# 算法设计与分析(2024年春季学期) NP-Completeness

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# NP-Completeness Theory

- The topics we discussed so far are positive results: how to design efficient algorithms for solving a given problem.
- NP-Completeness provides negative results: some problems can not be solved efficiently.

Q: Why do we study negative results?

# NP-Completeness Theory

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- NP-Completeness provides negative results: some problems can not be solved efficiently.

#### Q: Why do we study negative results?

- ullet A given problem X cannot be solved in polynomial time.
- Without knowing it, you will have to keep trying to find polynomial time algorithm for solving X. All our efforts are doomed!

## Efficient = Polynomial Time

- Polynomial time:  $O(n^k)$  for any constant k > 0
- Example:  $O(n), O(n^2), O(n^{2.5} \log n), O(n^{100})$
- Not polynomial time:  $O(2^n), O(n^{\log n})$

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## Reason for Efficient = Polynomial Time

- $\bullet$  For natural problems, if there is an  $O(n^k)\text{-time}$  algorithm, then k is small, say 4
- A good cut separating problems: for most natural problems, either we have a polynomial time algorithm, or the best algorithm runs in time  $\Omega(2^{n^c})$  for some c
- Do not need to worry about the computational model

## Outline

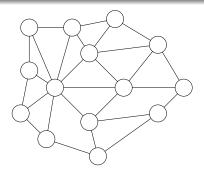
- Some Hard Problems
- P, NP and Co-NP
- 3 Polynomial Time Reductions and NP-Completeness
- 4 NP-Complete Problems
- Dealing with NP-Hard Problems
- **6** Summary

**Def.** Let G be an undirected graph. A Hamiltonian Cycle (HC) of G is a cycle C in G that passes each vertex of G exactly once.

## Hamiltonian Cycle (HC) Problem

**Input:** graph G = (V, E)

**Output:** whether G contains a Hamiltonian cycle

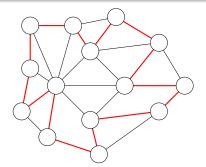


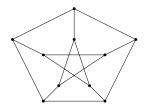
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• The graph is called the Petersen Graph. It has no HC.

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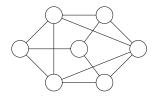
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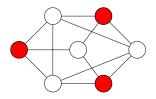
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- HC is NP-hard: it is unlikely that it can be solved in polynomial time.

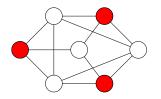
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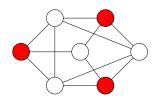


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Maximum Independent Set is NP-hard

# Formula Satisfiability

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**Input:** boolean formula with n variables, with  $\vee, \wedge, \neg$  operators.

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- Example:  $\neg((\neg x_1 \land x_2) \lor (\neg x_1 \land \neg x_3) \lor x_1 \lor (\neg x_2 \land x_3))$  is not satisfiable
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**Fact** For each optimization problem X, there is a decision version X' of the problem. If we have a polynomial time algorithm for the decision version X', we can solve the original problem X in polynomial time.

## Optimization to Decision

#### Shortest Path

**Input:** graph G = (V, E), weight w, s, t and a bound L

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## Example: Sorting problem

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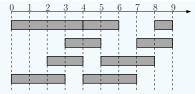
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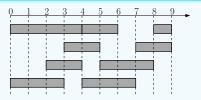
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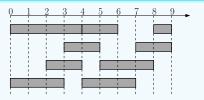
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#### Example: Interval Scheduling Problem



- (0, 3, 0, 4, 2, 4, 3, 5, 4, 6, 4, 7, 5, 8, 7, 9, 8, 9)
- Encode the sequence into a binary string as before

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**A:** No! As long as we are using a "natural" encoding. We only care whether the running time is polynomial or not

#### Define Problem as a Function

$$X: \{0,1\}^* \to \{0,1\}$$

**Def.** A decision problem X is a function mapping  $\{0,1\}^*$  to  $\{0,1\}$  such that for any  $s\in\{0,1\}^*$ , X(s) is the correct output for input s.

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**Def.** A has a polynomial running time if there is a polynomial function  $p(\cdot)$  so that for every string s, the algorithm A terminates on s in at most p(|s|) steps.

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• The decision versions of interval scheduling, shortest path and minimum spanning tree all in P.

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**Def.** The message Alice sends to Bob is called a certificate, and the algorithm Bob runs is called a certifier.

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- Certificate: a set of size k
- Certifier: check if the given set is really an independent set

## The Complexity Class NP

#### **Def.** B is an efficient certifier for a problem X if

- ullet B is a polynomial-time algorithm that takes two input strings s and t, and outputs 0 or 1.
- there is a polynomial function p such that, X(s)=1 if and only if there is string t such that  $|t| \leq p(|s|)$  and B(s,t)=1.

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$$HC(G) = 1 \iff \exists S, B(G, S) = 1$$

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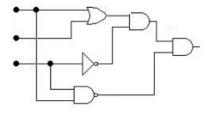
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- $MIS(G, k) = 1 \iff \exists S, B((G, k), S) = 1$

#### Circuit Satisfiablity (Circuit-Sat) Problem

Input: a circuit with and/or/not gates

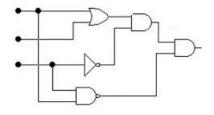
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Is Circuit-Sat ∈ NP?

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- $\overline{\mathsf{HC}} \in \mathsf{Co}\text{-}\mathsf{NP}$

# The Complexity Class Co-NP

**Def.** For a problem X, the problem  $\overline{X}$  is the problem such that  $\overline{X}(s)=1$  if and only if X(s)=0.

**Def.** Co-NP is the set of decision problems X such that  $\overline{X} \in NP$ .

**Def.** A tautology is a boolean formula that always evaluates to 1.

#### Tautology Problem

Input: a boolean formula

Output: whether the formula is a tautology

• e.g.  $(\neg x_1 \land x_2) \lor (\neg x_1 \land \neg x_3) \lor x_1 \lor (\neg x_2 \land x_3)$  is a tautology

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- Bob can certify that a formula is not a tautology
- Thus Tautology  $\in$  Co-NP

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$$P \subseteq NP$$

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- The certificate is an empty string
- Thus,  $X \in \mathsf{NP}$  and  $\mathsf{P} \subseteq \mathsf{NP}$
- Similarly,  $P \subseteq Co-NP$ , thus  $P \subseteq NP \cap Co-NP$

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- It would be too amazing if P = NP: if one can check a solution efficiently, then one can find a solution efficiently
- We assume  $P \neq NP$  and prove that problems do not have polynomial time algorithms.

