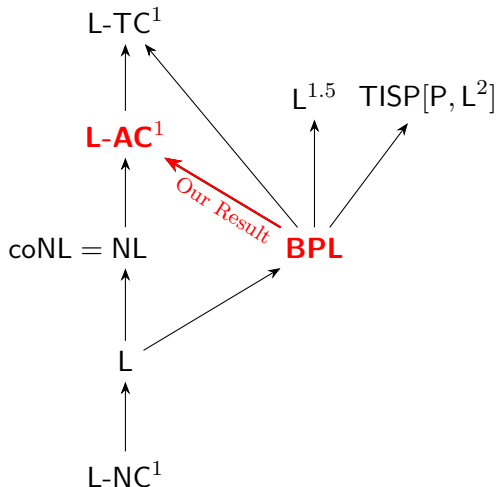


► Known Relations:

$$L\text{-NC}^1 \subseteq L \subseteq NL \subseteq L\text{-AC}^1 \subseteq L\text{-TC}^1$$

$$L \subseteq BPL \subseteq L\text{-TC}^1$$

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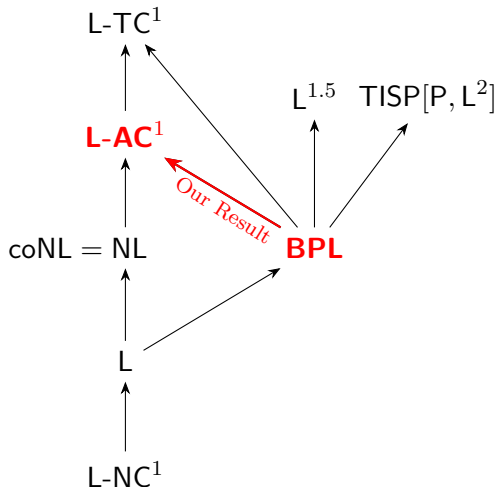
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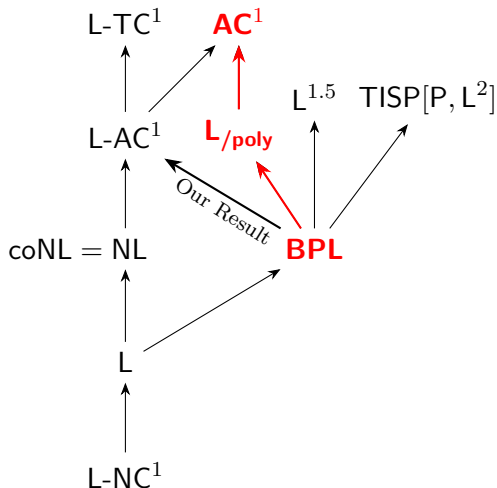
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- ▶ Partial progress towards $BPL \subseteq NL$.

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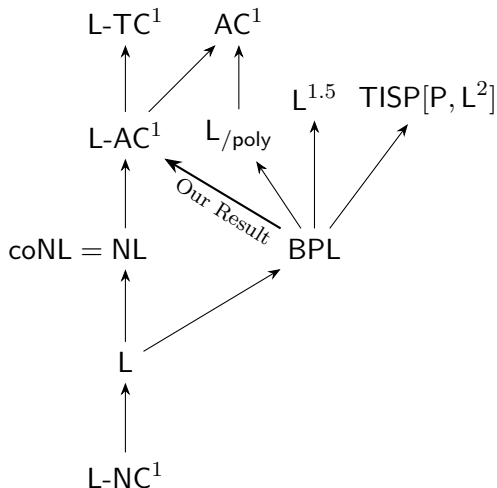
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- Remark: $BPL \subseteq AC^1$ (non-uniform AC^1) is trivial.

