

CSE 431/531: Algorithm Analysis and Design (Spring 2018)

## NP-Completeness

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3.36pt

# 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.

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

- 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!

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- Do not need to worry about the computational model

# Pseudo-Polynomial Is not Polynomial!

Polynomial:

- Kruskal's algorithm for minimum spanning tree:  
 $O(n \lg n + m)$
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Pseudo-Polynomial:

- Knapsack Problem:  $O(nW)$ , where  $W$  is the maximum weight the Knapsack can hold

Reason: to specify integer in  $[0, W]$ , we only need  $O(\lg W)$  bits.

# Outline

3.36pt

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## Recall: Knapsack Problem

**Input:**  $n$  items, each item  $i$  with a weight  $w_i$ , and a value  $v_i$ ;  
a bound  $W$  on the total weight the knapsack can hold

**Output:** the maximum value of items the knapsack can hold,  
i.e, a set  $S \subseteq \{1, 2, \dots, n\}$ :

$$\max \sum_{i \in S} v_i \quad \text{s.t.} \quad \sum_{i \in S} w_i \leq W$$

- DP is  $O(nW)$ -time algorithm, not a real polynomial time
- Knapsack is **NP-hard**: it is **unlikely** that the problem can be solved in polynomial time

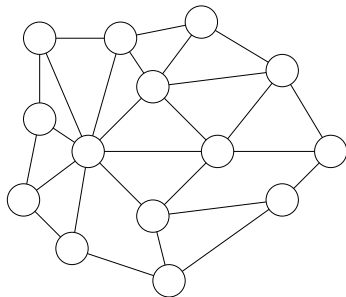
# Example: Hamiltonian Cycle Problem

**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  $G = (V, E)$

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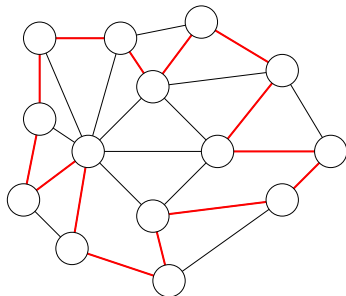
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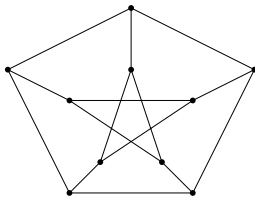
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- The graph is called the **Petersen Graph**. It has no HC.

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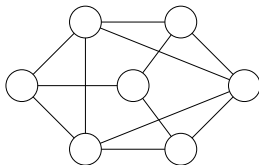
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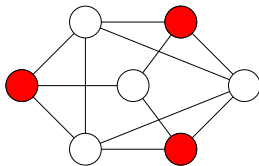
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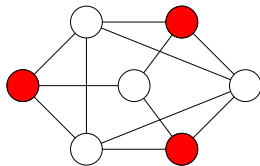
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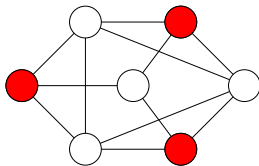
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- Maximum Independent Set is NP-hard

# Formula Satisfiability

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

**Output:** whether the boolean formula is satisfiable

- Example:  $\neg((\neg x_1 \wedge x_2) \vee (\neg x_1 \wedge \neg x_3) \vee x_1 \vee (\neg x_2 \wedge x_3))$  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.

## Shortest Path

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

**Output:** whether there is a path from  $s$  to  $t$  of length at most  $L$

# Optimization to Decision

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## Maximum Independent Set

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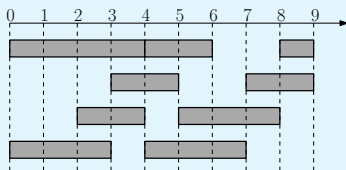
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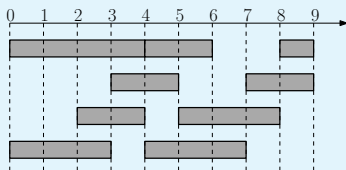
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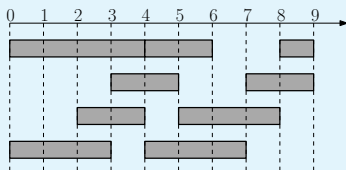


- (0, 3, 0, 4, 2, 4, 3, 5, 4, 6, 4, 7, 5, 8, 7, 9, 8, 9)

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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 Set

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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.

# Complexity Class P

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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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- Certifier: check if the given set is really an independent set

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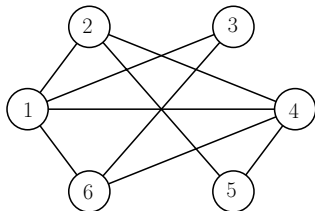
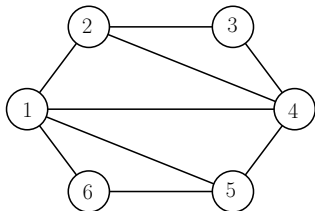
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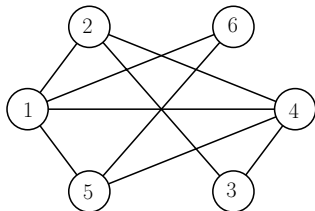
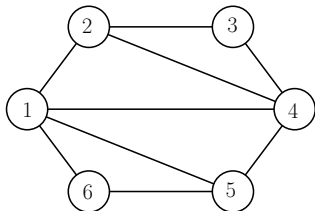


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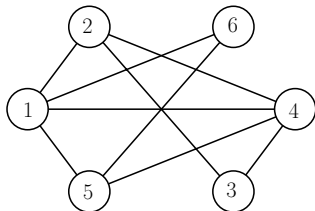
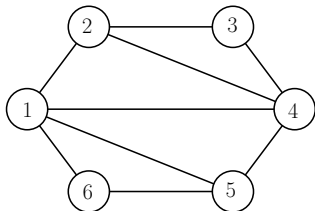


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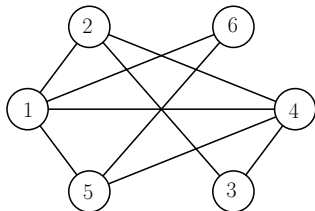
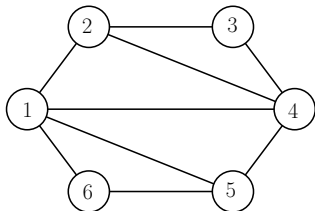
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- What is the certificate?
- What is the certifier?