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- Little progress has been made
- Most researchers believe  $P \neq NP$
- It would be too amazing if P = NP: if one can check a solution efficiently, then one can find a solution efficiently
- We assume  $P \neq NP$  and prove that problems do not have polynomial time algorithms.
- We said it is unlikely that Hamiltonian Cycle can be solved in polynomial time:
  - if  $P \neq NP$ , then  $HC \notin P$
  - HC  $\notin$  P, unless P = NP

### Is NP = Co-NP?

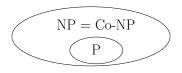
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### Is NP = Co-NP?

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# 4 Possibilities of Relationships

Notice that  $X \in \mathsf{NP} \Longleftrightarrow \overline{X} \in \mathsf{Co}\text{-}\mathsf{NP}$  and  $\mathsf{P} \subseteq \mathsf{NP} \cap \mathsf{Co}\text{-}\mathsf{NP}$ 







People commonly believe we are in the 4th scenario

#### Outline

- Some Hard Problems
- 2 P, NP and Co-NP
- 3 Polynomial Time Reductions and NP-Completeness
- 4 NP-Complete Problems
- 5 Dealing with NP-Hard Problems
- **6** Summary

## Polynomial-Time Reducations

**Def.** Given a black box algorithm A that solves a problem X, if any instance of a problem Y can be solved using a polynomial number of standard computational steps, plus a polynomial number of calls to A, then we say Y is polynomial-time reducible to X, denoted as  $Y \leq_P X$ .

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To prove positive results:

Suppose  $Y \leq_P X$ . If X can be solved in polynomial time, then Y can be solved in polynomial time.

To prove negative results:

Suppose  $Y \leq_P X$ . If Y cannot be solved in polynomial time, then X cannot be solved in polynomial time.

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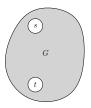
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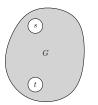


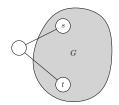
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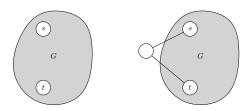


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**Lemma**  $HP \leq_P HC$ .



**Obs.** G has a HP from s to t if and only if graph on right side has a HC.

**Def.** A problem *X* is called NP-complete if

- ullet  $X \in \mathsf{NP}$ , and
- $Y \leq_{\mathsf{P}} X$  for every  $Y \in \mathsf{NP}$ .

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- NP-hard problems are at least as hard as NP-complete problems (a NP-hard problem is not required to be in NP)

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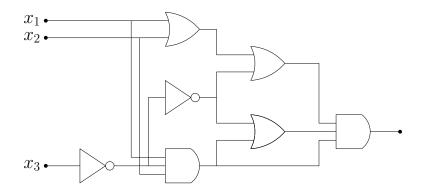
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  - How can we find a problem  $X \in \mathsf{NP}$  such that every problem  $Y \in \mathsf{NP}$  is polynomial time reducible to X? Are we asking for too much?
  - No! There is indeed a large family of natural NP-complete problems

### The First NP-Complete Problem: Circuit-Sat

### Circuit Satisfiability (Circuit-Sat)

Input: a circuit

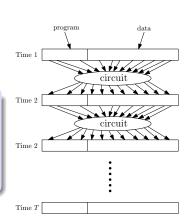
Output: whether the circuit is satisfiable



### Circuit-Sat is NP-Complete

 key fact: algorithms can be converted to circuits

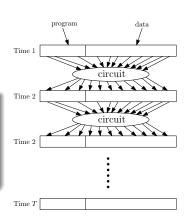
Fact Any algorithm that takes n bits as input and outputs 0/1 with running time T(n) can be converted into a circuit of size p(T(n)) for some polynomial function  $p(\cdot)$ .



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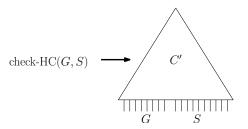
- Then, we can show that any problem  $Y \in \mathsf{NP}$  can be reduced to Circuit-Sat.
- We prove HC  $\leq_P$  Circuit-Sat as an example.

 $\mathrm{check\text{-}HC}(G,S)$ 

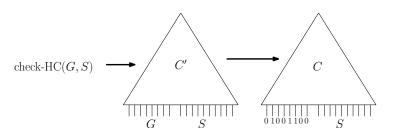
• Let check-HC(G,S) be the certifier for the Hamiltonian cycle problem: check-HC(G,S) returns 1 if S is a Hamiltonian cycle is G and 0 otherwise.

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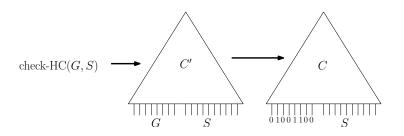
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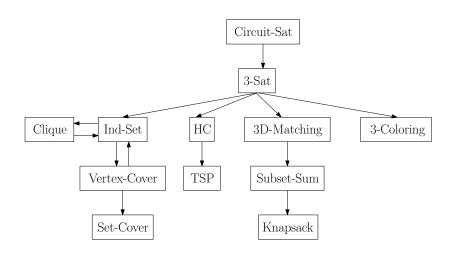
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**Theorem** Circuit-Sat is NP-complete.

