## COMP3121 Lecture - Week 11

## Computational Intractability

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## Outline

(1) Overview
(2) Turing Machines, P , and NP
(3) Reductions and NP-completeness

4 NP-complete problems
(5) Extended class 3821/9801

## Resources

- Chapter 34, NP-Completeness, in the textbook: Thomas H. Cormen, Charles E. Leiserson, Ronald L. Rivest, Clifford Stein. Introduction to Algorithms. The MIT Press, 3rd edition, 2009.
- Slides: http://www.cse.unsw.edu.au/~sergeg/np.pdf


## Polynomial time

## Polynomial-time algorithm

Polynomial-time algorithm:
There exists a constant $c \in \mathbb{N}$ such that the algorithm has (worst-case) running-time $O\left(n^{c}\right)$, where $n$ is the size of the input.

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## Example

Polynomial: $n ; n^{2} \log _{2} n ; n^{3} ; n^{20}$
Super-polynomial: $n^{\log _{2} n} ; 2^{\sqrt{n}} ; 1.001^{n} ; 2^{n} ; n$ !

## Time complexities

| $n=$ | 10 | 100 | 1,000 | 10,000 | 100,000 | $1,000,000$ |
| :--- | :--- | :--- | :--- | :--- | :--- | :--- |
| $n$ | $<1 \mathrm{~ms}$ | $<1 \mathrm{~ms}$ | $<1 \mathrm{~ms}$ | $<1 \mathrm{~ms}$ | $<1 \mathrm{~ms}$ | $<1 \mathrm{~ms}$ |
| $n^{2} \log _{2} n$ | $<1 \mathrm{~ms}$ | $<1 \mathrm{~ms}$ | $<1 \mathrm{~ms}$ | 13 ms | 1.66 sec | 3.3 min |
| $n^{3}$ | $<1 \mathrm{~ms}$ | $<1 \mathrm{~ms}$ | 10 ms | 10 sec | 2.78 hours | 3.86 months |
| $n^{20}$ | 31.7 years | $>1 \mathrm{U}$ | $>1 \mathrm{U}$ | $>1 \mathrm{U}$ | $>1 \mathrm{U}$ | $>1 \mathrm{U}$ |
| $2^{\sqrt{n}}$ | $<1 \mathrm{~ms}$ | $<1 \mathrm{~ms}$ | 33 ms | $>1 \mathrm{U}$ | $>1 \mathrm{U}$ | $>1 \mathrm{U}$ |
| $1.001^{n}$ | $<1 \mathrm{~ms}$ | $<1 \mathrm{~ms}$ | $<1 \mathrm{~ms}$ | $<1 \mathrm{~ms}$ | $>1 \mathrm{U}$ | $>1 \mathrm{U}$ |
| $2^{n}$ | $<1 \mathrm{~ms}$ | $>1 \mathrm{U}$ | $>1 \mathrm{U}$ | $>1 \mathrm{U}$ | $>1 \mathrm{U}$ | $>1 \mathrm{U}$ |
| $n!$ | $<1 \mathrm{~ms}$ | $>1 \mathrm{U}$ | $>1 \mathrm{U}$ | $>1 \mathrm{U}$ | $>1 \mathrm{U}$ | $>1 \mathrm{U}$ |

Table: Processing speed for various time complexities, assuming $10^{11}$ instructions are processed per second (Intel Core i7). Here, $\mathrm{U}=13.798 \cdot 10^{9}$ years.

## Tractable problems

## Central Question

Which computational problems have polynomial-time algorithms?

## Million-dollar question

Intriguing class of problems: NP-complete problems.

## NP-complete problems

It is unknown whether NP-complete problems have polynomial-time algorithms.

- A polynomial-time algorithm for one NP-complete problem would imply polynomial-time algorithms for all problems in NP.