# The Complexity Class NP

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

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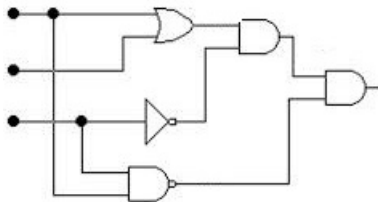
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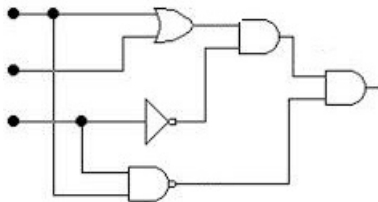
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# The Complexity Class Co-NP

**Def.** For a problem  $X$ , the problem  $\bar{X}$  is the problem such that  $s \in \bar{X}$  if and only if  $s \notin X$ .

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

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### Tautology Problem

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# Is $NP = Co-NP$ ?

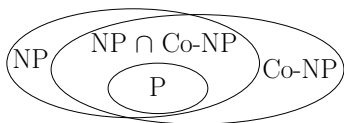
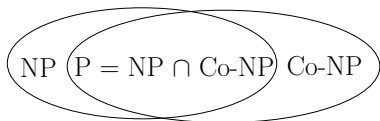
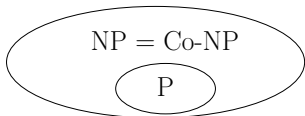
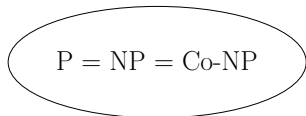
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# Is $NP = Co-NP$ ?

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## 4 Possibilities of Relationships

Notice that  $X \in \text{NP} \iff \bar{X} \in \text{Co-NP}$  and  $P \subseteq \text{NP} \cap \text{Co-NP}$



- General belief: we are in the 4th scenario

# Outline

3.36pt

- 1 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 Reductions

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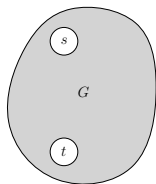
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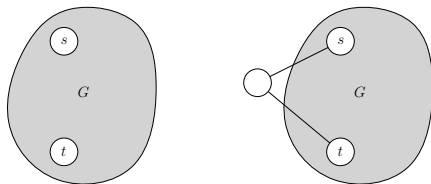
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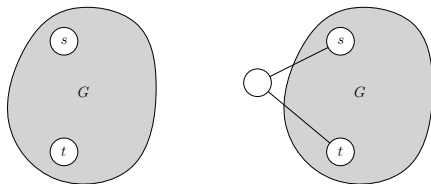
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**Obs.**  $G$  has a HP from  $s$  to  $t$  if and only if graph on right side has a HC.

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- NP-complete problems are the hardest problems in NP
- NP-hard problems are at least as hard as NP-complete problems (a NP-hard problem is not required to be in NP)
- To prove  $\text{P} = \text{NP}$  (if you believe it), you only need to give an efficient algorithm for **any** NP-complete problem
- If you believe  $\text{P} \neq \text{NP}$ , and proved that a problem  $X$  is NP-complete (or NP-hard), stop trying to design efficient algorithms for  $X$

# Outline

3.36pt

- 1 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

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

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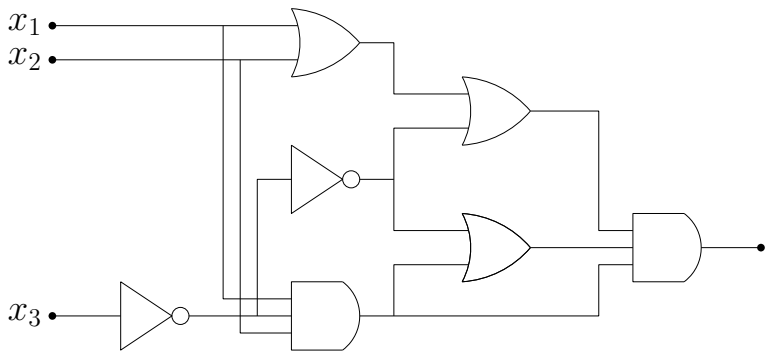
- How can we find a problem  $X \in \text{NP}$  such that every problem  $Y \in \text{NP}$  is polynomial time reducible to  $X$ ? Are we asking for too much?
- No! There is indeed a large family of natural NP-complete problems

# The First NP-Complete Problem: Circuit-Sat

## Circuit Satisfiability (Circuit-Sat)

**Input:** a circuit

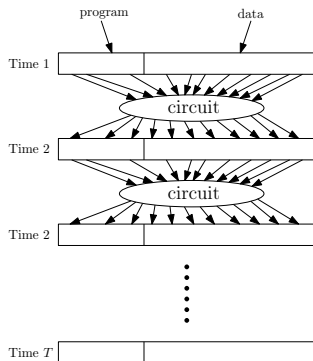
**Output:** whether the circuit is satisfiable



# Circuit-Sat is NP-Complete

- key fact: algorithms can be converted to circuits

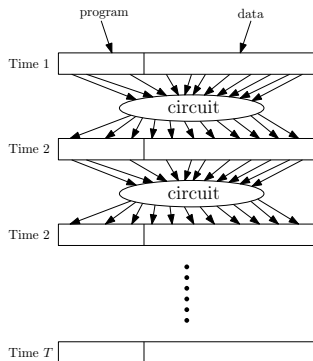
**Fact** Any algorithm that takes  $n$  bits as input and outputs 0/1 with running time  $T(n)$  can be converted into a circuit of size  $p(T(n))$  for some polynomial function  $p(\cdot)$ .



