



Computational Complexity Theory

Lecture 21: Complexity of Counting

Department of Computer Science,
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Natural counting problems

- What is the complexity of the following problems?
- **#SAT**: Count the number of satisfying assignments of a given Boolean circuit/CNF.
- **#HAMCYCLE**: Count the number of Hamiltonian cycles in an undirected graph.
- **Observation**. The above problems are **NP-hard**.

Natural counting problems

- What is the complexity of the following problems?
- **#PerfectMatching**: Count the number of perfect matchings in a bipartite graph.
- **#CYCLE**: Count the number of simple cycles in a directed graph.
- **Observation**. The corresponding decision problems are in **P**.

Natural counting problems

- What is the complexity of the following problems?
- **#PATH**: Count the number of simple paths between two vertices in a connected graph.
- **#SPANTREE**: Count the number of spanning trees in a connected graph.
- **Observation**. The corresponding decision problems are trivial.

An easy counting problem

- Theorem. (Kirchhoff 1847) #SPANTREE is in FP.

An easy counting problem

- **Theorem.** (Kirchhoff 1847) $\#SPANTREE$ is in **FP**.
- **Proof sketch.** Let G be an n -vertex connected graph without self loops. Label the vertices by $\{1, \dots, n\}$.
- **Definition.** The *Laplacian matrix* of G is an $n \times n$ matrix L_G defined as
$$\begin{aligned} L_G(i,j) &= \deg(i) && \text{if } i = j, \\ &= -1 && \text{if there's an edge } (i,j) \text{ in } G, \\ &= 0 && \text{otherwise.} \end{aligned}$$


An easy counting problem

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- **Definition.** The *Laplacian matrix* of G is an $n \times n$ matrix L_G defined as $L_G = D_G - A_G$, where D_G is the degree matrix and A_G the adjacency matrix of G .
- **Observation.** It is easy to compute L_G from A_G .

An easy counting problem

- **Theorem.** (Kirchhoff 1847) $\#SPANTREE$ is in **FP**.
- **Proof sketch.** Let G be an n -vertex connected graph without self loops. Label the vertices by $\{1, \dots, n\}$.
- Kirchhoff's matrix-tree theorem states that
no. of spanning trees of G = any cofactor of L_G .
- (i,j) cofactor of $L = (-1)^{i+j} \cdot \det(\text{submatrix of } L \text{ obtained by deleting the } i\text{-th row and the } j\text{-th column from } L)$.

An easy counting problem

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no. of spanning trees of G = any cofactor of L_G . 
- **Corollary.** As determinant computation is in (functional) **NC**, $\#SPANTREES$ is in (functional) **NC**.

A hard counting problem

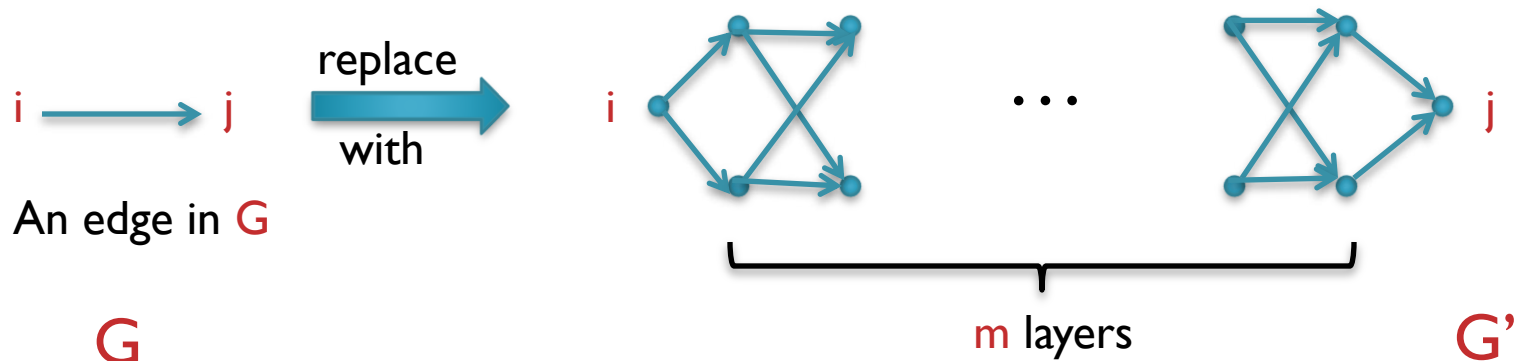
- **Theorem.** **#CYCLE** is in **NP-hard**.
- **Lesson.** A counting problem can be hard even if the corresponding decision problem is in **P**.