Gerhard Woeginger's P vs NP page:
http://www.win.tue.nl/~gwoegi/P-versus-NP.htm

## Polynomial vs. NP-complete

## NP-complete

- Longest Path: Given a graph $G$ and an integer $k$, does $G$ have a simple path of length at least $k$ ?
- Hamiltonian Cycle: Given a graph $G$, does $G$ have a simple cycle that visits each vertex of $G$ ?
- 3-CNF SAT: Given a propositional formula $F$ in 3-CNF, is $F$ satisfiable?
Example:
$(x \vee \neg y \vee z) \wedge(\neg x \vee z) \wedge(\neg y \vee \neg z)$.
- Shortest Path: Given a graph $G$, two vertices $a$ and $b$ of $G$, and an integer $k$, does $G$ have a simple $a-b$-path of length at most $k$ ?
- Euler Tour: Given a graph $G$, does $G$ have a cycle that traverses each edge of $G$ exactly once?
- 2-CNF SAT: Given a propositional formula $F$ in 2-CNF, is $F$ satisfiable?
A k-CNF formula is a conjunction (AND) of clauses, and each clause is a disjunction (OR) of at most $k$ literals, which are negated or unnegated Boolean variables.


## Overview

## What's next?

- Formally define P, NP, and NP-complete (NPC)
- New skill: show that a problem is NP-complete
- Briefly: what to do when confronted with an NP-complete problem?


## Outline

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## Decision problems and Encodings

$<$ Name of Decision Problem $>$
Input: $\quad<$ What constitutes an instance $>$
Question: <Yes/No question>

## Decision problems and Encodings

```
<Name of Decision Problem>
Input: <What constitutes an instance>
Question: <Yes/No question>
```

We want to know which decision problems can be solved in polynomial time polynomial in the size of the input $n$.

- Assume a "reasonable" encoding of the input
- Many encodings are polynomial-time equivalent; i.e., one encoding can be computed from another in polynomial time.
- Important exception: unary versus binary encoding of integers.
- An integer $x$ takes $\left\lceil\log _{2} x\right\rceil$ bits in binary and $x=2^{\log _{2} x}$ bits in unary.


## Exercise on Decision Problems

Cluster into groups of 4-5 students. Answer the following questions. Let $f: \mathbb{N} \rightarrow \mathbb{N}$ be a non-decreasing function.
(1) Given an $O(f(n))$-time algorithm for Maximum Independent Set, design an algorithm for Independent Set with running time $O(f(n) \cdot \operatorname{poly}(n))$.
(2) Given an $O(f(n))$-time algorithm for Independent Set, design an algorithm for Maximum Independent Set with running time $O(f(n) \cdot \operatorname{poly}(n))$.

## Independent Set

Input: Graph $G$, integer $k$
Question: Does $G$ have an independent set of size at least $k$ ?

Maximum Independent Set
Input: $\quad$ Graph $G$
Output: A largest independent set of $G$

Def. An independent set of a graph $G=(V, E)$ is a subset of vertices $S \subseteq V$ such that no two vertices of $S$ are adjacent in $G$.


## Formal-language framework

We can view decision problems as languages.

- Alphabet $\Sigma$ : finite set of symbols. W.I.o.g., $\Sigma=\{0,1\}$
- Language $L$ over $\Sigma$ : set of strings made with symbols from $\Sigma: L \subseteq \Sigma^{*}$
- Fix an encoding of instances of a decision problem $\Pi$ into $\Sigma$
- Define the language $L_{\Pi} \subseteq \Sigma^{*}$ such that

$$
x \in L_{\Pi} \Leftrightarrow x \text { is a Yes-instance for } \Pi
$$

## Non-deterministic Turing Machine (NTM)

- input word $x \in \Sigma^{*}$ placed on an infinite tape (memory)
- read-write head initially placed on the first symbol of $x$
- computation step: if the machine is in state $s$ and reads $a$, it can move into state $s^{\prime}$, writing $b$, and moving the head into direction $D \in\{L, R\}$ if $\left((s, a),\left(s^{\prime}, b, D\right)\right) \in \delta$.

- $Q$ : finite, non-empty set of states
- $\Gamma$ : finite, non-empty set of tape symbols
- $\quad \in \Gamma$ : blank symbol (the only symbol allowed to occur on the tape infinitely often)
- $\Sigma \subseteq \Gamma \backslash\{b\}$ : set of input symbols
- $q_{0} \in Q$ : start state
- $A \subseteq Q$ : set of accepting (final) states
- $\delta \subseteq(Q \backslash A \times \Gamma) \times(Q \times \Gamma \times\{L, R\})$ : transition relation, where $L$ stands for a move to the left and $R$ for a move to the right.


