

Lecture 21: Parallel Algorithms, Non-Uniform Algorithms & Linear Algebra in Parallel

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Overview

- Administrivia
- Parallel Algorithms: Computational Model
- Linear Algebra in Fast Parallel Time
- Conclusion
- Acknowledgements

Rate this course!

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from *November 24th until December 7th* and provide us with your evaluation and feedback on the course!

- This would really help me figuring out what worked and what didn't for the course
- And whether I should put memes or gifs into my slides...
- Teaching this course is also a learning experience for me :)

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Consider doing a URA, URF or USRA with a U Waterloo faculty!

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[https://cs.uwaterloo.ca/computer-science/
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undergraduate-research-assistantship-ura-program](https://cs.uwaterloo.ca/computer-science/current-undergraduate-students/research-opportunities/undergraduate-research-assistantship-ura-program)

- Undergraduate Research Fellowship (URF):

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- Undergraduate Research Internship (URI):

[https://cs.uwaterloo.ca/current-undergraduate-students/
research-opportunities/
undergraduate-research-internship-uri-program](https://cs.uwaterloo.ca/current-undergraduate-students/research-opportunities/undergraduate-research-internship-uri-program)

- For Canadians, please check out NSERC's USRA:

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Parallel Model of Computation

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- Each processor can do *one* of the following operations in *unit time* (called a step):
 - *fetch* from memory
 - any binary operation (i.e. $+$, $-$, \times , \div , \wedge , \vee)
 - *storing* to memory

A handwritten diagram in orange ink illustrating a single step of computation. On the left, two boxes contain the numbers 15 and 27. An arrow points from these two boxes to a larger box on the right containing the number 42. Above the arrow is a plus sign (+). Below the arrow is the time complexity notation $O(1)$.

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- Before starting the computation, *entire input* stored in memory (thus accessible by all processors)
- Complexity Measures:
 - *Depth*: number of *sequential* steps needed from start to end.
 - *Width*: *maximum* number of processors needed in one “level” of the computation.
 - *Total number of operations*: total number of operations performed by all processors.

Non-Uniform Model of Computation

- Turing Machines are the model we are used to:
A *fixed-length code* that can handle inputs *of any size*.

One algorithm to rule
them (inputs) all!

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- Non-Uniform Model of Computation:

Specific code C_n which handles only inputs from Σ^n .

$\Sigma \leftarrow$ alphabet
($\{0, 1\}$)

length n

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- In non-uniform model, your “code” is a family of codes $\{C_n\}_{n \geq 0}$ where C_n only handles input of size n
- Is that a reasonable model of computation?

- Used in design of VLSI circuits

https://en.wikipedia.org/wiki/Very_Large_Scale_Integration

- Used for any “special purpose” computations
- Such non-uniform codes are called *circuits*.

Parallel Model in Algebraic Setting

- For algebraic computations (multiplying two matrices, computing determinants, solving linear systems, solving polynomial equations...) it makes sense to try algorithms which *only use algebraic operations* (i.e. $+$, $-$, \times , \div)

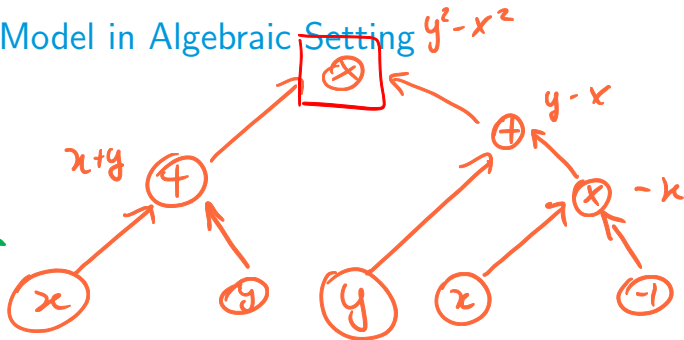
arithmetic complexity

Parallel Model in Algebraic Setting

- For algebraic computations (multiplying two matrices, computing determinants, solving linear systems, solving polynomial equations...) it makes sense to try algorithms which *only use algebraic operations* (i.e. $+$, $-$, \times , \div)
- Algorithms in algebraic setting will compute:
 - polynomials
 - matrices
 - group elements
 - other algebraic objects