A hard counting problem

- **Theorem.** **#CYCLE** is in **NP-hard**.
- **Proof.** We will give a poly-time reduction from the Hamiltonian cycle problem to the **#CYCLE** problem.

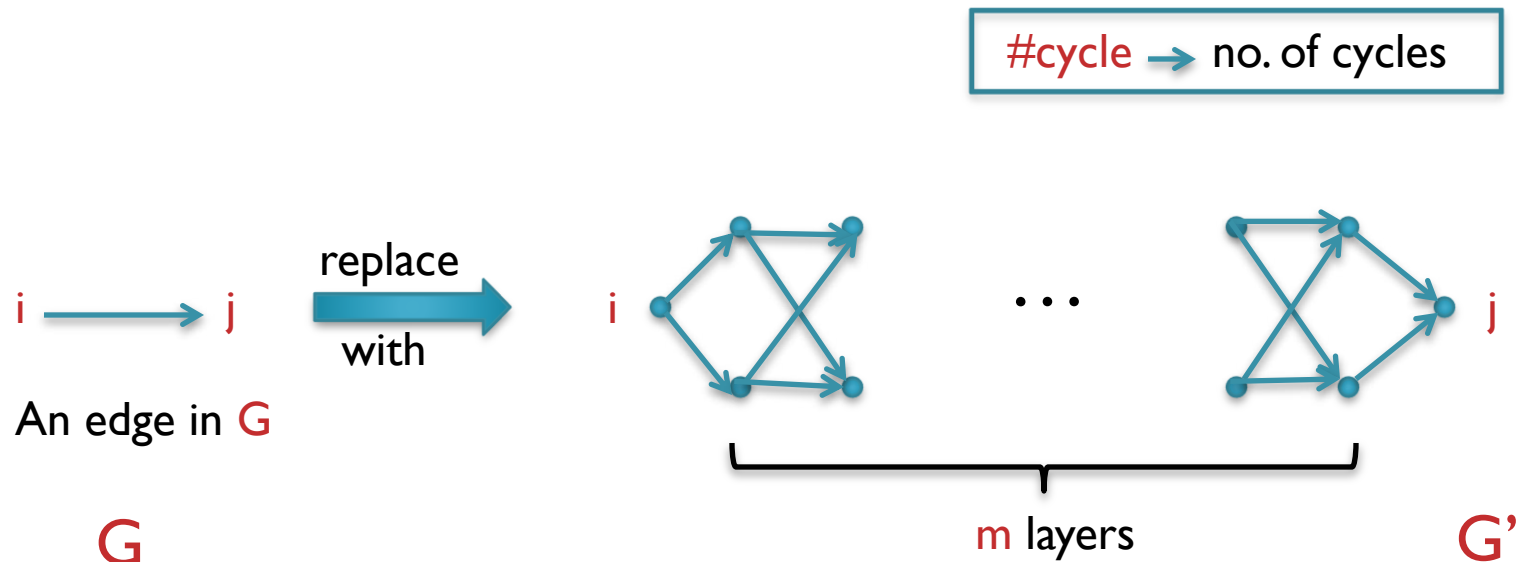
A hard counting problem

- **Theorem.** $\#CYCLE$ is in NP-hard.
- **Proof.** Let G be an n -vertex digraph. We'll efficiently construct a new graph G' from G s.t. the presence of a Hamiltonian cycle in G can be readily derived from the number of cycles in G' . Construction of G' :