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$$L \subseteq \text{BPL} \subseteq L\text{-TC}^1$$

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Overview of our Algorithm $\mathbf{BPL} \subseteq \mathbf{L-AC}^1$

- ▶ **Part1.** Non-trivial L-AC algorithms
 - ▶ Approximate counting in L-AC.
 - ▶ Low-precision matrix operations in L-AC.
(e.g. Multiply $n \times n$ matrices with $1/3$ error in $\mathbf{L-AC}^0$)
- ▶ **Part2.** Use low-precision operations to compute matrix powering
 - ▶ Recall: estimate $\mathbf{A} \mapsto \mathbf{A}^n$ with $1/n$ -error is BPL-complete.
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(Reminder: exact majority cannot be computed in AC⁰.)

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- ▶ Later generalized in [Viola'07] [Viola'11] [Cook'20] etc. for different purposes.

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error	depth	size
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(If there are S 1's, we need to output an estimate in $[(1 - \varepsilon)S, (1 + \varepsilon)S]$.)

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Proof Sketch: Use *Samplers/Universal Hash Functions* to reduce to the standard approximate counting.

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A Nontrivial L-AC Algorithm

- ▶ A non-trivial algorithm: Approximate counting in $L-AC^0$ [Ajtai'90]

(1)

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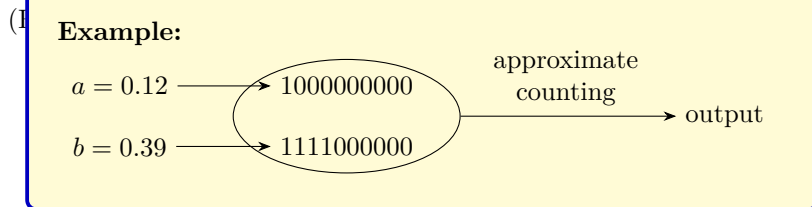
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Just compute each entry respectively.

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 - ▶ Low-precision matrix operations in L-AC.
(e.g. Multiply $n \times n$ matrices with $1/3$ error)

A General Framework:

1. Compute some weak approximations.
2. “Boost” to high precision.

Example: Richardson Iteration

[AKM+20] [CDRST21] [PV21]
[CDST22] [PP22] [CHLTW23]...

- ▶ **Part2.** Use low-precision operations to compute matrix powering
 - ▶ Recall: estimate $\mathbf{A} \mapsto \mathbf{A}^n$ with $1/n$ -error is **BPL**-complete.
 - ▶ Numerical analysis techniques! (Popular in recent years)

Framework

- ▶ Intermediate matrices $\mathbf{A}(k, t)$: a $1/2^t$ -approximation of \mathbf{A}^{2^k} (for $k, t \leq O(\log n)$)
(Goal: given \mathbf{A} , compute a valid $\mathbf{A}(\log n, \log n)$)

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Lemma (Subroutine)

For any k, t , given all $\mathbf{A}(k - i, \lfloor t/2 \rfloor + 2i)$'s ($1 \leq i \leq \min\{k, O(t)\}$), we can compute a valid $\mathbf{A}(k, t)$ in $O(t)$ -depth.

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- ▶ **Proof Sketch of Lemma**
- ▶ **Lemma $\implies \mathbf{BPL} \subseteq \mathbf{L-AC}^1$**

Boost weaker approximation to stronger approximation

▶ **Example:** (For simplicity, assume matrix multiplication commutes)

▶ **Weak Approximations:**

$$\left\| \widetilde{\mathbf{A}}^{16} - \mathbf{A}^{16} \right\| \leq \varepsilon_4, \quad \left\| \widetilde{\mathbf{A}}^8 - \mathbf{A}^8 \right\| \leq \varepsilon_3, \quad \left\| \widetilde{\mathbf{A}}^4 - \mathbf{A}^4 \right\| \leq \varepsilon_2, \quad \left\| \widetilde{\mathbf{A}}^2 - \mathbf{A}^2 \right\| \leq \varepsilon_1$$

▶ **Approximate \mathbf{A}^{32} :**

Boost weaker approximation to stronger approximation

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$$\left\| \widetilde{\mathbf{A}}^{16} - \mathbf{A}^{16} \right\| \leq \varepsilon_4, \quad \left\| \widetilde{\mathbf{A}}^8 - \mathbf{A}^8 \right\| \leq \varepsilon_3, \quad \left\| \widetilde{\mathbf{A}}^4 - \mathbf{A}^4 \right\| \leq \varepsilon_2, \quad \left\| \widetilde{\mathbf{A}}^2 - \mathbf{A}^2 \right\| \leq \varepsilon_1$$