Parallel Model in Algebraic Setting $y^2 - x^2$

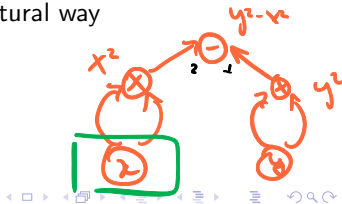
Formula \rightarrow



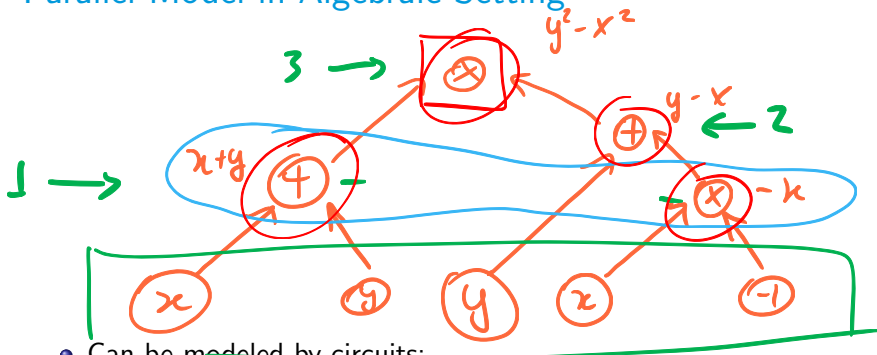
- Can be modeled by circuits:

- Directed Acyclic Graphs
- Each gate is either: input, algebraic operation
- Non-input gates compute polynomial in natural way
- Choose one gate to be the “output gate”

circuit



Parallel Model in Algebraic Setting



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 - Directed Acyclic Graphs
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 - Choose one gate to be the “output gate”
- Complexity measures:
 - *Depth*: length of longest path from input to output
 - *Width*: length of largest “layer”
 - *Operations*: total number of operations

Main Objects for Today's Class

① Determinant:

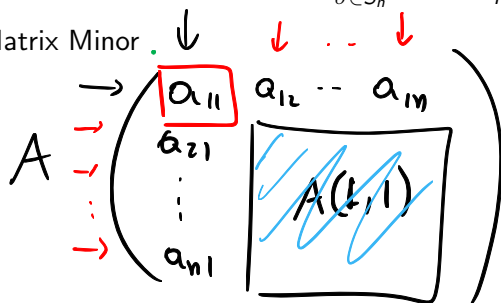
$$\det(X) = \sum_{\sigma \in S_n} \operatorname{sgn}(\sigma) \cdot \prod_{i=1}^n x_{i\sigma(i)}$$

Main Objects for Today's Class

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- 2 Matrix Minor



square submatrices

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- 3 Matrix Adjugate: the matrix $\operatorname{Adj}(X)$ is the unique matrix such that

$$\underline{\operatorname{Adj}(X)} \cdot \underline{X} = \underline{\det(X) \cdot I_n}$$

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$$\operatorname{Adj}(X) \cdot X = \det(X) \cdot I_n$$

- ④ Inverse of matrix:

$$X^{-1} = \frac{1}{\det(X)} \cdot \operatorname{Adj}(X)$$

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- 4 Inverse of matrix:

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- 5 Characteristic polynomial of matrix:

$$p_X(\lambda) = \det(X - \lambda \cdot I_n) = \sum_{i=0}^n p_{n-i} \lambda^i$$

$$p_0 = p_X(0) = \det(X)$$

encode useful info.

Foundational Problems in Linear Algebra

- Computing the determinant of a matrix
- Solving a linear system of equations
- Inverting a matrix
- Computing the adjugate of a matrix
- Computing characteristic polynomial of matrix

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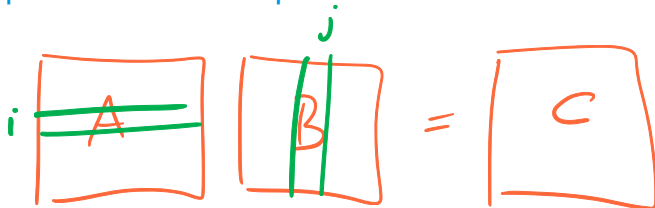
$$N = n^2$$

Can we solve the problems above fast in parallel time?