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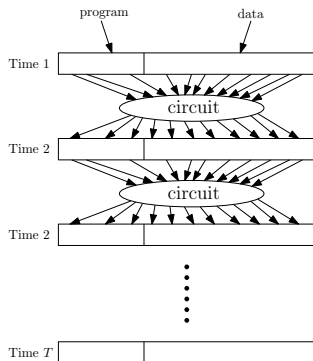


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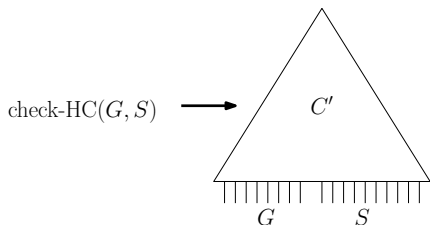
- Then, we can show that any problem  $Y \in \text{NP}$  can be reduced to Circuit-Sat.
- We prove  $\text{HC} \leq_P \text{Circuit-Sat}$  as an example.

check-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 in  $G$  and 0 otherwise.

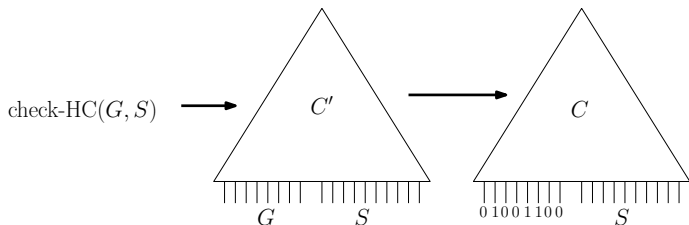
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- $G$  is a yes-instance if and only if there is an  $S$  such that check-HC( $G, S$ ) returns 1

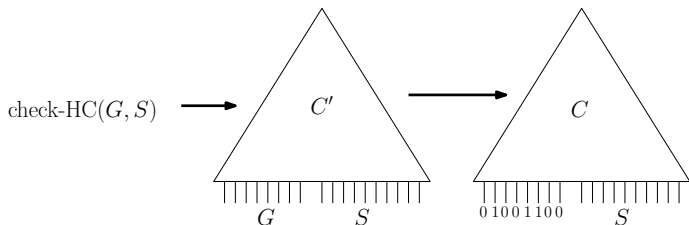


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# $Y \leq_P \text{Circuit-Sat}$ , For Every $Y \in \text{NP}$

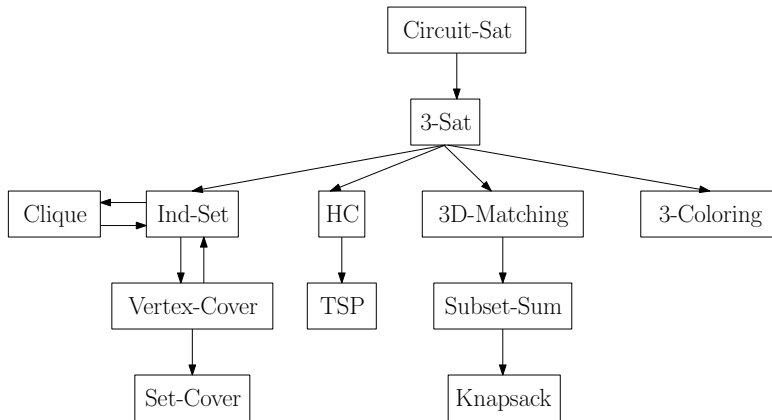
- Let  $\text{check-}Y(s, t)$  be the certifier for problem  $Y$ :  
 $\text{check-}Y(s, t)$  returns 1 if  $t$  is a valid certificate for  $s$ .
- $s$  is a yes-instance if and only if there is a  $t$  such that  $\text{check-}Y(s, t)$  returns 1
- Construct a circuit  $C'$  for the algorithm  $\text{check-}Y$
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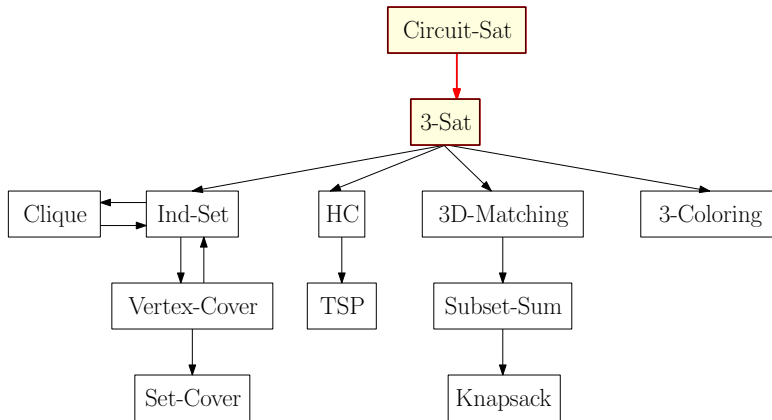
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**Theorem**  $\text{Circuit-Sat}$  is NP-complete.