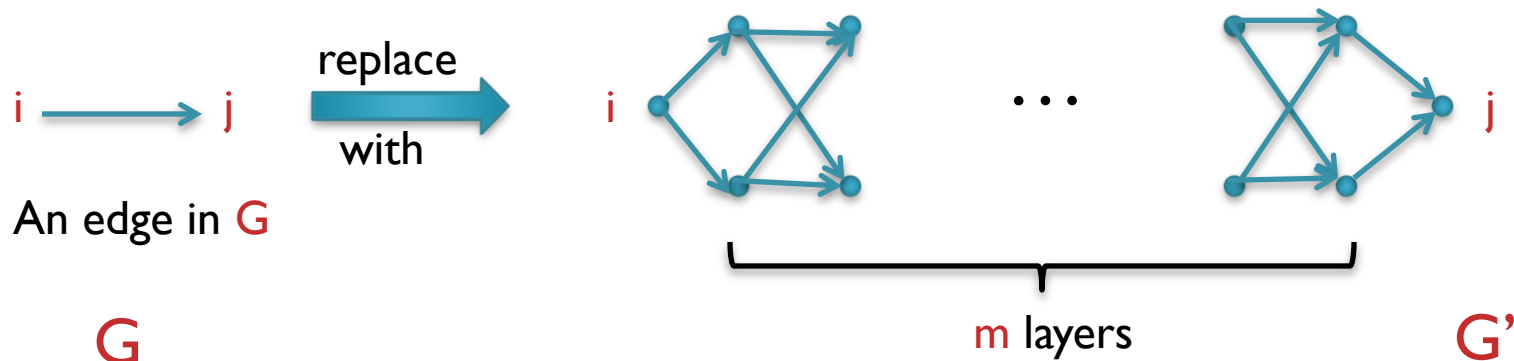
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- Theorem. $\#CYCLE$ is in NP-hard.
- Proof. Case 1: If G has a HC, then $\#cycle(G') \geq 2^{mn}$.
- Case 2: If G has no HC, then $\#cycle(G) \leq n^{n-1}$
 $\#cycle(G') \leq n^{n-1} \cdot 2^{m(n-1)}$.



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 $\#cycle(G') \leq n^{n-1} \cdot 2^{m(n-1)}$.
- If we choose m such that $n^{n-1} \cdot 2^{m(n-1)} < 2^{mn}$, then we can find out if G has a HC from $\#cycle(G')$.
- Set $m = n^2$.

Class #P

- **Definition.** We say a function $f: \{0,1\}^* \rightarrow \mathbb{N}$ is in #P if there's a poly-time TM M and a polynomial function $p: \mathbb{N} \rightarrow \mathbb{N}$ such that for every $x \in \{0,1\}^*$,

$$f(x) = \left| \{u \in \{0,1\}^{p(|x|)} : M(x, u) = 1\} \right| .$$

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- **Observation.** Problems #SAT, #HAMCYCLE, #PerfectMatching, #CYCLE, #PATH and #SPANTREE are in #P.
- In fact, with every language in NP we can associate a counting problem that is in #P.

#P-completeness

- Recall, to define completeness of a complexity class, we need an appropriate notion of a reduction.
- What kind of reductions will be suitable is guided by a complexity question, like a comparison between the complexity class under consideration & another class.
- Is $\#P = FP$?

#P-completeness

- **Definition.** A function $f: \{0,1\}^* \rightarrow \mathbb{N}$ is in #P-complete if f is in #P and for every $g \in \#P$, we have $g \in \text{FP}^f$ i.e., g is poly-time Cook/Turing reducible to f .
- In other words, for every $x \in \{0,1\}^*$, we can compute $g(x)$ in polynomial time using oracle access to f .

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- In other words, for every $x \in \{0,1\}^*$, we can compute $g(x)$ in polynomial time using oracle access to f .
- **Observation.** If a **#P-complete** language is in **FP** then $\#P = \text{FP}$.

Natural #P-complete problems

- Theorem. #SAT is #P-complete.
- Proof. #SAT is in #P. Let $g \in \#P$. We intend to show that $g \in \text{FP}^{\text{#SAT}}$.

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- **Algorithm:** On input x , convert $M(x, ..)$ to a 3CNF ϕ_x using Cook-Levin theorem. Give ϕ_x as input to the #SAT oracle. Output whatever the oracle outputs.

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- **Algorithm:** On input x , convert $M(x, ..)$ to a 3CNF ϕ_x using Cook-Levin theorem. Give ϕ_x as input to the #SAT oracle. Output whatever the oracle outputs.

Note: Only one query to the oracle. Resembles a poly-time Karp reduction.

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$$g(x) = \left| \{u \in \{0,1\}^{p(|x|)} : M(x, u) = 1\} \right| .$$

- **Correctness:** Follows from the fact that the Cook-Levin reduction is parsimonious, i.e.,

$$\left| \{u \in \{0,1\}^{p(|x|)} : M(x, u) = 1\} \right| = \#\phi_x .$$

The no. of satisfying assignments of ϕ_x .