## Accepted Language

## Definition 1

A NTM accepts a word $x \in \Sigma^{*}$ if there exists a sequence of computation steps starting in the start state and ending in an accept state.

## Definition 2

The language accepted by an NTM is the set of words it accepts.

## Discussion: Non-deterministic Turing Machines

In groups, discuss whether you think that NTMs are realistic computation models

- Is this a good representation of how our computing devices work?
- What is different?


## Video

The LEGO Turing Machine<br>https://www.youtube.com/watch?v=cYw2ewo06c4

## Accept and Decide in polynomial time

## Definition 3

A language $L$ is accepted in polynomial time by an NTM $M$ if

- $L$ is accepted by $M$, and
- there is a constant $k$ such that for any word $x \in L$, the NTM $M$ accepts $x$ in $O\left(|x|^{k}\right)$ computation steps.


## Definition 4

A language $L$ is decided in polynomial time by an NTM $M$ if

- there is a constant $k$ such that for any word $x \in L$, the NTM $M$ accepts $x$ in $O\left(|x|^{k}\right)$ computation steps, and
- there is a constant $k^{\prime}$ such that for any word $x \in \Sigma^{*} \backslash L$, on input $x$ the NTM $M$ halts in a non-accepting state $(Q \backslash A)$ in $O\left(|x|^{k^{\prime}}\right)$ computation steps.


## Deterministic Turing Machine

## Definition 5

A Deterministic Turing Machine (DTM) is a Non-deterministic Turing Machine where the transition relation contains at most one tuple $((s, a),(\cdot, \cdot, \cdot))$ for each $s \in Q \backslash A$ and $a \in \Gamma$.

The transition relation $\delta$ can be viewed as a function $\delta: Q \backslash A \times \Gamma \rightarrow Q \times \Gamma \times\{L, R\}$.
$\Rightarrow$ For a given input word $x \in \Sigma^{*}$, there is exactly one sequence of computation steps starting in the start state.

## Exercise: DTM

In groups:
Design a DTM $\left(Q, \Gamma, \Sigma=\{0,1\}, q_{0}, A, \delta\right)$ that accepts palindromes. A palindrome is a word that is equal to its reverse; e.g., 011010110. Recall:

- $Q$ : finite, non-empty set of states
- $\Gamma$ : finite, non-empty set of tape symbols
- _ $\in \Gamma$ : blank symbol (the only symbol allowed to occur on the tape infinitely often)
- $\Sigma \subseteq \Gamma \backslash\{b\}$ : set of input symbols
- $q_{0} \in Q$ : start state
- $A \subseteq Q$ : set of accepting (final) states
- $\delta: Q \backslash A \times \Gamma \rightarrow Q \times \Gamma \times\{L, R\}$ : transition function, where $L$ stands for a move to the left and $R$ for a move to the right.


## DTM equivalents

Many computational models are polynomial-time equivalent to DTMs:

- Random Access Machine (RAM, used for algorithms in the textbook)
- variants of Turing machines (multiple tapes, infinite only in one direction, ...)


## $P$ and NP

## Definition 6 ( P )

$\mathrm{P}=\left\{L \subseteq \Sigma^{*}\right.$ : there is a DTM accepting $L$ in polynomial time $\}$

## Definition 7 (NP)

NP $=\left\{L \subseteq \Sigma^{*}\right.$ : there is a NTM accepting $L$ in polynomial time $\}$

## Definition 8 (coNP) <br> $\mathrm{coNP}=\left\{L \subseteq \Sigma^{*}: \Sigma^{*} \backslash L \in \mathrm{NP}\right\}$

## coP?

## Theorem 9

$\mathrm{P}=\left\{L \subseteq \Sigma^{*}\right.$ : there is a DTM deciding $L$ in polynomial time $\}$

## coP?

## Theorem 9

$\mathrm{P}=\left\{L \subseteq \Sigma^{*}\right.$ : there is a DTM deciding $L$ in polynomial time $\}$

## Proof sketch.

Need to show:
if $L$ is accepted by a DTM $M$ in polynomial time, then there is a DTM that decides $L$ in polynomial time.
Idea: design a DTM $M^{\prime}$ that simulates $M$ for $c \cdot n^{k}$ steps, where $c \cdot n^{k}$ is the running time of $M$.
(Note that this proof is nonconstructive: we might not know the running time of M.)