# Reductions of NP-Complete Problems



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- Clause: disjunction ("or") of at most 3 literals:  $x_3 \vee \neg x_4,$   
 $x_1 \vee x_8 \vee \neg x_9, \quad \neg x_2 \vee \neg x_5 \vee x_7$

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 $x_1 \vee x_8 \vee \neg x_9$ ,  $\neg x_2 \vee \neg x_5 \vee x_7$
- 3-CNF formula: conjunction (“and”) of clauses:  
 $(x_1 \vee \neg x_2 \vee \neg x_3) \wedge (x_2 \vee x_3 \vee x_4) \wedge (\neg x_1 \vee \neg x_3 \vee \neg x_4)$

# 3-Sat

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**Input:** a 3-CNF formula

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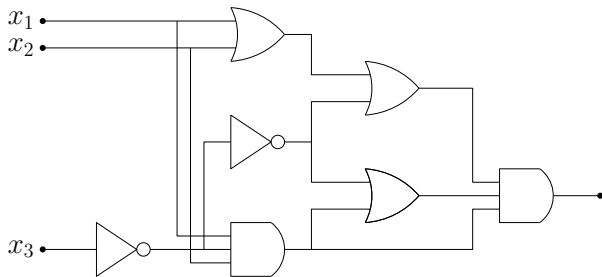
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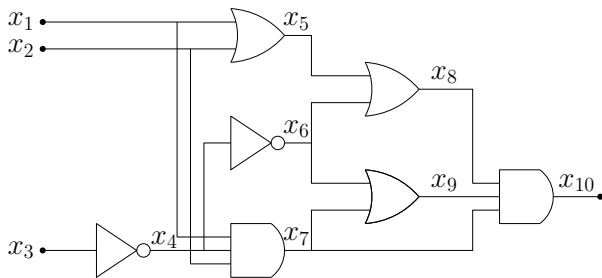
- To satisfy a 3-CNF, we need to satisfy all clauses
- To satisfy a clause, we need to satisfy at least 1 literal
- Assignment  $x_1 = 1, x_2 = 1, x_3 = 0, x_4 = 0$  satisfies  
 $(x_1 \vee \neg x_2 \vee \neg x_3) \wedge (x_2 \vee x_3 \vee x_4) \wedge (\neg x_1 \vee \neg x_3 \vee \neg x_4)$

# Circuit-Sat $\leq_P$ 3-Sat



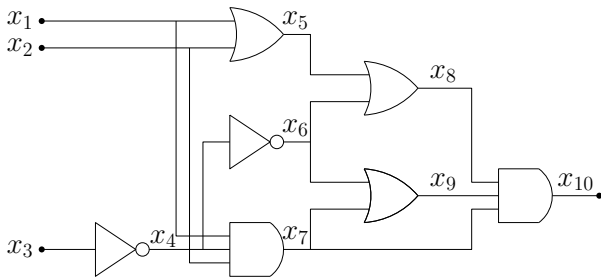


# Circuit-Sat $\leq_P$ 3-Sat



- Associate every wire with a new variable

# Circuit-Sat $\leq_P$ 3-Sat



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

$$\begin{aligned} & (x_4 = \neg x_3) \wedge (x_5 = x_1 \vee x_2) \wedge (x_6 = \neg x_4) \\ & \wedge (x_7 = x_1 \wedge x_2 \wedge x_4) \wedge (x_8 = x_5 \vee x_6) \\ & \wedge (x_9 = x_6 \vee x_7) \wedge (x_{10} = x_8 \wedge x_9 \wedge x_7) \wedge x_{10} \end{aligned}$$

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

$x_1$	$x_2$	$x_5$	$x_5 \leftrightarrow x_1 \vee x_2$
0	0	0	1
0	0	1	0
0	1	0	0
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$(x_1 \vee x_2 \vee \neg x_5) \wedge$	0	1	1	1
$(x_1 \vee \neg x_2 \vee x_5) \wedge$	1	0	0	0
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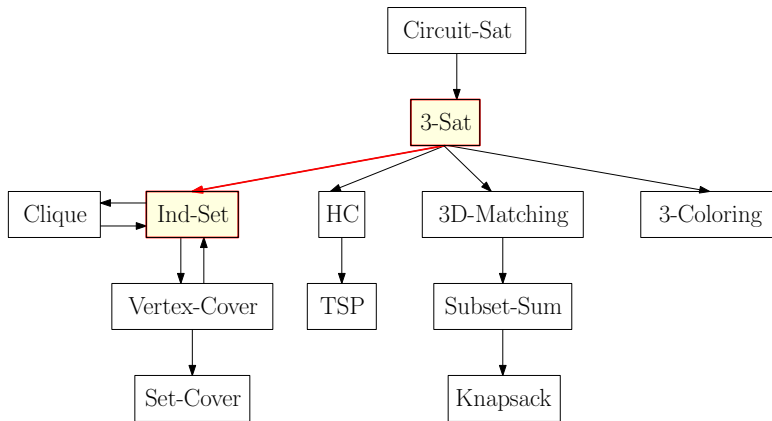
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# Circuit-Sat $\leq_P$ 3-Sat

- Circuit  $\iff$  Formula  $\iff$  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

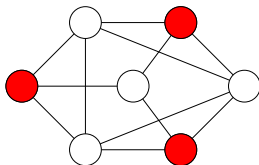


# Reductions of NP-Complete Problems



# 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:**  $G = (V, E), k$

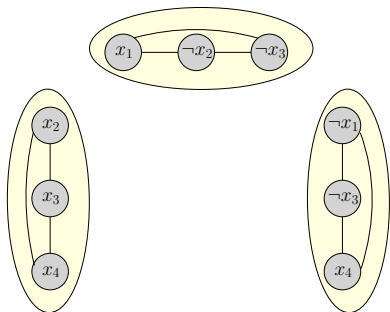
**Output:** whether there is an independent set of size  $k$  in  $G$