# Reductions of NP-Complete Problems



3-CNF (conjunctive normal form) is a special case of formula:

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- 3-CNF (conjunctive normal form) is a special case of formula:
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  - Literals:  $x_i$  or  $\neg x_i$
  - Clause: disjunction ("or") of at most 3 literals:  $x_3 \vee \neg x_4$ ,  $x_1 \vee x_8 \vee \neg x_9$ ,  $\neg x_2 \vee \neg x_5 \vee x_7$

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- 3-CNF formula: conjunction ("and") of clauses:  $(x_1 \lor \neg x_2 \lor \neg x_3) \land (x_2 \lor x_3 \lor x_4) \land (\neg x_1 \lor \neg x_3 \lor \neg x_4)$

#### 3-Sat

**Input:** a 3-CNF formula

Output: whether the 3-CNF is satisfiable

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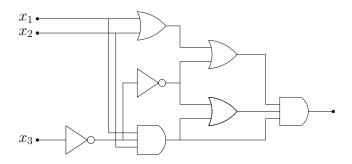
- To satisfy a 3-CNF, we need to satisfy all clauses
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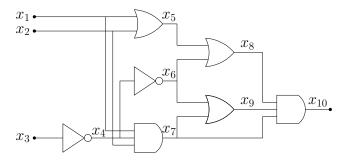
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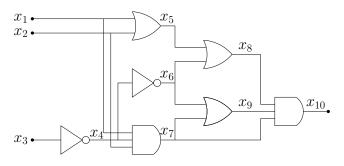
Output: whether the 3-CNF is satisfiable

- To satisfy a 3-CNF, we need to satisfy all clauses
- To satisfy a clause, we need to satisfy at least 1 literal
- Assignment  $x_1=1, x_2=1, x_3=0, x_4=0$  satisfies  $(x_1\vee \neg x_2\vee \neg x_3)\wedge (x_2\vee x_3\vee x_4)\wedge (\neg x_1\vee \neg x_3\vee \neg x_4)$





• Associate every wire with a new variable



- Associate every wire with a new variable
- The circuit is equivalent to the following formula:

$$(x_4 = \neg x_3) \land (x_5 = x_1 \lor x_2) \land (x_6 = \neg x_4)$$
  
 
$$\land (x_7 = x_1 \land x_2 \land x_4) \land (x_8 = x_5 \lor x_6)$$
  
 
$$\land (x_9 = x_6 \lor x_7) \land (x_{10} = x_8 \land x_9 \land x_7) \land x_{10}$$

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$$x_5 = x_1 \vee x_2 \quad \Leftrightarrow \quad$$

$x_1$	$x_2$	$x_5$	$x_5 \leftrightarrow x_1 \lor x_2$
0	0	0	1
0	0	1	0
0	1	0	0
0	1	1	1
1	0	0	0
1	0	1	1
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### Convert each clause to a 3-CNF

$$x_5 = x_1 \lor x_2 \quad \Leftrightarrow \quad (x_1 \lor x_2 \lor \neg x_5) \quad \land$$

		1
$x_2$	$x_5$	$x_5 \leftrightarrow x_1 \lor x_2$
0	0	1
0	1	0
1	0	0
1	1	1
0	0	0
0	1	1
1	0	0
1	1	1
	0 0 1 1 0 0	0 0 0 1 1 1 0 1 1 0 0 0 0 1

45/90

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1	0	1	1
1	1	0	0
1	1	1	1
	0 0 0 0 1	0 0 0 0 0 0 1 0 1 1 0 1 0 0	0 0 0 0 0 1 0 1 0 0 1 1 1 0 0 1 0 1

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$(x_1 \vee \neg x_2 \vee x_5)  / $	\
$(\neg x_1 \lor x_2 \lor x_5)  / $	\

$x_1$	$x_2$	$x_5$	$x_5 \leftrightarrow x_1 \lor x_2$
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	U
$x_5 = x_1 \lor x_2  \Leftrightarrow $	0
	0
$(x_1 \lor x_2 \lor \neg x_5) \land$	0
$(x_1 \vee \neg x_2 \vee x_5) \wedge$	1
$(\neg x_1 \lor x_2 \lor x_5) \land$	1
	1
$(\neg x_1 \lor \neg x_2 \lor x_5)$	1

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1	1	0	0
1	1	1	1

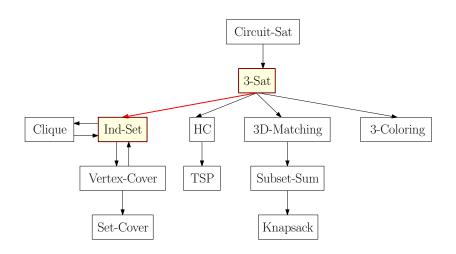
ullet Circuit  $\Longleftrightarrow$  Formula  $\Longleftrightarrow$  3-CNF

- Circuit ←⇒ Formula ←⇒ 3-CNF
- The circuit is satisfiable if and only if the 3-CNF is satisfiable

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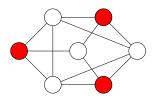
- Circuit ←⇒ Formula ←⇒ 3-CNF
- The circuit is satisfiable if and only if the 3-CNF is satisfiable
- The size of the 3-CNF formula is polynomial (indeed, linear) in the size of the circuit
- Thus, Circuit-Sat  $\leq_P$  3-Sat

# Reductions of NP-Complete Problems



#### Recall: Independent Set Problem

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



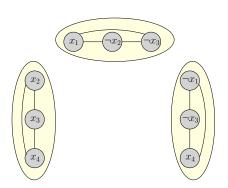
#### Independent Set (Ind-Set) Problem

Input: G = (V, E), k

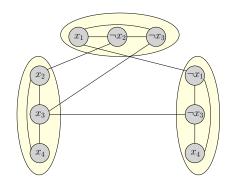
**Output:** whether there is an independent set of size k in G

 $\bullet \ (x_1 \vee \neg x_2 \vee \neg x_3) \wedge (x_2 \vee x_3 \vee x_4) \wedge (\neg x_1 \vee \neg x_3 \vee x_4)$ 

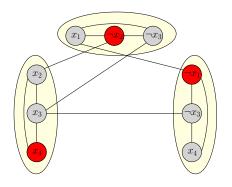
- $\bullet \ (x_1 \vee \neg x_2 \vee \neg x_3) \wedge (x_2 \vee x_3 \vee x_4) \wedge (\neg x_1 \vee \neg x_3 \vee x_4)$
- A clause ⇒ a group of 3 vertices, one for each literal
- An edge between every pair of vertices in same group



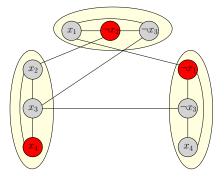
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- A clause ⇒ a group of 3 vertices, one for each literal
- An edge between every pair of vertices in same group
- An edge between every pair of contradicting literals



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- Problem: whether there is an IS of size k = #clauses

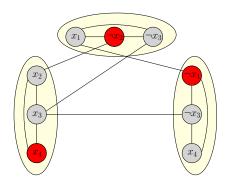


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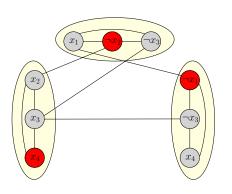
3-Sat instance is yes-instance ⇔ Ind-Set instance is yes-instance:

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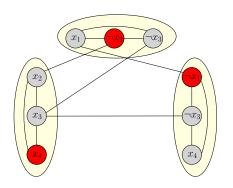


- 3-Sat instance is yes-instance ⇔ Ind-Set instance is yes-instance:
- ullet satisfying assignment  $\Rightarrow$  independent set of size k
- independent set of size  $k \Rightarrow$  satisfying assignment

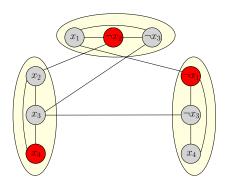
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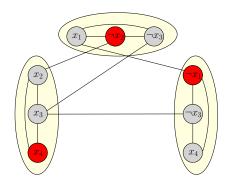
- $\bullet \ (x_1 \vee \neg x_2 \vee \neg x_3) \wedge (x_2 \vee x_3 \vee x_4) \wedge (\neg x_1 \vee \neg x_3 \vee x_4)$
- For every clause, at least 1 literal is satisfied



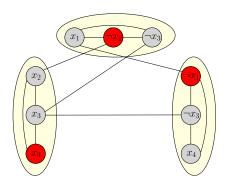
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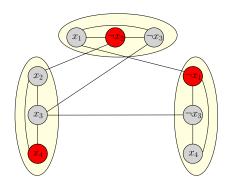
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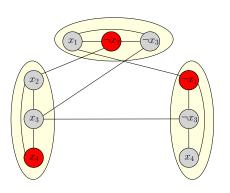
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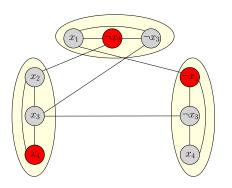
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- So, 1 literal from each group
- No contradictions among the selected literals
- An IS of size k



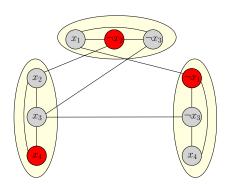
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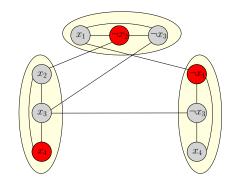
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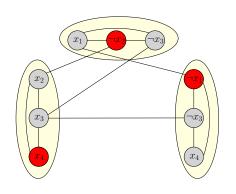
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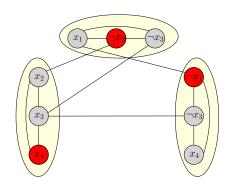
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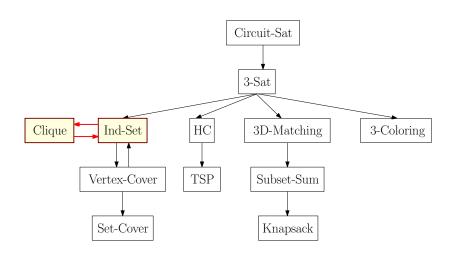
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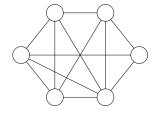


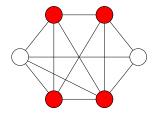
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- Otherwise, set  $x_i$  arbitrarily

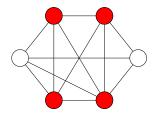


# Reductions of NP-Complete Problems





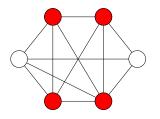




#### Clique Problem

**Input:** G = (V, E) and integer k > 0,

**Output:** whether there exists a clique of size k in G



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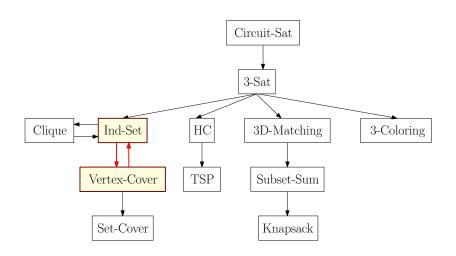
• What is the relationship between Clique and Ind-Set?

#### $Clique =_P Ind-Set$

**Def.** Given a graph G=(V,E), define  $\overline{G}=(V,\overline{E})$  be the graph such that  $(u,v)\in \overline{E}$  if and only if  $(u,v)\notin E$ .

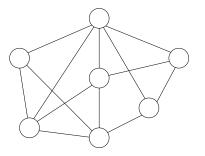
**Obs.** S is an independent set in G if and only if S is a clique in  $\overline{G}$ .

# Reductions of NP-Complete Problems



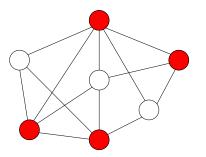
#### Vertex-Cover

**Def.** Given a graph G=(V,E), a vertex cover of G is a subset  $S\subseteq V$  such that for every  $(u,v)\in E$  then  $u\in S$  or  $v\in S$ .



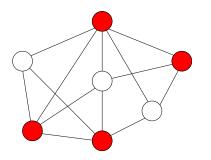
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#### Vertex-Cover Problem

**Input:** G = (V, E) and integer k

# $\mathsf{Vertex}\text{-}\mathsf{Cover} =_P \mathsf{Ind}\text{-}\mathsf{Set}$

## $\mathsf{Vertex}\text{-}\mathsf{Cover} =_P \mathsf{Ind}\text{-}\mathsf{Set}$

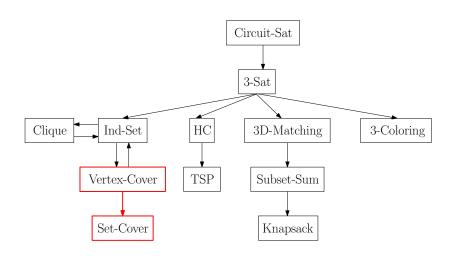
**Q:** What is the relationship between Vertex-Cover and Ind-Set?

Vertex-Cover  $=_P$  Ind-Set

Q: What is the relationship between Vertex-Cover and Ind-Set?