▶ **Approximate \mathbf{A}^{32} :**

$$\begin{aligned} \left\| \widetilde{\mathbf{M}} - \mathbf{M} \right\| \leq \varepsilon &\implies \left\| (\widetilde{\mathbf{M}} - \mathbf{M})^2 \right\| \leq \varepsilon^2 \\ \implies \mathbf{M}^2 &\overset{\varepsilon^2}{\approx} 2\mathbf{M}\widetilde{\mathbf{M}} - \widetilde{\mathbf{M}}^2 \end{aligned}$$

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\mathbf{A}^{32}

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▶ **Approximate \mathbf{A}^{32} :**

$$\mathbf{A}^{32} \overset{\varepsilon_4^2}{\approx} 2\mathbf{A}^{16} \left(\widetilde{\mathbf{A}^{16}} \right) - \left(\widetilde{\mathbf{A}^{16}} \right)^2$$

$$\begin{aligned} \left\| \widetilde{\mathbf{M}} - \mathbf{M} \right\| \leq \varepsilon &\implies \left\| \left(\widetilde{\mathbf{M}} - \mathbf{M} \right)^2 \right\| \leq \varepsilon^2 \\ &\implies \mathbf{M}^2 \overset{\varepsilon^2}{\approx} 2\mathbf{M}\widetilde{\mathbf{M}} - \widetilde{\mathbf{M}}^2 \end{aligned}$$

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$$\left\| \widetilde{\mathbf{A}}^{16} - \mathbf{A}^{16} \right\| \leq \varepsilon_4, \quad \left\| \widetilde{\mathbf{A}}^8 - \mathbf{A}^8 \right\| \leq \varepsilon_3, \quad \left\| \widetilde{\mathbf{A}}^4 - \mathbf{A}^4 \right\| \leq \varepsilon_2, \quad \left\| \widetilde{\mathbf{A}}^2 - \mathbf{A}^2 \right\| \leq \varepsilon_1$$

► **Approximate \mathbf{A}^{32} :** (error: $\varepsilon_4^2 + 2\varepsilon_3^2 + 4\varepsilon_2^2 + 16\varepsilon_1$)

$$\begin{aligned} \mathbf{A}^{32} &\stackrel{\varepsilon_4^2}{\approx} 2\mathbf{A}^{16} \left(\widetilde{\mathbf{A}}^{16} \right) - \left(\widetilde{\mathbf{A}}^{16} \right)^2 \\ &\stackrel{2\varepsilon_3^2}{\approx} 4\mathbf{A}^8 \left(\widetilde{\mathbf{A}}^8 \right) \left(\widetilde{\mathbf{A}}^{16} \right) - 2 \left(\widetilde{\mathbf{A}}^8 \right)^2 \left(\widetilde{\mathbf{A}}^{16} \right) - \left(\widetilde{\mathbf{A}}^{16} \right)^2 \\ &\stackrel{4\varepsilon_2^2}{\approx} 8\mathbf{A}^4 \left(\widetilde{\mathbf{A}}^4 \right) \left(\widetilde{\mathbf{A}}^8 \right) \left(\widetilde{\mathbf{A}}^{16} \right) - 4 \left(\widetilde{\mathbf{A}}^4 \right)^2 \left(\widetilde{\mathbf{A}}^8 \right) \left(\widetilde{\mathbf{A}}^{16} \right) - 2 \left(\widetilde{\mathbf{A}}^8 \right)^2 \left(\widetilde{\mathbf{A}}^{16} \right) - \left(\widetilde{\mathbf{A}}^{16} \right)^2 \\ &\stackrel{16\varepsilon_1}{\approx} 8 \left(\widetilde{\mathbf{A}}^2 \right)^2 \left(\widetilde{\mathbf{A}}^4 \right) \left(\widetilde{\mathbf{A}}^8 \right) \left(\widetilde{\mathbf{A}}^{16} \right) - 4 \left(\widetilde{\mathbf{A}}^4 \right)^2 \left(\widetilde{\mathbf{A}}^8 \right) \left(\widetilde{\mathbf{A}}^{16} \right) - 2 \left(\widetilde{\mathbf{A}}^8 \right)^2 \left(\widetilde{\mathbf{A}}^{16} \right) - \left(\widetilde{\mathbf{A}}^{16} \right)^2 \end{aligned}$$