Natural #P-complete problems

- **Theorem.** #HAMCYCLE is #P-complete.
- Most (all?) NP-complete problems known till date have defining verifiers such that the corresponding counting problems are #P-complete.
- **Open.** Does every NP-complete problem have a defining verifier such that the corresponding counting problem is #P-complete ?

Issue: The reduction that shows NP-completeness of a problem needn't have to be parsimonious.

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Natural #P-complete problems

- **Theorem.** (Valiant 1979) **#PATH** is **#P-complete**.
- In fact, **#PATH** is **#P-complete** for both directed and undirected graphs.
- **Theorem.** (Valiant 1979) **#PerfectMatching** is **#P-complete**.
- **Proof.** We'll see a proof later.

Relation between #P and other classes

- Observation. $\#P \subseteq PSPACE$.
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- Observation. $\#P \subseteq PSPACE$.
- Also, $PH \subseteq PSPACE$. How does $\#P$ relate to PH ?
- Theorem. (*Toda 1991*) $PH \subseteq P^{\#SAT}$.
- Hence, $\#P$ is harder than PH .

Approximations of #P functions

- **Observation.** If $\#P = FP$, then $P = NP$.
- **Open.** Does $P = NP$ imply $\#P = FP$?
- But, we do know that $P = NP$ implies every $\#P$ problem has a randomized polynomial-time approximation algorithm.

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Can be derandomized!

Approximations of #P functions

- **Definition.** A function $f: \{0,1\}^* \rightarrow \mathbb{N}$ has a *Fully Polynomial-time Randomized Approximation Scheme* (**FPRAS**) if for every $\epsilon, \delta > 0$, there's a PTM M such that for every $x \in \{0,1\}^*$,
 - $(1-\epsilon).f(x) \leq M(x) \leq (1+\epsilon).f(x)$ with prob. $\geq 1 - \delta$,
 - M runs in $\text{poly}(|x|, \epsilon^{-1}, \log \delta^{-1})$ time.

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- **Theorem.** If $P = NP$ then every #P function has a FPRAS.
- **Proof.** We'll see a proof later.

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- **Theorem.** If $P = NP$ then every #P function has a **FPRAS**.
- **Remark.** In fact the above **FPRAS** can be replaced by a **FPTAS** (**Fully Poly-Time Approximation Scheme**).


Approximations of #P functions

- Some **#P-complete** problems do admit **FPRAS** unconditionally!
- **Theorem.** (*Jerrum, Sinclair, Vigoda 2001*) **#PerfectMatching** has a **FPRAS**.
- **Remark.** No derandomization of this algorithm is known!

Approximations of #P functions

- Some **#P-complete** problems do admit **FPRAS** unconditionally!
- **Theorem.** (*Jerrum, Sinclair, Vigoda 2001*) Permanent of a square matrix with non-negative entries has a **FPRAS**.
- If $X = (x_{ij})_{i,j \in n}$ then $\text{Perm}(X) = \sum_{\sigma \in S_n} \prod_{i \in [n]} x_{i \sigma(i)} .$

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- **Note.** If B_G is the biadjacency matrix of a bipartite graph G , then $\text{Perm}(B_G) = \# \text{PerfectMatchings}(G).$

0/1 matrix

0/1-Permanent is #P-complete

- Theorem. (Valiant 1979) 0/1-Perm is #P-complete.
- It implies that #PerfectMatchings is #P-complete.

0/1-Permanent is #P-complete

- Theorem. (Valiant 1979) 0/1-Perm is #P-complete.
- Proof. 0/1-Perm is in #P. (Why?)

0/1-Permanent is #P-complete

- **Theorem.** (Valiant 1979) 0/1-Perm is #P-complete.
- **Proof.** We'll show that $\#3SAT \in FP^{0/1-Perm}$.
- In fact, we'll give a poly-time “Karp-like” reduction from $\#3SAT$ to 0/1-Perm, i.e., we'll give a poly-time computable function that maps a 3CNF ϕ to a 0/1-matrix A_ϕ s.t. $\#\phi$ is efficiently computable from A_ϕ .
- This means only one query to the 0/1-Perm oracle is required.