# 3-Sat $\leq_P$ Ind-Set

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

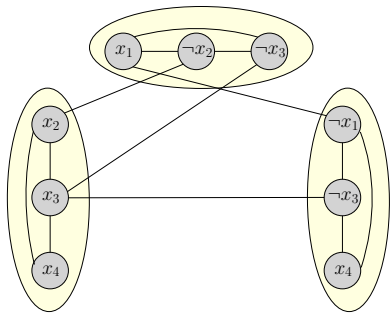
# 3-Sat $\leq_P$ Ind-Set

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



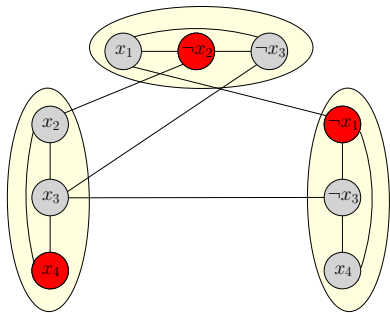
# 3-Sat $\leq_P$ Ind-Set

- $(x_1 \vee \neg x_2 \vee \neg x_3) \wedge (x_2 \vee x_3 \vee x_4) \wedge (\neg x_1 \vee \neg x_3 \vee x_4)$
- A clause  $\Rightarrow$  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



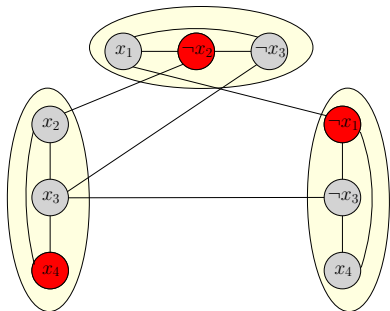
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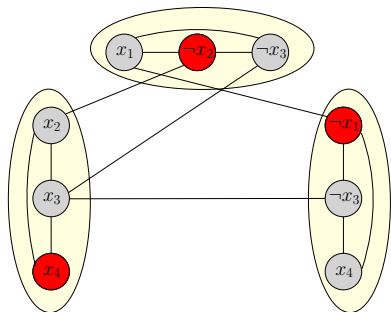
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3-Sat instance is yes-instance  $\Leftrightarrow$  clique instance is yes-instance:

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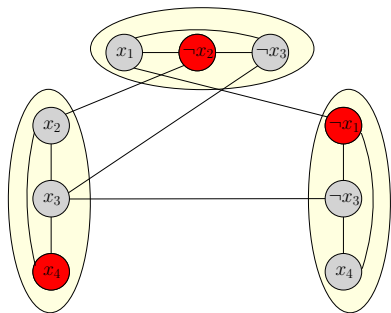
3-Sat instance is yes-instance  $\Leftrightarrow$  clique instance is yes-instance:

- satisfying assignment  $\Rightarrow$  independent set of size  $k$
- independent set of size  $k \Rightarrow$  satisfying assignment



# Satisfying Assignment $\Rightarrow$ IS of Size $k$

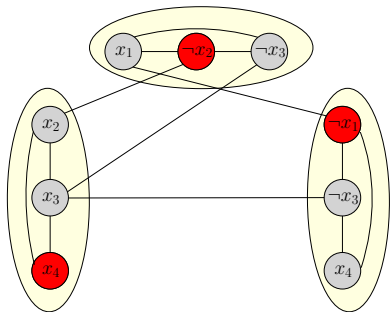
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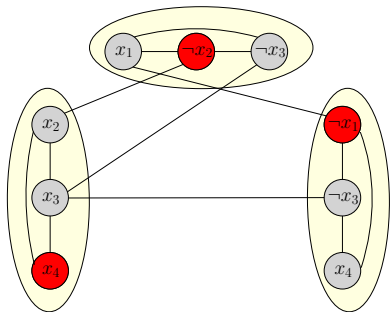
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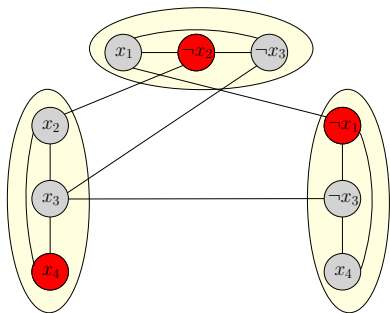
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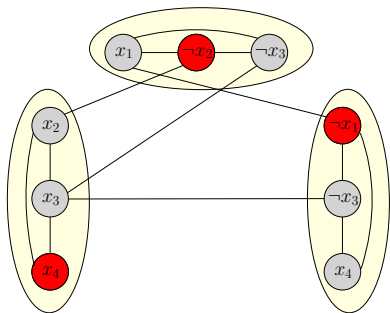
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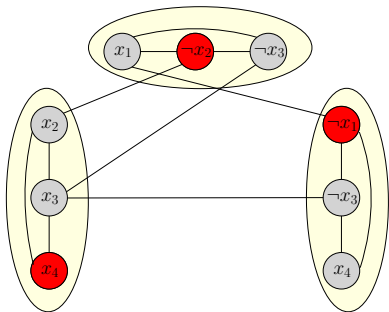
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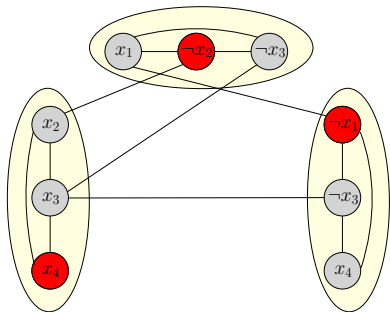
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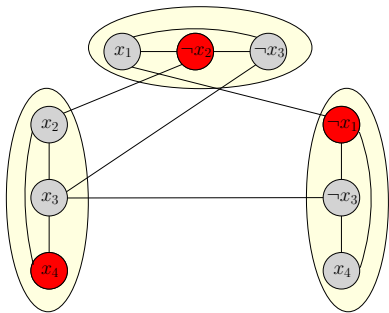
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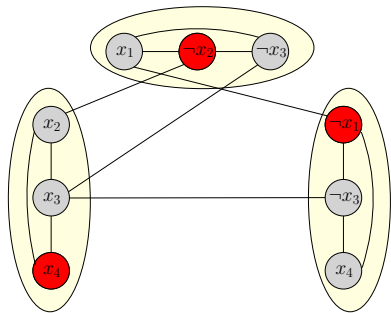
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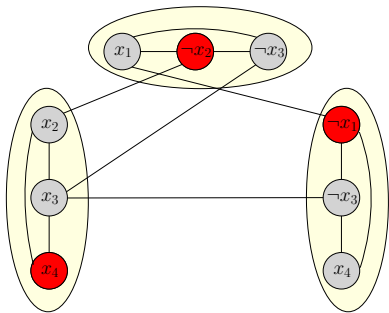
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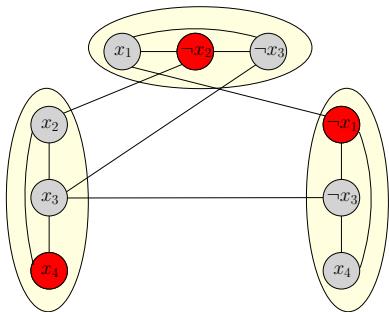
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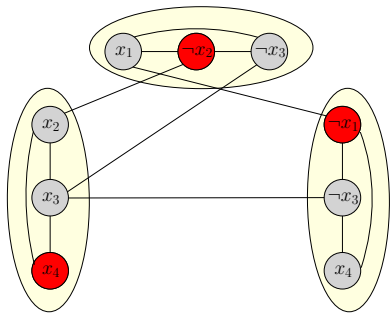
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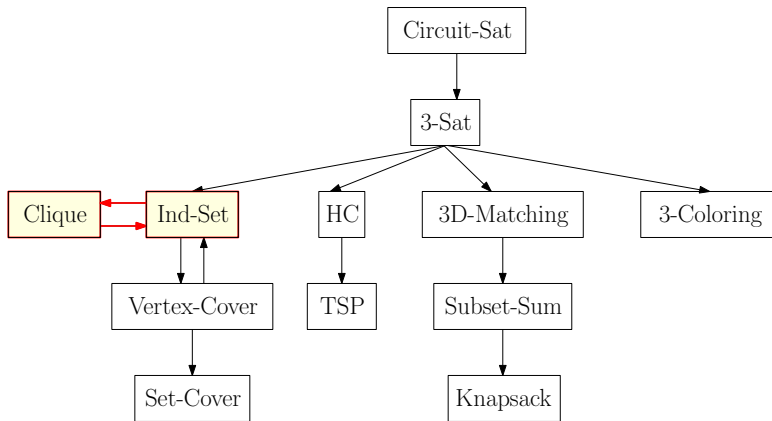