Fast here means: on input of size N , we have an algebraic circuit of

- size $\text{poly}(N)$ (i.e. total number of operations)
- depth $\log^c(N)$, for some constant $c > 0$.

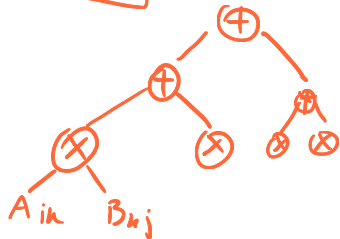
Example: Matrix Multiplication



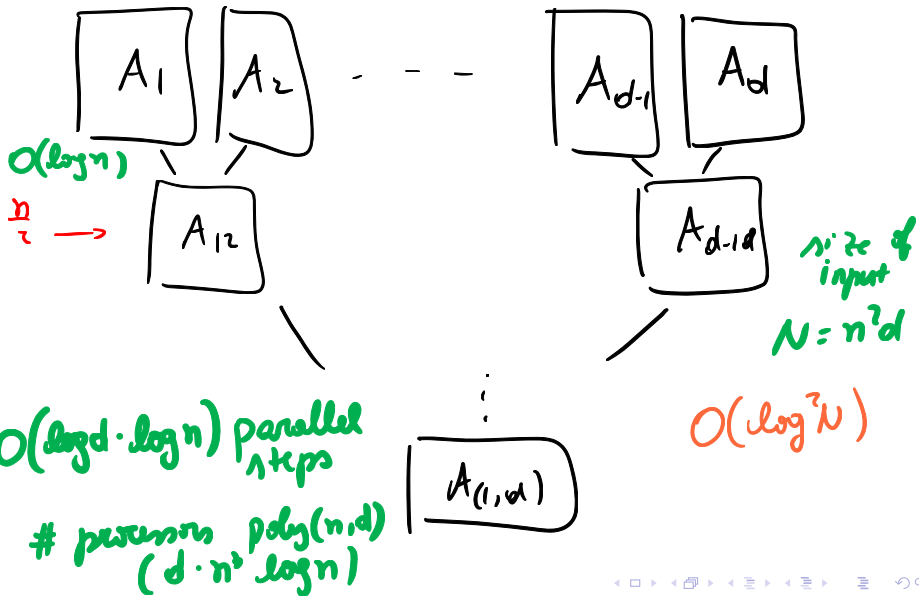
$$C_{ij} = \sum_{k=1}^n A_{ik} \cdot B_{kj}$$

$$(A_{i1}, \dots, A_{in}) \begin{pmatrix} B_{1j} \\ \vdots \\ B_{nj} \end{pmatrix}$$

$O(\log n)$ parallel time
 n^3 processors



Example: Multiplication of Sequence of Matrices



- Administrivia
- Parallel Algorithms: Computational Model
- **Linear Algebra in Fast Parallel Time**
- Conclusion
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Our Task

- 1 Computing the determinant of a matrix

$$\textcircled{5} \Rightarrow \textcircled{1}$$

- 2 Solving a linear system of equations

$$\textcircled{3} \Rightarrow \textcircled{2}$$

- 3 Inverting a matrix

$$\textcircled{1} + \textcircled{4} \Rightarrow \textcircled{3}$$

- 4 Computing the adjugate of a matrix

$$\textcircled{5} \Rightarrow \textcircled{4}$$

- 5 Computing characteristic polynomial of matrix

TODAY ↙

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Cayley-Hamilton Theorem

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Cayley-Hamilton

$$0 = p_A(A) = \det(A) \cdot I + \sum_{i=1}^n p_{n-i} \cdot A^i \Rightarrow$$

all elements are multiples of A

$$\Rightarrow \det(A) \cdot I = - \sum_{i=1}^n p_{n-i} \cdot A^i$$

by uniqueness

$$= A \cdot \left(- \sum_{i=1}^n p_{n-i} \cdot A^{i-1} \right) = A \cdot \text{Adj}(A)$$

Adj(A)

Berkowitz's Algorithm - Outline

- 1 Strategy: compute characteristic polynomial via sequence of matrix multiplications.