## NP and certificates

## Non-deterministic choices

A NTM for an NP-language $L$ makes a polynomial number of non-deterministic choices on input $x \in L$.
We can encode these non-deterministic choices into a certificate $c$, which is a polynomial-length word.
Now, there exists a DTM, which, given $x$ and $c$, verifies that $x \in L$.
Thus, $L \in$ NP iff for each $x \in L$ there exists a polynomial-length certificate $c$ and a DTM $M$ such that given $x$ and $a, M$ can verify in polynomial time that $x \in L$.

## CNF-SAT is in NP

- A CNF formula is a propositional formula in conjunctive normal form: a conjunction (AND) of clauses; each clause is a disjunction (OR) of literals; each literal is a negated or unnegated Boolean variable.
- An assignment $\alpha: \operatorname{var}(F) \rightarrow\{0,1\}$ satisfies a clause $C$ if it sets a literal of $C$ to true, and it satisfies $F$ if it satisfies all clauses in $F$.


## CNF-SAT

Input: $\quad$ CNF formula $F$
Question: Does $F$ have a satisfying assignment?
Example: $(x \vee \neg y \vee z) \wedge(\neg x \vee z) \wedge(\neg y \vee \neg z)$.

## Lemma 10

$C N F-S A T \in N P$.

## Proof.

Exercise.

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## Polynomial-time reduction

## Definition 11

A language $L_{1}$ is polynomial-time reducible to a language $L_{2}$, written $L_{1} \leq_{P} L_{2}$, if there exists a polynomial-time computable function $f: \Sigma^{*} \rightarrow \Sigma^{*}$ such that for all $x \in \Sigma^{*}$,

$$
x \in L_{1} \Leftrightarrow f(x) \in L_{2} .
$$

A polynomial time algorithm computing $f$ is a reduction algorithm.

## New polynomial-time algorithms via reductions

Lemma 12
If $L_{1}, L_{2} \in \Sigma^{*}$ are languages such that $L_{1} \leq_{P} L_{2}$, then $L_{2} \in \mathrm{P}$ implies $L_{1} \in \mathrm{P}$.

## Proof.

Exercise.

## NP-completeness

## Definition 13 (NP-hard)

A language $L \subseteq \Sigma^{*}$ is NP-hard if

$$
L^{\prime} \leq_{P} L \text { for every } L^{\prime} \in \mathrm{NP} .
$$

## Definition 14 (NP-complete)

A language $L \subseteq \Sigma^{*}$ is NP-complete (in NPC) if
(1) $L \in N P$, and
(2) $L$ is NP-hard.

## A first NP-complete problem

Theorem 15CNF-SAT is NP-complete.
Proved by encoding NTMs into SAT and then CNF-SAT (Cook-Levin 1971/1973 and Karp 1972).

## Proving NP-completeness

## Lemma 16

If $L$ is a language such that $L^{\prime} \leq_{P} L$ for some $L^{\prime} \in$ NPC, then $L$ is NP-hard. If, in addition, $L \in \mathrm{NP}$, then $L \in \mathrm{NPC}$.

## Proving NP-completeness

## Lemma 16

If $L$ is a language such that $L^{\prime} \leq_{P} L$ for some $L^{\prime} \in$ NPC, then $L$ is NP-hard. If, in addition, $L \in \mathrm{NP}$, then $L \in \mathrm{NPC}$.

## Proof.

For all $L^{\prime \prime} \in N P$, we have $L^{\prime \prime} \leq_{P} L^{\prime} \leq_{P} L$.
By transitivity, we have $L^{\prime \prime} \leq_{P} L$.
Thus, $L$ is NP-hard.

## Proving NP-completeness (2)

Method to prove that a language $L$ is NP-complete:
(1) Prove $L \in \mathrm{NP}$
(2) Prove $L$ is NP-hard.