**A:** S is a vertex-cover of G=(V,E) if and only if  $V\setminus S$  is an independent set of G.

## Reductions of NP-Complete Problems



#### Set Cover

**Input:**  $S_1, S_2, \dots, S_M \subseteq [N]$  with  $\bigcup_{i \in [m]} S_i = [N]$ 

**Output:** The smallest set  $I \subseteq [M]$  satisfying  $\bigcup_{i \in I} S_i = [N]$ 

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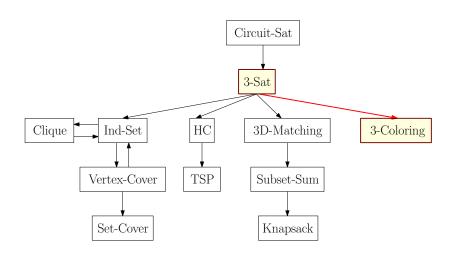
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#### Vertex Cover $\leq_P$ Set Cover

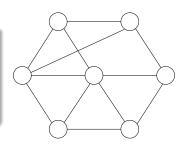
- ullet m edges  $\Leftrightarrow$  N elements
- n vertices  $\Leftrightarrow$  M sets
- ullet vertex is incident to edge  $e \quad \Leftrightarrow \quad$  set contains element
- Vertex cover is the special case of set cover where each element appears in exactly two sets.

## Reductions of NP-Complete Problems



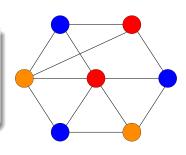
#### *k*-coloring problem

**Def.** A k-coloring of G=(V,E) is a function  $f:V \to \{1,2,3,\cdots,k\}$  so that for every edge  $(u,v) \in E$ , we have  $f(u) \neq f(v)$ . G is k-colorable if there is a k-coloring of G.



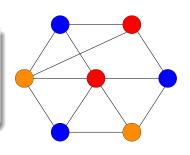
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#### *k*-coloring problem

**Input:** a graph G = (V, E)

**Output:** whether G is k-colorable or not

#### 2-Coloring Problem

**Obs.** A graph G is 2-colorable if and only if it is bipartite.

**Q:** How do we check if a graph G is 2-colorable?

#### 2-Coloring Problem

**Obs.** A graph G is 2-colorable if and only if it is bipartite.

**Q:** How do we check if a graph G is 2-colorable?

**A:** We check if *G* is bipartite.

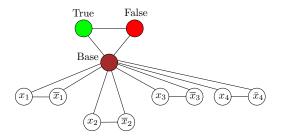
Construct the base graph

#### Base Graph



Construct the base graph

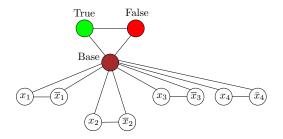
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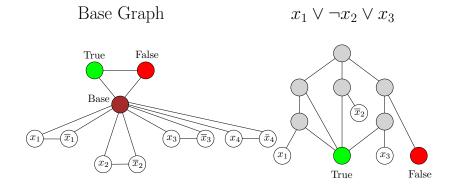
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Base Graph