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- 2 Reduce computation of characteristic polynomial of A to computation of characteristic polynomial of principal minor $A(1 | 1)$

$$\boxed{A} = \begin{pmatrix} a_{11} & R \\ S & \boxed{A(1|1)} \end{pmatrix}$$

↓

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Useful Lemmas

Lemma

Let $A = \begin{pmatrix} a_{11} & R \\ S & M_1 \end{pmatrix}$. Then $A \sim \begin{pmatrix} 1 & \\ & \end{pmatrix}$

$$p_A(\lambda) = (a_{11} - \lambda) \cdot \det(M_1 - \lambda \cdot I) + R \cdot \text{adj}(M_1 - \lambda \cdot I) \cdot S$$

$p_{M_1}(\lambda)$

can be
computed
from $p_{M_1}(\lambda)$

Can compute $p_A(\lambda)$ from $p_{M_1}(\lambda)$!

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$$\left(\begin{array}{c|c} X_{11} & X_{12} \\ \hline X_{21} & X_{22} \end{array} \right) =: X$$

$X_{21} X_{11}$ $X_{11} X_{12}$ $X_{22} X_{21}$ $X_{12} X_{22}$
 X, X_{11}, X_{22} square

Lemma :

$$\begin{array}{|c|c|} \hline X_{11} & 0 \\ \hline * & X_{22} \\ \hline \end{array} \quad A$$

$$\sim \begin{array}{|c|c|} \hline X_{11} & * \\ \hline 0 & X_{22} \\ \hline \end{array} \quad B$$

$$\det(A) = \det(B) = \det(X_{11}) \det(X_{22})$$

$$\begin{pmatrix} X_{11} & X_{12} \\ X_{21} & X_{22} \end{pmatrix} \begin{pmatrix} I & \\ & -X_{22}^{-1} X_{21} \end{pmatrix} \begin{pmatrix} 0 \\ X_{22}^{-1} \end{pmatrix} = \begin{pmatrix} X_{11} - X_{12} X_{22}^{-1} X_{21} & X_{12} X_{22}^{-1} \\ \underline{0} & I \end{pmatrix}$$

Useful Lemmas

Lemma

Let $A = \begin{pmatrix} a_{11} & R \\ S & M_1 \end{pmatrix}$. Then $A - \lambda I = \begin{pmatrix} a_{11} - \lambda & R \\ S & M_1 - \lambda I \end{pmatrix}$

$$p_A(\lambda) = (a_{11} - \lambda) \cdot \det(M_1 - \lambda \cdot I) + R \cdot \text{adj}(M_1 - \lambda \cdot I) \cdot S$$

$$\det(X) = \det(x_{22}) \cdot \det(x_{11} - x_{12} x_{22}^{-1} x_{21})$$

$$x_{11} = a_{11} - \lambda \quad x_{12} = R \quad x_{21} = S \quad x_{22} = M_1 - \lambda I$$

$$\det(A - \lambda I) = \det(M_1 - \lambda I) \det(\underbrace{(a_{11} - \lambda) - R(M_1 - \lambda I)^{-1} S}_{1 \times 1})$$

$p_A(\lambda)$

$$= (a_{11} - \lambda) \cdot \det(M_1 - \lambda I) - R \text{adj}(M_1 - \lambda I) S \quad \square$$

Useful Lemmas Computing Adj by using char. poly

Lemma

Let M be an $(n-1) \times (n-1)$ matrix and $p_M(\lambda) = \sum_{i=0}^{n-1} q_{n-1-i} \lambda^i$. Then

$$\text{adj}(M - \lambda \cdot I) = - \sum_{k=2}^n (M^{k-2} q_0 + \dots + I \cdot q_{k-2}) \cdot \lambda^{n-k}$$

CH $\Rightarrow p_M(M) = 0$

$$(M - \lambda I) \cdot \text{adj}(M - \lambda I) = \overbrace{\det(M - \lambda I)}^{p_M(\lambda)} \cdot I_{n-1}$$

$$(M - \lambda I) \cdot \text{RHS} = - \sum_{k=2}^n (\cancel{M^{k-2}} q_0 + \cancel{M^{k-3}} q_1 + \dots + \cancel{M} q_{k-2}) \lambda^{n-k}$$

$$+ \sum_{k=1}^{n-1} (M^{k-1} q_0 + \dots + I q_{k-1}) \lambda^{n-k} = \sum_{k=1}^{n-1} I \cdot q_{k-1} \cdot \lambda^{n-k}$$