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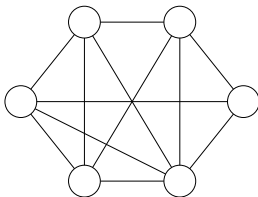
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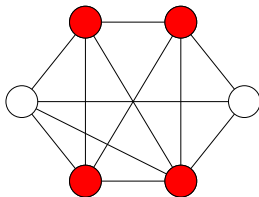
# Reductions of NP-Complete Problems



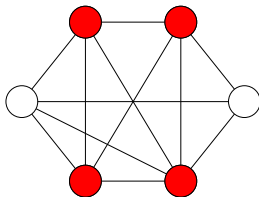
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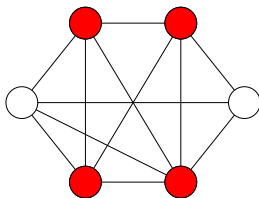
### Clique Problem

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

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



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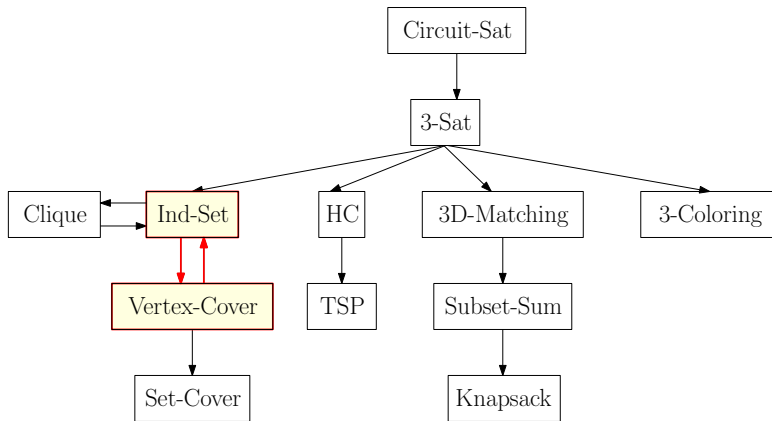
**Output:** whether there exists a clique of size  $k$  in  $G$

- What is the relationship between Clique and 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  $(u, v) \notin E$ .

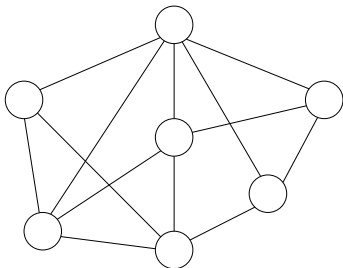
**Obs.**  $S$  is an independent set in  $G$  if and only if  $S$  is a clique in  $\overline{G}$ .

# Reductions of NP-Complete Problems



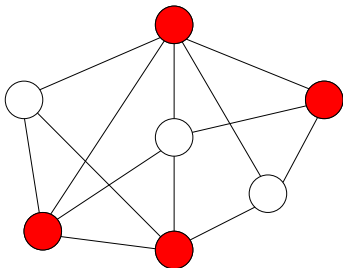
# Vertex-Cover

**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  $v \in S$ .



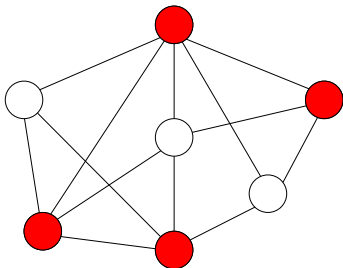
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## Vertex-Cover Problem

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

**Output:** whether there is a vertex cover of  $G$  of size at most  $k$

# Vertex-Cover $=_P$ Ind-Set

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



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**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  $G$ .