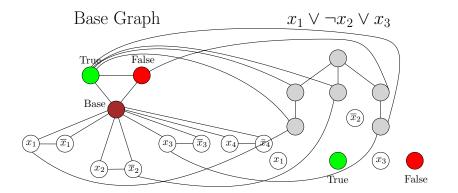
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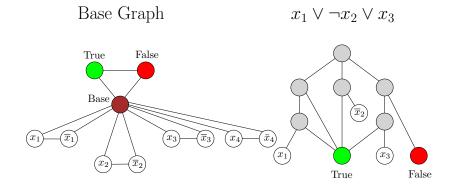
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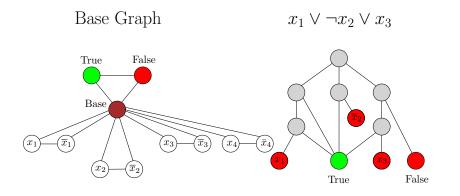
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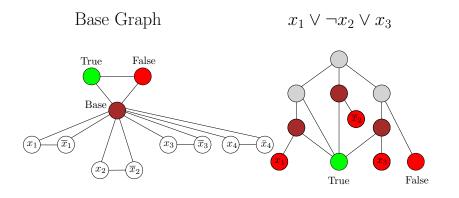
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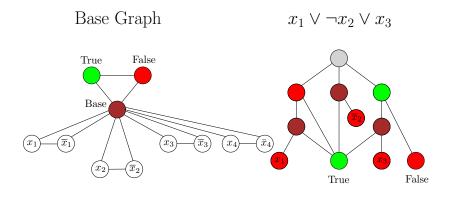
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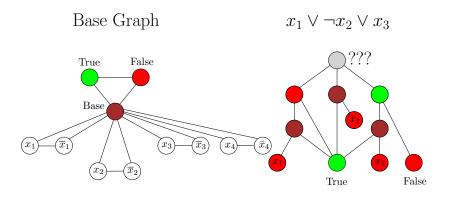
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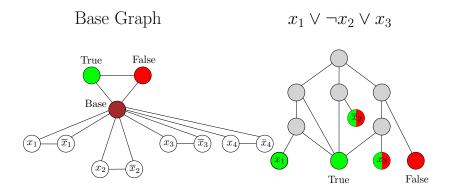
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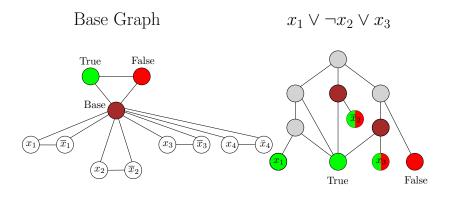
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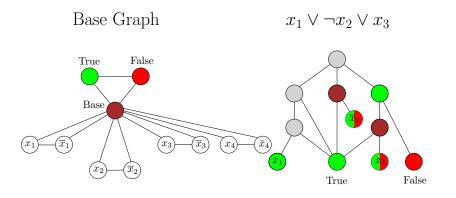
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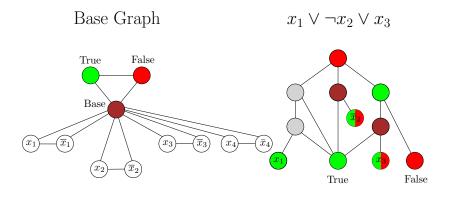
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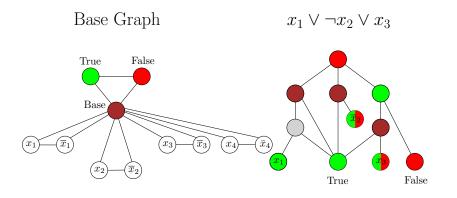
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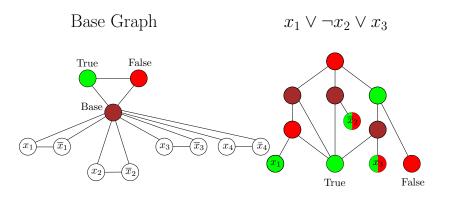
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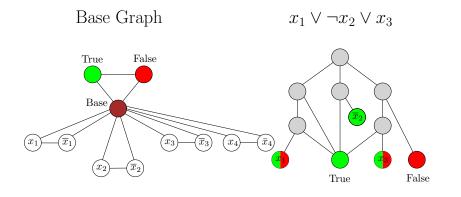
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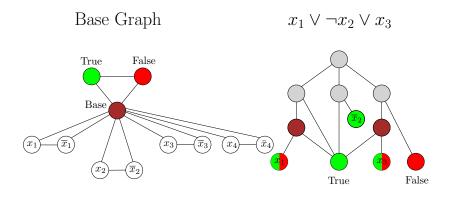
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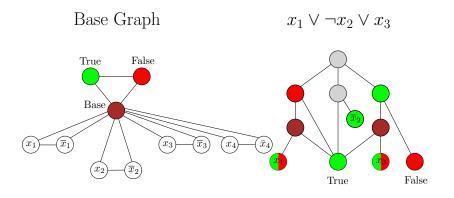
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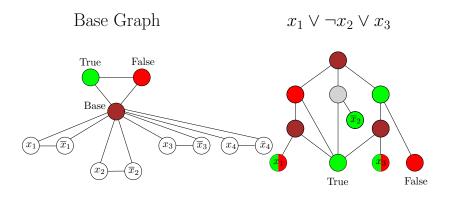
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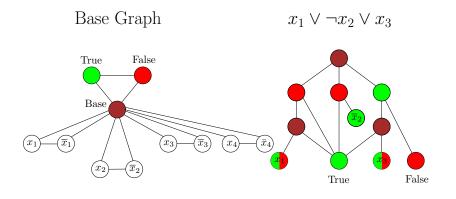
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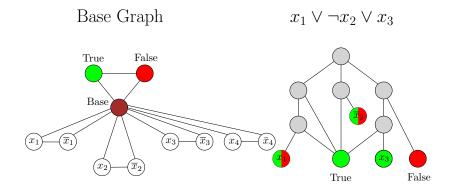
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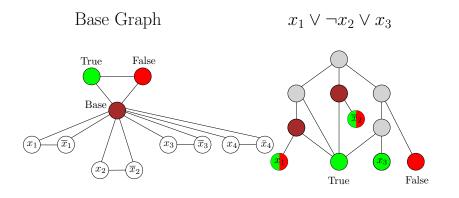
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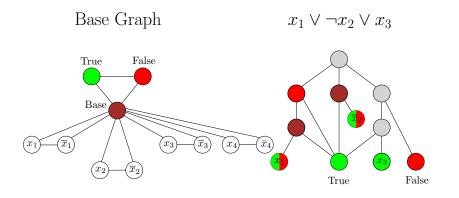
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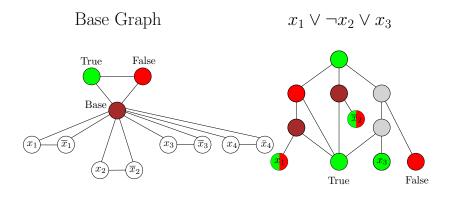


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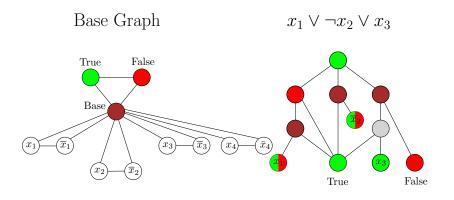
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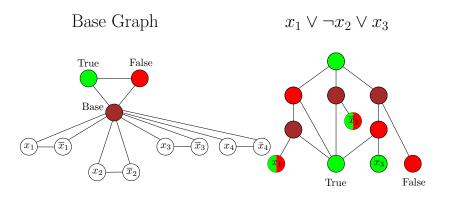
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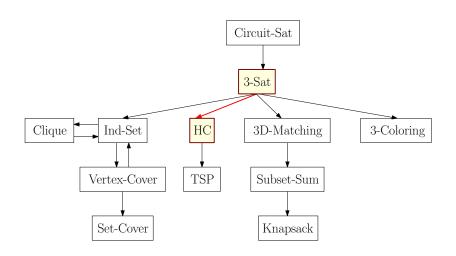


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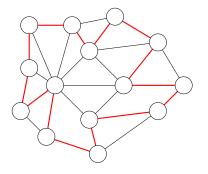
# Reductions of NP-Complete Problems



#### Recall: Hamiltonian Cycle (HC) Problem

**Input:** graph G = (V, E)

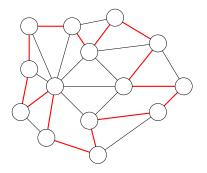
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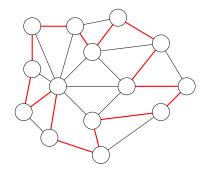


• We consider Hamiltonian Cycle Problem in directed graphs

#### Recall: Hamiltonian Cycle (HC) Problem

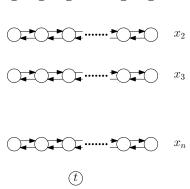
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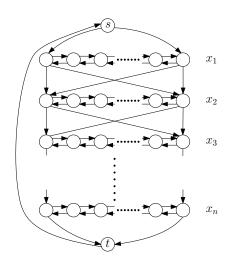


- We consider Hamiltonian Cycle Problem in directed graphs
- Exercise: HC-directed  $\leq_P$  HC

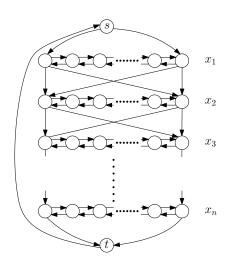
(s)