- Select a known NP-complete language $L^{\prime}$.
- Describe an algorithm that computes a function $f$ mapping every instance $x \in \Sigma^{*}$ of $L^{\prime}$ to an instance $f(x)$ of $L$.
- Prove that $x \in L^{\prime} \Leftrightarrow f(x) \in L$ for all $x \in \Sigma^{*}$.
- Prove that the algorithm computing $f$ runs in polynomial time.


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## 3-CNF SAT is NP-hard

## Theorem 17 <br> 3-CNF SAT is NP-complete.

## Proof.

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3-CNF SAT is in NP, since it is a special case of CNF-SAT.

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To show that 3-CNF SAT is NP-hard, we give a polynomial reduction from CNF-SAT.

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To show that 3-CNF SAT is NP-hard, we give a polynomial reduction from CNF-SAT.
Let $F$ be a CNF formula. The reduction algorithm constructs a 3-CNF formula $F^{\prime}$ as follows. For each clause $C$ in $F$ :

- If $C$ has at most 3 literals, then copy $C$ into $F^{\prime}$.
- Otherwise, denote $C=\left(\ell_{1} \vee \ell_{2} \vee \cdots \vee \ell_{k}\right)$.


## 3-CNF SAT is NP-hard

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- If $C$ has at most 3 literals, then copy $C$ into $F^{\prime}$.
- Otherwise, denote $C=\left(\ell_{1} \vee \ell_{2} \vee \cdots \vee \ell_{k}\right)$. Create $k-3$ new variables $y_{1}, \ldots, y_{k-3}$, and add the clauses

$$
\left(\ell_{1} \vee \ell_{2} \vee y_{1}\right),\left(\neg y_{1} \vee \ell_{3} \vee y_{2}\right),\left(\neg y_{2} \vee \ell_{4} \vee y_{3}\right), \ldots,\left(\neg y_{k-3} \vee \ell_{k-1} \vee \ell_{k}\right) .
$$

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$$

Show that $F$ is satisfiable $\Leftrightarrow F^{\prime}$ is satisfiable.
Show that $F^{\prime}$ can be computed in polynomial time (trivial; use a RAM).

## Clique

A clique in a graph $G=(V, E)$ is a subset of vertices $S \subseteq V$ such that every two vertices of $S$ are adjacent in $G$.

## Clique

Input: $\quad$ Graph $G$, integer $k$
Question: Does $G$ have a clique of size $k$ ?


## Theorem 18

Clique is NP-complete.
Groupwork.

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Clique is NP-complete.
Groupwork.
Hint: Reduce from 3-CNF SAT.

## Clique (2)

## - Clique is in NP

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- Clique is in NP
- Let $F=C_{1} \wedge C_{2} \wedge \ldots C_{k}$ be a 3-CNF formula
- Construct a graph $G$ that has a clique of size $k$ iff $F$ is satisfiable
$(\neg x \vee y \vee z) \wedge(x \vee \neg y \vee \neg z) \wedge(x \vee y)$


## Clique (2)



$$
(\neg x \vee y \vee z) \wedge(x \vee \neg y \vee \neg z) \wedge(x \vee y)
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## Clique (2)



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- Let $F=C_{1} \wedge C_{2} \wedge \ldots C_{k}$ be a 3-CNF formula
- Construct a graph $G$ that has a clique of size $k$ iff $F$ is satisfiable
- For each clause $C_{r}=\left(\ell_{1}^{r} \vee \cdots \vee \ell_{w}^{r}\right)$, $1 \leq r \leq k$, create $w$ new vertices $v_{1}^{r}, \ldots, v_{w}^{r}$
- Add an edge between $v_{i}^{r}$ and $v_{j}^{s}$ if

$$
\begin{array}{ll}
r \neq s & \\
\ell_{i}^{r} \neq \neg \ell_{j}^{s} & \\
\text { and } \\
\text { where } \neg \neg x=x
\end{array}
$$

- Check correctness and polynomial running time


## Clique (2)



- Correctness: $F$ has a satisfying assignment iff $G$ has a clique of size $k$.

$$
(\neg x \vee y \vee z) \wedge(x \vee \neg y \vee \neg z) \wedge(x \vee y)
$$

## Clique (2)



- Correctness: $F$ has a satisfying assignment iff $G$ has a clique of size $k$.
- $(\Rightarrow)$ : Let $\alpha$ be a sat. assignment for $F$. For each clause $C_{r}$, choose a literal $\ell_{i}^{r}$ with $\alpha\left(\ell_{i}^{r}\right)=1$, and denote by $s^{r}$ the corresponding vertex in $G$. Now, $\left\{s^{r}: 1 \leq r \leq k\right\}$ is a clique of size $k$ in $G$ since $\alpha(x) \neq \alpha(\neg x)$.