# A Strategy of Polynomial Reduction

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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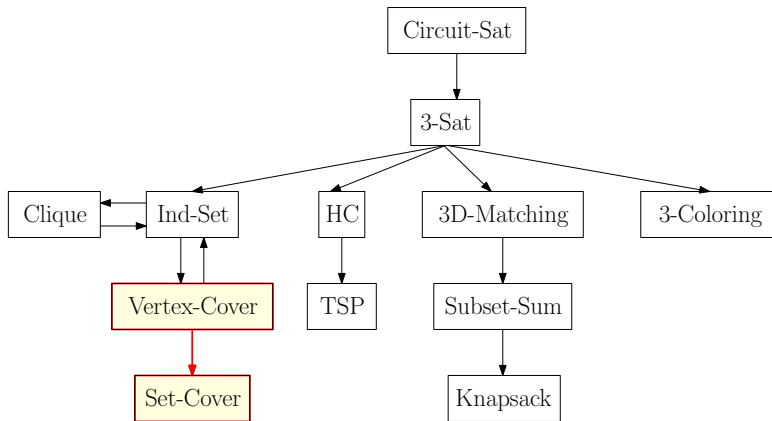
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- In general, algorithm for  $Y$  can call the algorithm for  $X$  many times.
- However, for most reductions, we call algorithm for  $X$  only once
- That is, for a given instance  $s_Y$  for  $Y$ , we only construct one instance  $s_X$  for  $X$

# A Strategy of Polynomial Reduction

- 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  $X$
  - $s_X$  is a yes-instance of  $X \Rightarrow s_Y$  is a yes-instance of  $Y$

# Reductions of NP-Complete Problems



## Set-Cover Problem

**Input:** ground set  $U$  and  $m$  subsets  $S_1, S_2, \dots, S_m$  of  $U$  and an integer  $k$

**Output:** whether there is a set  $I \subseteq \{1, 2, 3, \dots, m\}$  of size  $\leq k$  such that  $\bigcup_{i \in I} S_i = U$



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### Example:

- $U = \{1, 2, 3, 4, 5, 6\}$ ,  $S_1 = \{1, 3, 4\}$ ,  $S_2 = \{2, 3\}$ ,  $S_3 = \{3, 6\}$ ,  $S_4 = \{2, 5\}$ ,  $S_5 = \{1, 2, 6\}$
- Then  $S_1 \cup S_4 \cup S_5 = U$ ; we need 3 subsets to cover  $U$

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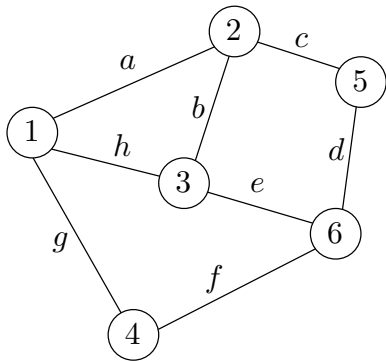
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### Sample Application

- $m$  available packages for a software
- $U$  is the set of features
- The package  $i$  covers the set  $S_i$  of features
- want to cover all features using fewest number of packages

# Vertex-Cover $\leq_P$ Set-Cover



$$U = \{a, b, c, d, e, f, g\}$$

$$S_1 = \{a, g, h\}$$

$$S_2 = \{a, b, c\}$$

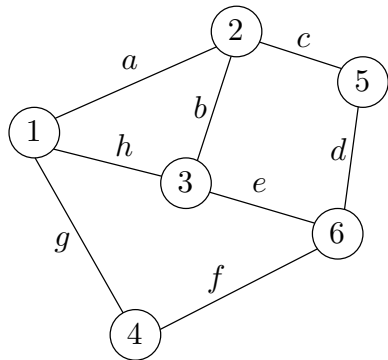
$$S_3 = \{b, e, h\}$$

$$S_4 = \{g, h\}$$

$$S_5 = \{c, d\}$$

$$S_6 = \{d, e, f\}$$

# Vertex-Cover $\leq_P$ Set-Cover



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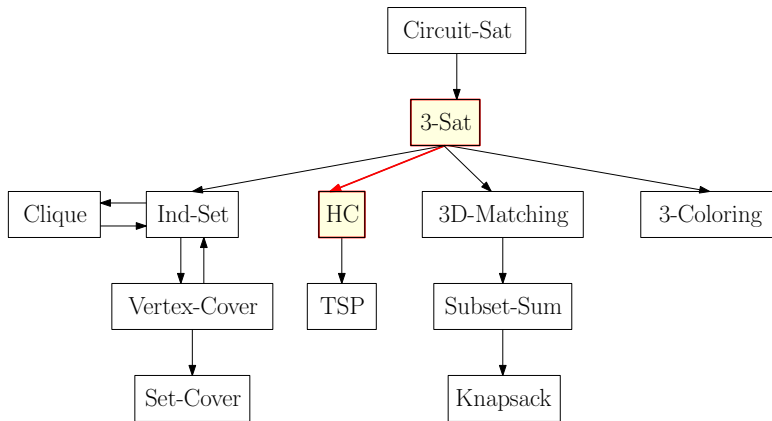
$$S_4 = \{g, h\}$$

$$S_5 = \{c, d\}$$

$$S_6 = \{d, e, f\}$$

- edges  $\implies$  elements in  $U$
- vertices  $\implies$  sets
- edge incident on vertex  $\implies$  element contained in set
- use vertices to cover edges  $\implies$  use sets to cover elements