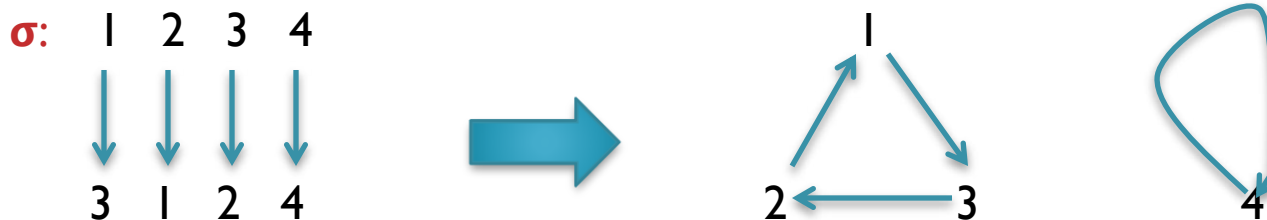
...the proof will be given in the next lecture

Graph theoretic interpretation of Perm

- Let $A = (a_{ij})_{i,j \in r}$, where $a_{ij} \in \mathbb{R}$.
- Then, $\text{Perm}(A) = \sum_{\sigma \in S_r} \prod_{i \in [r]} a_{i \sigma(i)}$.
- Let G be the weighted digraph on r vertices with adjacency matrix A , i.e., the edge (i, j) in G has weight a_{ij} .

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- Let G be the weighted digraph on r vertices with adjacency matrix A , i.e., the edge (i, j) in G has weight a_{ij} .
- Every permutation $\sigma: [r] \rightarrow [r]$ can be expressed (uniquely) as a product of disjoint cycles.



Graph theoretic interpretation of Perm

- **Definition.** A cycle cover of a digraph G is a subgraph of G having in-degree and out-degree of every vertex exactly 1, i.e., the subgraph is a disjoint union of cycles covering all the vertices of G .
- Weight of a cycle cover C , denoted $wt(C)$, is defined as the product of the weights of the edges in C .

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- **Observation.** $Perm(A) = \sum_{\substack{C: C \text{ is cycle} \\ \text{cover of } G}} wt(C) .$

Every “contributing” permutation σ corresponds to a cycle cover C and vice versa.

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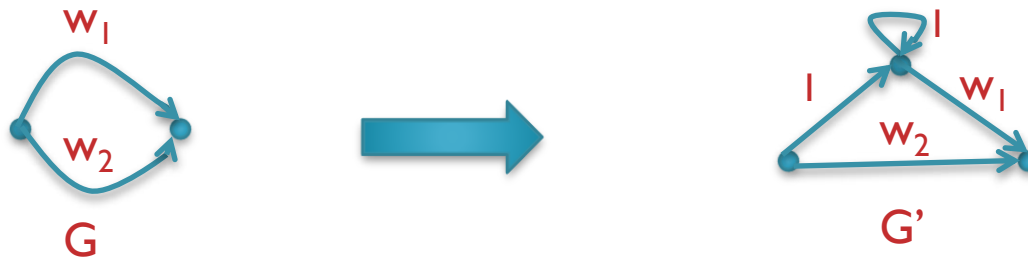
We can denote A as A_G , the adjacency matrix of G

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Graph with parallel edges

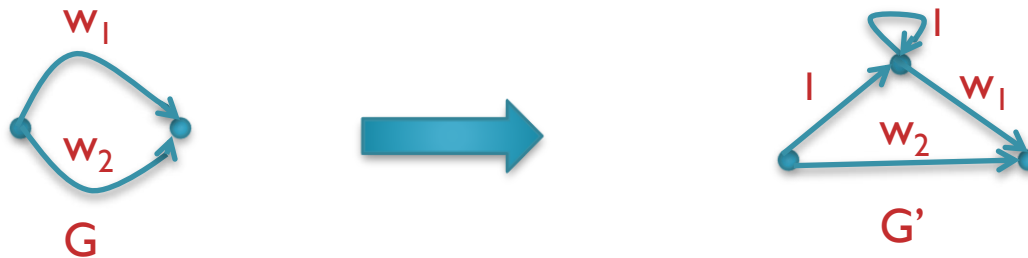
- **Note.** We can talk about “adjacency matrix” of a graph G that has parallel edges by defining a new graph G' :



- Denote the adjacency matrix of a graph H (without parallel edges) by A_H . Then, A_G is defined as $A_{G'}$.

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- **Observation.**
$$\sum_{C: C \text{ is cycle cover of } G} \text{wt}(C) = \sum_{C: C \text{ is cycle cover of } G'} \text{wt}(C).$$