## Clique (2)


$(\neg x \vee y \vee z) \wedge(x \vee \neg y \vee \neg z) \wedge(x \vee y)$

- Correctness: $F$ has a satisfying assignment iff $G$ has a clique of size $k$.
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- $(\Leftarrow)$ : Let $S$ be a clique of size $k$ in $G$. Then, $S$ contains exactly one vertex $s_{r} \in\left\{v_{1}^{r}, \ldots, v_{w}^{r}\right\}$ for each $r \in\{1, \ldots, k\}$. Denote by $l^{r}$ the corresponding literal. Now, for any $r, r^{\prime}$, it is not the case that $l_{r}=\neg l_{r^{\prime}}$. Therefore, there is an assignment $\alpha$ to $\operatorname{var}(F)$ such that $\alpha\left(l_{r}\right)=1$ for each $r \in\{1, \ldots, k\}$ and $\alpha$ satisfies $F$.


## Vertex Cover

A vertex cover in a graph $G=(V, E)$ is a subset of vertices $S \subseteq V$ such that every edge of $G$ has an endpoint in $S$.

```
Vertex Cover
    Input: Graph G, integer k
    Question: Does G}\mathrm{ have a vertex cover of size k?
```


## Theorem 19

Vertex Cover is NP-complete.
Groupwork.

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## Theorem 19

Vertex Cover is NP-complete.
Groupwork.
Hint: Reduce from Clique.
Hint 2: The complement of $G=(V, E)$ is the graph $\bar{G}=(V, \bar{E})$, where $\bar{E}=\{\{u, v\}: u, v \in V$ and $\{u, v\} \notin E\}$.

## Hamiltonian Cycle

A Hamiltonian Cycle in a graph $G=(V, E)$ is a cycle visiting each vertex exactly once.
(Alternatively, a permutation of $V$ such that every two consecutive vertices are adjacent and the first and last vertex in the permutation are adjacent.)

```
Hamiltonian Cycle
    Input: Graph G
    Question: Does G have a Hamiltonian Cycle?
```


## Theorem 20

Hamiltonian Cycle is NP-complete.

## Proof sketch.

## Hamiltonian Cycle

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## Proof sketch.

- Hamiltonian Cycle is in NP: the certificate is a Hamiltonian Cycle of $G$.


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## Theorem 20

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## Proof sketch.

- Hamiltonian Cycle is in NP: the certificate is a Hamiltonian Cycle of $G$.
- Let us show: Vertex Cover $\leq_{P}$ Hamiltonian Cycle


## Hamiltonian Cycle (2)

## Theorem 21

Hamiltonian Cycle is NP-complete.

## Proof sketch (continued).

- Let us show: Vertex Cover $\leq_{P}$ Hamiltonian Cycle


## Hamiltonian Cycle (2)

## Theorem 21

Hamiltonian Cycle is NP-complete.

## Proof sketch (continued).

- Let us show: Vertex Cover $\leq_{P}$ Hamiltonian Cycle
- Let $(G=(V, E), k)$ be an instance for Vertex Cover (VC).
- We will construct an equivalent instance $G^{\prime}$ for Hamiltonian Cycle (HC).


## Hamiltonian Cycle (2)

## Theorem 21

Hamiltonian Cycle is NP-complete.

## Proof sketch (continued).

- Let us show: Vertex Cover $\leq_{P}$ Hamiltonian Cycle
- Let $(G=(V, E), k)$ be an instance for Vertex Cover (VC).
- We will construct an equivalent instance $G^{\prime}$ for Hamiltonian Cycle (HC).
- Intuition: Non-deterministic choices
- for VC: which vertices to select in the vertex cover
- for HC: which route the cycle takes
- ...