The Iteration Formula

- ▶ Intermediate matrices $\mathbf{A}(k, t)$: a $1/2^t$ -approximation of \mathbf{A}^{2^k} (for $k, t \leq O(\log n)$)
(Goal: given \mathbf{A} , compute a valid $\mathbf{A}(\log n, \log n)$)

Lemma (Subroutine)

For any k, t , given all $\mathbf{A}(k - i, \lfloor t/2 \rfloor + 2i)$'s ($1 \leq i \leq \min\{k, O(t)\}$), we can compute a valid $\mathbf{A}(k, t)$ in $O(t)$ -depth.

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Lemma (Iteration Formula)

For any positive integers $k \geq t$, suppose \mathbf{B}_i is an approximation of \mathbf{A}^{2^i} such that

$$\|\mathbf{B}_i - \mathbf{A}^{2^i}\| \leq \varepsilon_i \quad (\text{for } i = 1, 2, \dots, k-1). \text{ Define}$$

$$\mathbf{C} := - \sum_{i=1}^{t-1} \sum_{\substack{\{j_1 < \dots < j_p\} \uplus \{j'_1 < \dots < j'_q\} \\ = \{k-1, k-2, \dots, k-i+1\}}} \mathbf{B}_{j_p} \cdots \mathbf{B}_{j_1} \mathbf{B}_{k-i}^2 \mathbf{B}_{j'_1} \cdots \mathbf{B}_{j'_q} + \sum_{\substack{\{j_1 < \dots < j_p\} \uplus \{j'_1 < \dots < j'_q\} \\ = \{k-1, k-2, \dots, k-t+1\}}} \mathbf{B}_{j_p} \cdots \mathbf{B}_{j_1} \mathbf{B}_{k-t}^2 \mathbf{B}_{j'_1} \cdots \mathbf{B}_{j'_q}.$$

$$\text{Then } \|\mathbf{C} - \mathbf{A}^{2^k}\| \leq \varepsilon_{k-1}^2 + 2\varepsilon_{k-2}^2 + 4\varepsilon_{k-3}^2 + \cdots + 2^{t-2}\varepsilon_{k-t+1}^2 + 2^t\varepsilon_{k-t}.$$

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Lemma (Iteration Formula)

For any positive integers $k \geq t$, suppose

$$\varepsilon_{k-i} \leq 1/2^{\lfloor t/2 \rfloor + 2i} \implies \left\| \mathbf{C} - \mathbf{A}^{2^k} \right\| \leq 0.99/2^t$$

$\left\| \mathbf{B}_i - \mathbf{A}^{2^i} \right\| \leq \varepsilon_i$ (for $i = 1, 2, \dots, k-1$). Define

$$\mathbf{C} := - \sum_{i=1}^{t-1} \sum_{\substack{\{j_1 < \dots < j_p\} \uplus \{j'_1 < \dots < j'_q\} \\ = \{k-1, k-2, \dots, k-i+1\}}} \mathbf{B}_{j_p} \cdots \mathbf{B}_{j_1} \mathbf{B}_{k-i}^2 \mathbf{B}_{j'_1} \cdots \mathbf{B}_{j'_q} + \sum_{\substack{\{j_1 < \dots < j_p\} \uplus \{j'_1 < \dots < j'_q\} \\ = \{k-1, k-2, \dots, k-t+1\}}} \mathbf{B}_{j_p} \cdots \mathbf{B}_{j_1} \mathbf{B}_{k-t}^2 \mathbf{B}_{j'_1} \cdots \mathbf{B}_{j'_q}.$$