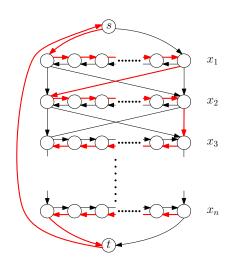
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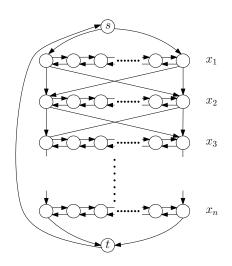
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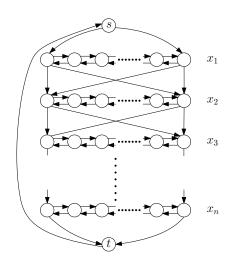
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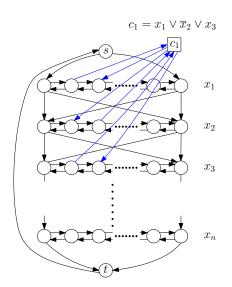
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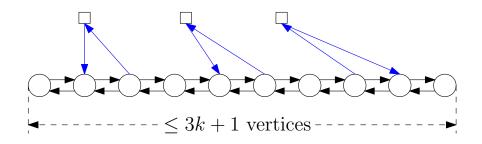


 There are exactly 2<sup>n</sup> different Hamiltonian cycles, each correspondent to one assignment of variables



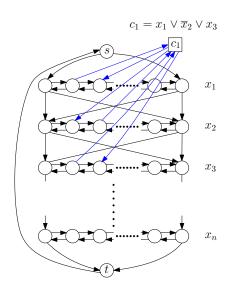
- There are exactly 2<sup>n</sup> different Hamiltonian cycles, each correspondent to one assignment of variables
- Add a vertex for each clause, so that the vertex can be visited only if one of the literals is satisfied.

# A Path Should Be Long Enough



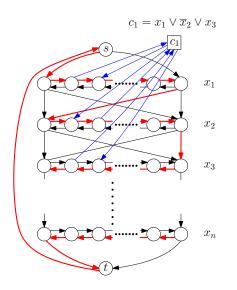
• k: number of clauses

#### Yes-Instance for 3-Sat $\Rightarrow$ Yes-Instance for Di-HC



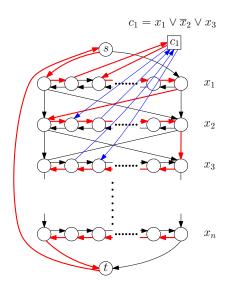
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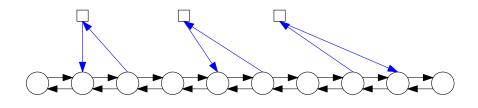


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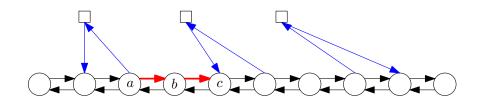
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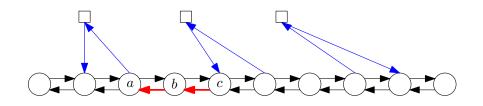
- In base graph, construct an HC according to the satisfying assignment
- For every clause, one literal is satisfied
- Visit the vertex for the clause by taking a "detour" from the path for the literal



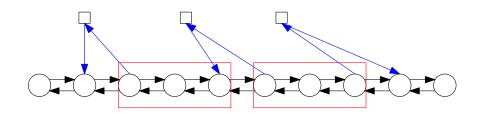
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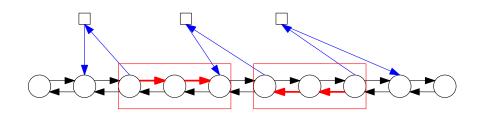
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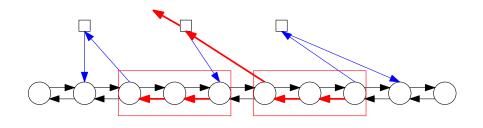
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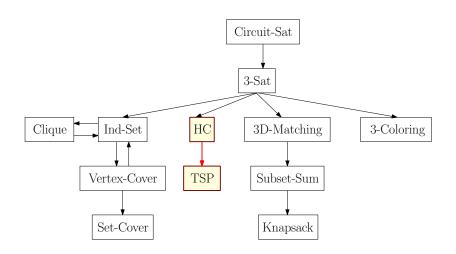


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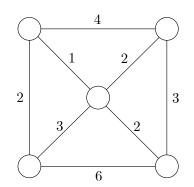


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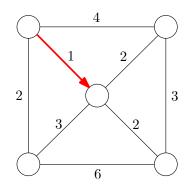
# Reductions of NP-Complete Problems



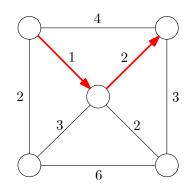
- A salesman needs to visit n cities  $1, 2, 3, \dots, n$
- ullet He needs to start from and return to city 1
- Goal: find a tour with the minimum cost



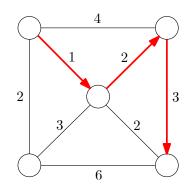
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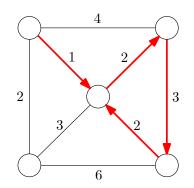
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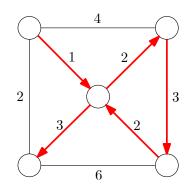
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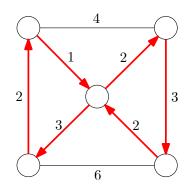
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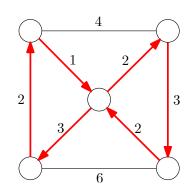
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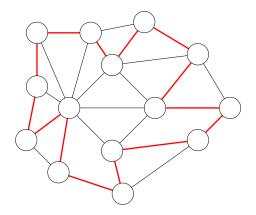


#### Travelling Salesman Problem (TSP)

**Input:** a graph G=(V,E), weights  $w:E\to\mathbb{R}_{\geq 0}$ , and L>0

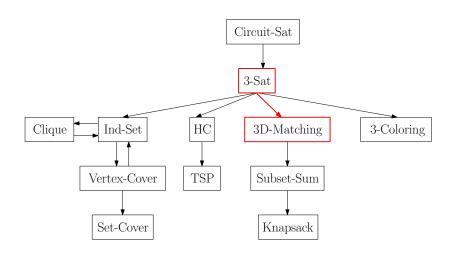
**Output:** whether there is a tour of length at most D