## Hamiltonian Cycle (3)

## Theorem 22

Hamiltonian Cycle is NP-complete.

Proof sketch (continued).

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- Attention: we need to allow for an edge to be covered by both endpoints


## Hamiltonian Cycle (4)

Gadget representing the edge $\{u, v\} \in E$ Its states: 'covered by $u$ ', 'covered by $u$ and $v$ ', 'covered by $v$ '

(a)

(b)

(c)

(d)

## Hamiltonian Cycle (5)



## Subset Sum

## Subset Sum <br> Input: $\quad$ Set of positive integers $S$, target integer $t$ Question: Is there a subset $X \subseteq S$ such that $\sum_{x \in X} x=t$ ?

On your own: read the NP-completeness proof of Subsection 34.5.5 in Chapter 34 of the textbook; stop at any time to see if you can finish it on your own.

## Coping with NP-hardness

- Approximation algorithms
- There is an algorithm, which, given an instance $(G, k)$ for Vertex Cover, finds a vertex cover of size at most $2 k$ or correctly determines that $G$ has no vertex cover of size $k$.
- Exact exponential time algorithms
- There is an algorithm solving Vertex Cover in time $O\left(1.2002^{n}\right)$, where $n=|V|$.
- Fixed parameter algorithms
- There is an algorithm solving Vertex Cover in time $O\left(1.2738^{k}+k n\right)$.
- Heuristics
- Heuristic $A$ finds a smaller vertex cover than Heuristic $B$ on benchmark instances $C_{1}, \ldots, C_{m}$.
- Restricting the inputs
- Vertex Cover can be solved in polynomial time on bipartite graphs, trees, interval graphs, etc.


## Advertisements

- Algorithms @ UNSW
http://www.cse.unsw.edu.au/~algo/
- COMP6741 - Parameterized and Exact Computation http://www.cse.unsw.edu.au/~cs6741/


## Outline

## (1) Overview

## (2) Turing Machines, $P$, and NP

## 3 Reductions and NP-completeness

(4) NP-complete problems
(5) Extended class 3821/9801

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Subset Sum can be solved in time $O(n \cdot t)$ (pseudo-polynomial algorithm).

## Weak vs Strong NP-completeness

For problems whose input contains integers:

- Weakly NP-hard = NP-hard
- Strongly NP-hard = NP-hard, even if the integers in the input are represented in unary


## P, NP, and certificates

- In the following, $F$ represents poly-time computable predicates (function returning true or false)
- P: class of languages $\{x: F(x)\}$
- NP: class of languages $\left\{x: \exists c_{1} F\left(x, c_{1}\right)\right\}$
- coNP: class of languages $\left\{x: \forall c_{1} F\left(x, c_{1}\right)\right\}$
- where $\left|c_{1}\right| \leq \operatorname{poly}(|x|)$


## Polynomial Hierarchy



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$$
N P^{N P}=N P^{S A T}
$$

## PSPACE



## Counting Problems

$$
\begin{array}{ll}
\hline \text { <Name of } & \text { Counting Problem> } \\
\text { Input: } & <\text { What constitutes an instance> } \\
\text { Question: } & <\text { Number of Yes-instances }>
\end{array}
$$

- FP: class of polynomial-time solvable counting problems
- \#P: class of counting problems whose solution is the number of accept paths of a polynomial-time Non-deterministic Turing Machine
- Alternatively: a counting problem $\Pi$ is in \#P if there exists a polynomial-time computable function $F$ such that $\Pi(x)=|\{c: F(x, c)\}|$


## \#P-completeness

- Turing reduction: $\Pi_{1} \leq_{T} \Pi_{2}$ if there is an algorithm that solves $P_{1}$ in polynomial time using an oracle for $\Pi_{2}$
- $\Pi$ is \#P-hard if every problem in \#P can be Turing reduced to $\Pi$
- $\Pi$ is \#P-complete if $\Pi$ is in \#P and $\Pi$ is \#P-hard.


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Exercise: Show that \#3-CNF-SAT is \#P-complete.
Hint: What goes wrong when using our reduction CNF-SAT $\leq_{P} 3-$ CNF-SAT? How to fix it?