$(\cancel{M^{k-1}} q_0 + \cancel{M^{k-2}} q_1 + \dots + \cancel{M} q_{k-2} + I q_{k-1})$

$$\underline{(M - \lambda I) RHS} = I \cdot \underbrace{\left(\sum_{k=1}^{n-1} q_{k-1} \lambda^{n-k} \right)}_{P_M(\lambda)}$$

$$j = n - 1 - k$$

$$\cancel{(M - \lambda I)} \text{ Adj}(\cancel{M - \lambda I}) = \cancel{(M - \lambda I)} \cdot \text{RHS}$$

Computing Characteristic Polynomial as Matrix

Multiplications

(i.e. put two lemmas together)

$$P_A(\lambda) = (a_{11} - \lambda) \cdot p_n(\lambda) -$$

$$R \left(\sum_{k=2}^n (M^{k-2} q_0 + \dots + I q_{k-2}) \lambda^{n-k} \right) S$$

coeff. of $p_n(\lambda)$

$$\begin{pmatrix} p_0 \\ p_1 \\ \hline \hline \vdots \\ p_n \end{pmatrix} = \underbrace{\begin{pmatrix} & & & \\ & & & \\ & & I & \\ & & & \\ & & & \end{pmatrix}}_{(n+1) \times n} \begin{pmatrix} q_0 \\ \vdots \\ q_{n-1} \end{pmatrix}$$

p_i is the coefficient of λ^{n-i}

$$p_n(\lambda) = \sum p_{n-i} \lambda^i$$

Computing Characteristic Polynomial as Matrix Multiplications

$$P_A(\lambda) = (a_{11} - \lambda) \cdot p_n(\lambda) -$$

$$\rightarrow R \left(\sum_{k=2}^n (M^{k-2} q_0 + \dots + \pm q_{k-2}) \lambda^{n-k} \right) S$$

$$b_i = R M^i S \quad (\text{number } 1 \times 1)$$

k^{th} row of T_i is the coeff. of λ^{n-k} in expression above:

$$a_{11} q_{k-1} - q_k - (b_{k-2} \cdot q_0 + b_{k-3} q_1 + \dots + b_0 q_{k-2})$$

Computing Characteristic Polynomial as Matrix Multiplications

$$a_{11}q_{k+1} - q_k \cdot 1 - (b_{n-2} \cdot q_0 + b_{n-3}q_1 + \dots + b_0q_{n-2})$$

$$\underbrace{(-b_{n-2} \ -b_{n-3} \ \dots \ -b_0 \ a_{11} \ -1)}_{k+1} \underbrace{\begin{matrix} 0 & \dots & 0 \\ \hline (n+1) - (k+1) \\ = n-k \end{matrix}} \begin{pmatrix} q_0 \\ q_1 \\ \vdots \\ q_{n-1} \end{pmatrix} = P_k$$

Putting things together

$$\begin{pmatrix} p_0 \\ p_1 \\ \vdots \\ p_n \end{pmatrix} = \begin{pmatrix} -1 & 0 & \dots & 0 \\ a_{11} & -1 & 0 & \dots & 0 \\ -b_0 & a_{11} & -1 & 0 & \dots & 0 \\ -b_1 & -b_0 & a_{11} & -1 & 0 & \dots & 0 \\ \vdots & & -b_0 & a_{11} & \dots & \dots & \vdots \\ -b_{n-2} & \dots & \dots & \dots & -1 & \dots & -b_0 a_{11} \end{pmatrix} \begin{pmatrix} q_0 \\ \vdots \\ q_{n-1} \end{pmatrix}$$

$\underbrace{\hspace{15em}}_{T_1}$

\downarrow
 $P_A(\lambda)$

in $O(\log^2 n)$
parallel
time

to compute T_1 , we need to
compute $b_i = R M^i S$

← can compute
fast in
parallel

Putting things together

$O(\log^2 n)$

$$\begin{pmatrix} p_0 \\ p_1 \\ \vdots \\ p_n \end{pmatrix} = \underbrace{T_1 \cdot T_2 \cdots T_n}_{\text{product of matrices}}$$