Then $\left\| \mathbf{C} - \mathbf{A}^{2^k} \right\| \leq \varepsilon_{k-1}^2 + 2\varepsilon_{k-2}^2 + 4\varepsilon_{k-3}^2 + \dots + 2^{t-2}\varepsilon_{k-t+1}^2 + 2^t\varepsilon_{k-t}.$

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For any positive integers $k \geq t$,

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1. Compute all matrix operations with **error** $1/2^{O(t)}$.

$$\text{Depth: } O\left(\frac{t}{\log \log n} + 1\right) \leq O\left(\frac{t}{\log t}\right).$$

2. Multiplication of $O(t)$ matrices in each term.

$$\mathbf{C} := - \sum_{i=1}^{t-1} \sum_{\substack{\{j_1 < \dots < j_p\} \uplus \{j'_1 < \dots < j'_q\} \\ = \{k-1, k-2, \dots, k-i+1\}}} \mathbf{B}_{j_p} \cdots \mathbf{B}_{j_1} \mathbf{B}_{k-i}^2 \mathbf{B}_{j'_1} \cdots \mathbf{B}_{j'_q} + \sum_{\substack{\{j_1 < \dots < j_p\} \uplus \{j'_1 < \dots < j'_q\} \\ = \{k-1, k-2, \dots, k-t+1\}}} \mathbf{B}_{j_p} \cdots \mathbf{B}_{j_1} \mathbf{B}_{k-t}^2 \mathbf{B}_{j'_1} \cdots \mathbf{B}_{j'_q}.$$

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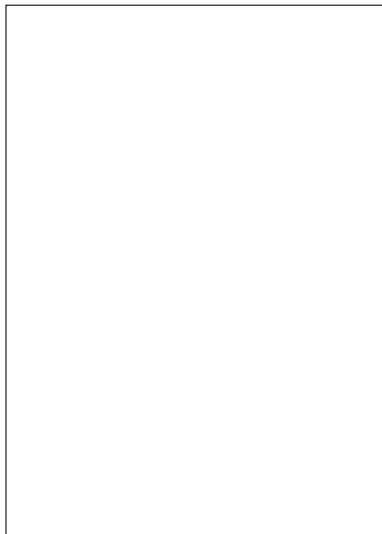
Subroutine \rightarrow Complete Algorithm

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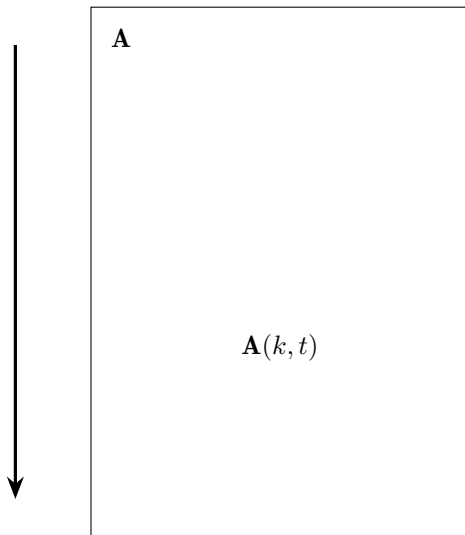
A

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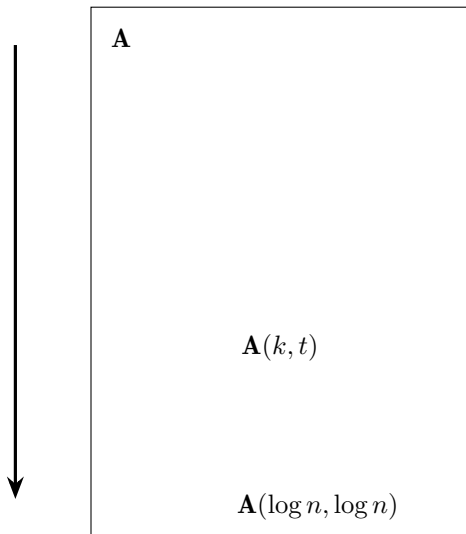


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For any k, t , given all $\mathbf{A}(k - i, \lfloor t/2 \rfloor + 2i)$'s ($1 \leq i \leq \min\{k, O(t)\}$), we can compute a valid $\mathbf{A}(k, t)$ in $O(t)$ -depth.