# $HC \leq_P TSP$



**Obs.** There is a Hamilton cycle in G if and only if there is a tour for the salesman of length n=|V|.

# Reductions of NP-Complete Problems



#### 3D-Matching

Input: 
$$|X| = |Y| = |Z| = n$$
,  $(x_1, y_1, z_1), (x_2, y_2, z_2), \dots, (x_m, y_m, z_m) \in X \times Y \times Z$ 

**Output:** whether there exists  $S \subseteq [m], |S| = n$  such that

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$$\{x_i : i \in S\} = X, \{y_i : i \in S\} = Y, \{z_i : i \in S\} = Z$$

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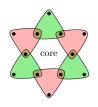
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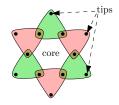


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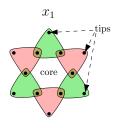


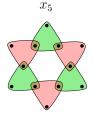
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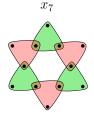
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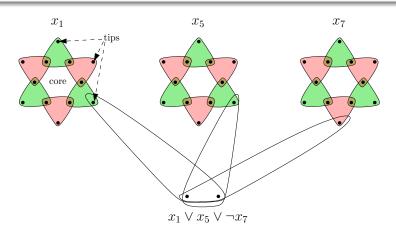


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Recall the definition of polynomial time reductions:

**Def.** Given a black box algorithm A that solves a problem X, if any instance of a problem Y can be solved using a polynomial number of standard computational steps, plus a polynomial number of calls to A, then we say Y is polynomial-time reducible to X, denoted as  $Y \leq_P X$ .

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- ullet However, for most reductions, we call algorithm for X only once
- ullet That is, for a given instance  $s_Y$  for Y, we only construct one instance  $s_X$  for X

- Given an instance  $s_Y$  of problem Y, show how to construct in polynomial time an instance  $s_X$  of problem such that:
  - $s_Y$  is a yes-instance of  $Y \Rightarrow s_X$  is a yes-instance of X
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### Outline

- Some Hard Problems
- 2 P, NP and Co-NP
- Opening Time Reductions and NP-Completeness
- 4 NP-Complete Problems
- 5 Dealing with NP-Hard Problems
- **6** Summary

• Try to prove an "unconditional" lower bound on running time of algorithm solving a NP-complete problem.

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- Essentially we have no techniques for proving lower bound for running time

## Dealing with NP-Hard Problems

- Faster exponential time algorithms
- Solving the problem for special cases
- Fixed parameter tractability
- Approximation algorithms

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#### Travelling Salesman Problem:

- Brute-force:  $O(n! \cdot poly(n))$
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- In practice: TSP Solver can solve Euclidean TSP instances with more than 100,000 vertices

Maximum independent set problem is NP-hard on general graphs, but easy on

trees

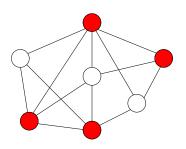
- trees
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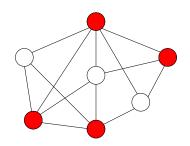
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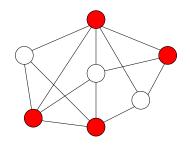
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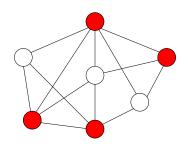
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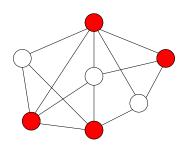
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- Vertex-Cover is fixed-parameter tractable.



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- There is an 2-approximation for the vertex cover problem: we can
  efficiently find a vertex cover whose size is at most 2 times that of
  the optimal vertex cover

#### Outline

- Some Hard Problems
- P, NP and Co-NP
- Polynomial Time Reductions and NP-Completeness
- 4 NP-Complete Problems
- 5 Dealing with NP-Hard Problems
- **6** Summary

- We consider decision problems
- ullet Inputs are encoded as  $\{0,1\}$ -strings

**Def.** The complexity class P is the set of decision problems X that can be solved in polynomial time.

- Alice has a supercomputer, fast enough to run an exponential time algorithm
- Bob has a slow computer, which can only run a polynomial-time algorithm

**Def.** (Informal) The complexity class NP is the set of problems for which Alice can convince Bob a yes instance is a yes instance

#### **Def.** B is an efficient certifier for a problem X if

- $\bullet$  B is a polynomial-time algorithm that takes two input strings s and t
- there is a polynomial function p such that, X(s)=1 if and only if there is string t such that  $|t| \leq p(|s|)$  and B(s,t)=1.

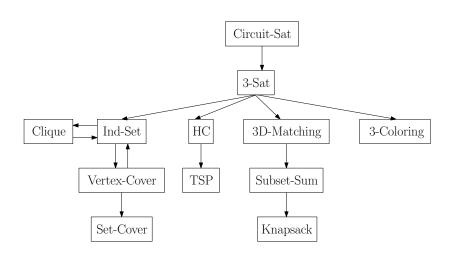
The string t such that B(s,t)=1 is called a certificate.

**Def.** The complexity class NP is the set of all problems for which there exists an efficient certifier.

**Def.** Given a black box algorithm A that solves a problem X, if any instance of a problem Y can be solved using a polynomial number of standard computational steps, plus a polynomial number of calls to A, then we say Y is polynomial-time reducible to X, denoted as  $Y \leq_P X$ .

**Def.** A problem X is called NP-complete if

- $\bullet$   $X \in \mathsf{NP}$ , and
- $Y \leq_{\mathsf{P}} X$  for every  $Y \in \mathsf{NP}$ .
  - $\bullet$  If any NP-complete problem can be solved in polynomial time, then P=NP
  - $\bullet$  Unless P=NP, a NP-complete problem can not be solved in polynomial time



#### Proof of NP-Completeness for Circuit-Sat

- Fact 1: a polynomial-time algorithm can be converted to a polynomial-size circuit
- Fact 2: for a problem in NP, there is a efficient certifier.
- Given a problem  $X \in \mathsf{NP}$ , let B(s,t) be the certifier
- ullet Convert B(s,t) to a circuit and hard-wire s to the input gates
- ullet s is a yes-instance if and only if the resulting circuit is satisfiable
- Proof of NP-Completeness for other problems by reductions