$T_i = (n+2-i) \times (n+1-i)$
matrix

Computing T_i matrices simultaneously

to compute T_i
we needed to compute

$$b_i = R \cdot M_i \cdot S$$

input \nearrow \nearrow also input \nearrow input

$$\begin{array}{|c|c|} \hline a_{11} & R \\ \hline S & \boxed{M_1} \\ \hline \end{array}$$

$$\begin{array}{|c|c|} \hline a_{12} & R_2 \\ \hline S_2 & \boxed{M_2} \\ \hline \end{array}$$

Analysis of Algorithm

- 1 Strategy: compute characteristic polynomial via sequence of matrix multiplications.

$$\begin{pmatrix} P_0 \\ \vdots \\ P_n \end{pmatrix} = T_1 T_2 \cdots T_n$$

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- 5 Show that all matrices can be computed simultaneously
- 6 By first part, know that can compute product of matrices in $O(\log^2 n)$ parallel time.

$$O(\log^2 n) + \underbrace{O(\log^R n)}_{\text{product of } T_i\text{'s}} = O(\log^2 n)$$

all T_i 's

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- *Parallel model of computation*: different model from usual (sequential) algorithms, non-uniform.
- Saw how to compute foundational objects from linear algebra in parallel time.

Acknowledgement

- Lecture based largely on:
 - Csanky's paper [Csanky 1976]
 - Berkowitz's paper [Berkowitz 1984]
- For combinatorial interpretation of Berkowitz's algorithm, see <https://arxiv.org/pdf/math/0201315.pdf>

References I



Berkowitz, S. J. (1984).

On computing the determinant in small parallel time using a small number of processors.

[Information processing letters](#), 18(3), 147-150.



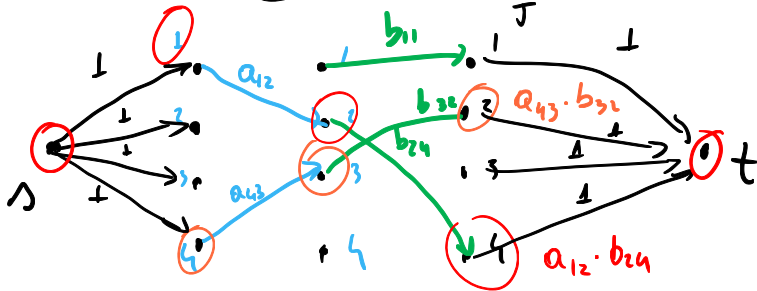
Csanky, L. (1975).

Fast parallel matrix inversion algorithms.

[In 16th Annual Symposium on Foundations of Computer Science \(FOCS\)](#) (pp. 11-12). IEEE.

ABP (Algebraic Branching Program)

$$\sum a_{ik} \cdot b_{ki} = \text{tr} \left(A \cdot B \begin{pmatrix} 1 & & & \\ & \ddots & & \\ & & 1 & \\ & & & \ddots \end{pmatrix} \right)_{n \times n} \quad (n=4)$$



$$\sum (\text{paths } s \rightarrow t)$$

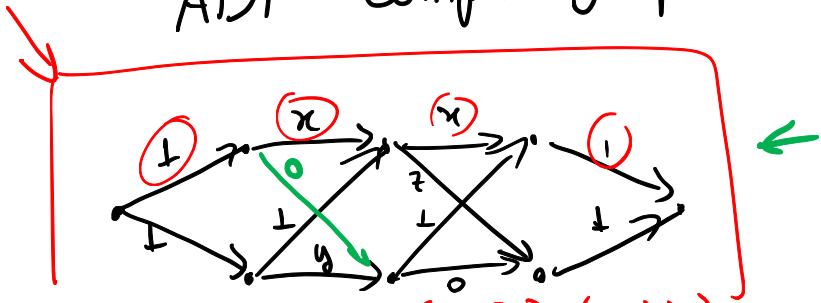
$$1 \cdot a_{12} \cdot b_{24} \cdot 1$$

$$\sum a_{ik} b_{ki}$$

today

$$\text{trn}(X_1 X_2 \cdots X_d) = P(x)$$

ABP computing $p(x)$



$$\text{trn} \left(\begin{pmatrix} x & 0 \\ 1 & y \end{pmatrix} \begin{pmatrix} x & z \\ 1 & 0 \end{pmatrix} \begin{pmatrix} 1 & 1 \\ 1 & 1 \end{pmatrix} \right)$$