Subroutine \rightarrow Complete Algorithm

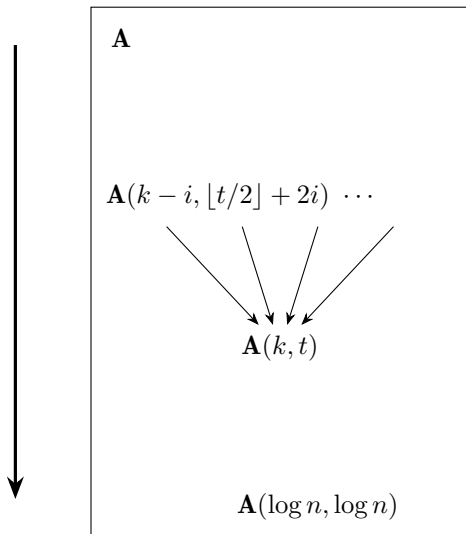


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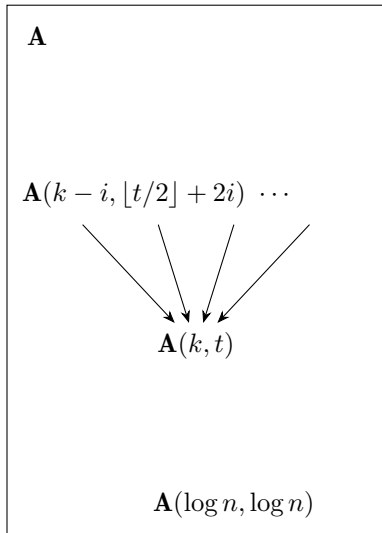
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Depth

0



$C \cdot (2k + t)$

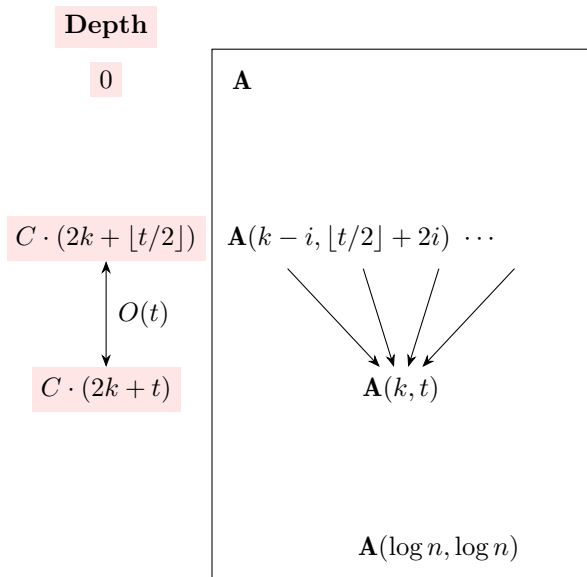
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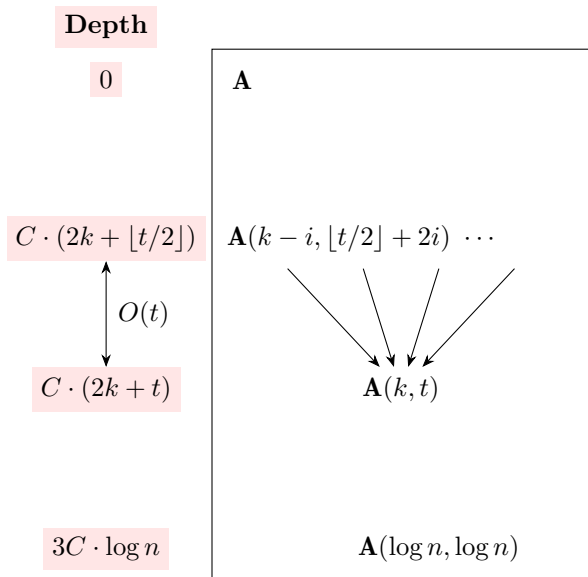
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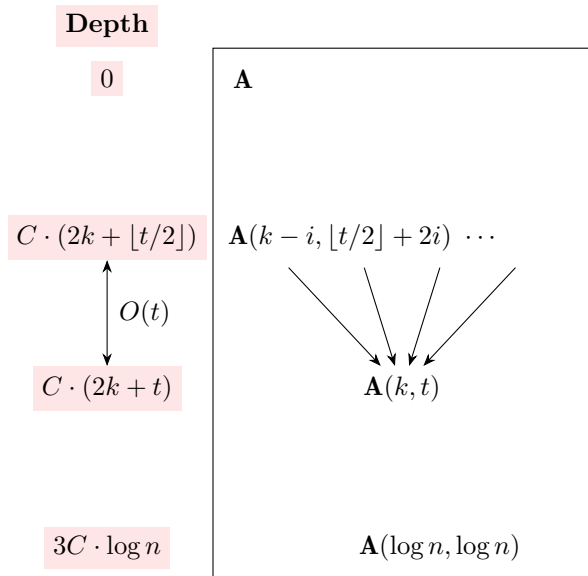
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Summary

- ▶ **Part1.** Non-trivial L-AC algorithms
 - ▶ Approximate counting in L-AC.
 - ▶ Low-precision matrix operations in L-AC.
(e.g. Multiply $n \times n$ matrices with $1/3$ error in L-AC⁰)
- ▶ **Part2.** Use low-precision operations to compute matrix powering
 - ▶ Recall: estimate $\mathbf{A} \mapsto \mathbf{A}^n$ with $1/n$ -error is BPL-complete.
 - ▶ Numerical analysis techniques! (Popular in recent years)

Subroutine \rightarrow Complete Algorithm



- ▶ Intermediate matrices $\mathbf{A}(k, t)$: a $1/2^t$ -approximation of \mathbf{A}^{2^k} (for $k, t \leq O(\log n)$)
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Subroutine \rightarrow Complete Algorithm

Depth

0

A

$C \cdot (2k + \lfloor t/2 \rfloor)$

$O(t)$

$C \cdot (2k + t)$

$\mathbf{A}(k - i, \lfloor t/2 \rfloor + 2i) \dots$

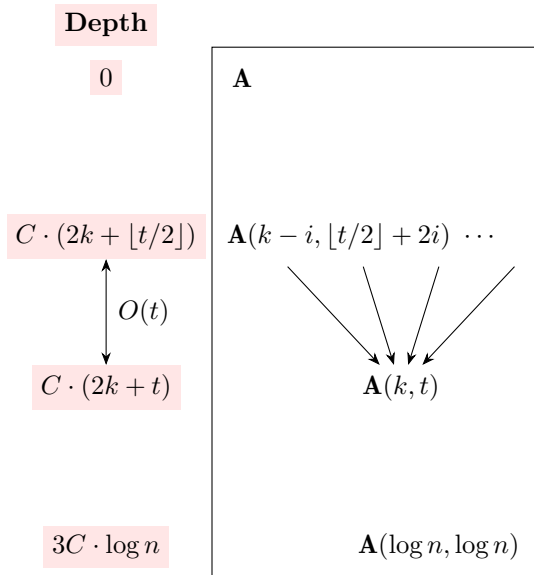
$\mathbf{A}(k, t)$

$3C \cdot \log n$

$\mathbf{A}(\log n, \log n)$

Our Iteration Formula v.s. Richardson

Subroutine \rightarrow Complete Algorithm



Our Iteration Formula v.s. Richardson

► Richardson

► Saks-Zhou argument:

$\mathbf{A} \mapsto \mathbf{A}^{2^{\sqrt{\log n}}}$ for $\sqrt{\log n}$ rounds.

► Weaker result: $\text{BPL} \subseteq \text{L-AC}^{1.5}$.

► Each round depends on the previous round, not efficiently parallelized!

► Our Iteration Formula

► More efficiently parallelized!

Thank you!

▶ Q&A

Thank you!

- ▶ Q&A
- ▶ Thank you for listening!