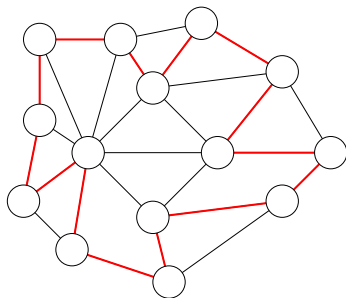
# Reductions of NP-Complete Problems



## Recall: Hamiltonian Cycle (HC) Problem

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

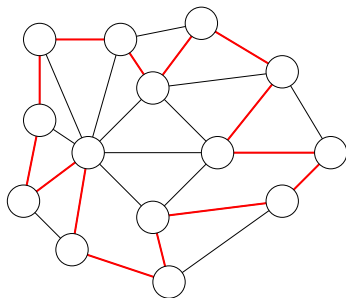
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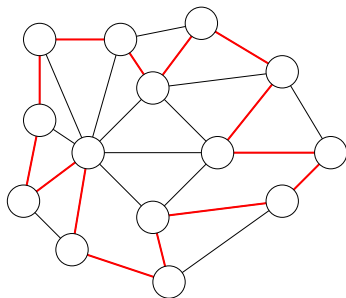


- We consider Hamiltonian Cycle Problem in **directed** graphs

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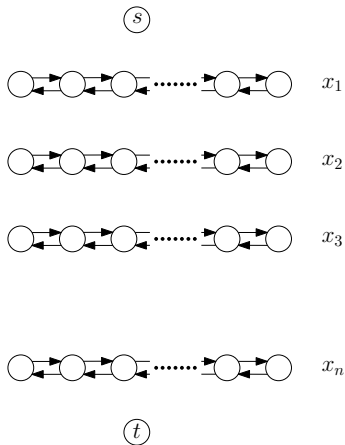
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- We consider Hamiltonian Cycle Problem in **directed** graphs
- Exercise:  $\text{HC-directed} \leq_P \text{HC}$



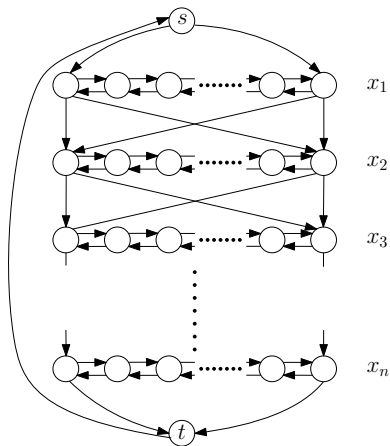
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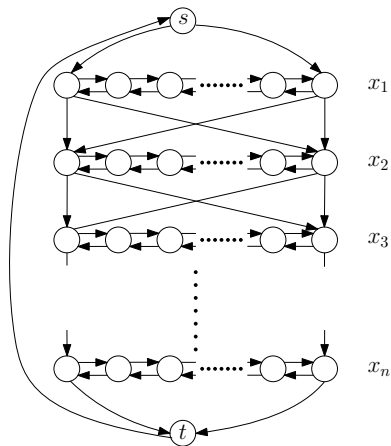
- Vertices  $s, t$
- A long enough double-path  $P_i$  for each variable  $x_i$

# 3-Sat $\leq_P$ Directed-HC

- Vertices  $s, t$
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- Edges from  $s$  to  $P_1$
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- Edges from  $P_i$  to  $P_{i+1}$

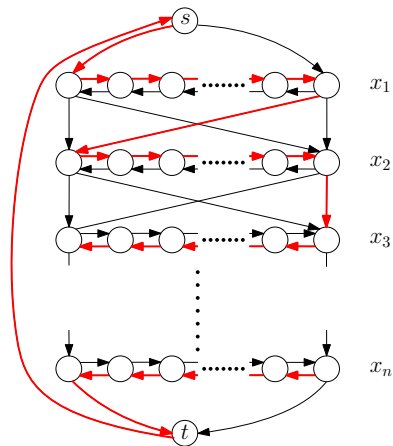


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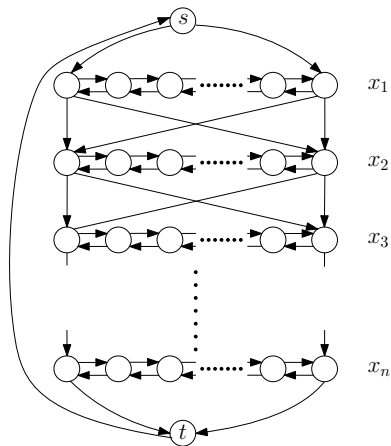
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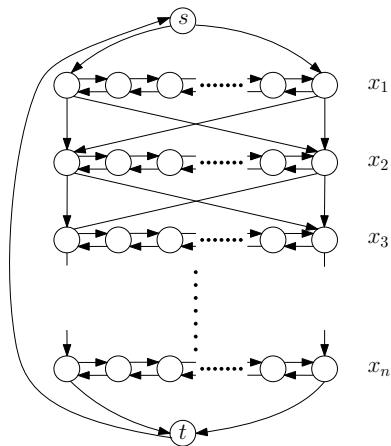
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- e.g.  $x_1 = 1, x_2 = 1, x_3 = 0, x_4 = 0$

# 3-Sat $\leq_P$ Directed-HC



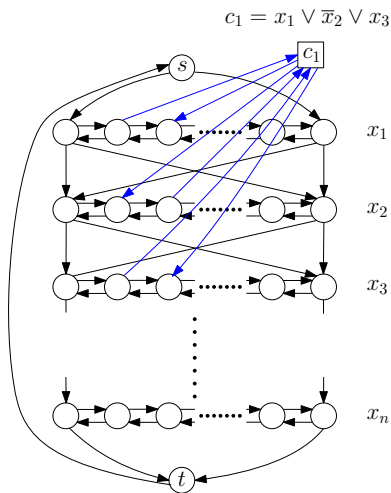
- Vertices  $s, t$
- A long enough double-path  $P_i$  for each variable  $x_i$
- Edges from  $s$  to  $P_1$
- Edges from  $P_n$  to  $t$
- Edges from  $P_i$  to  $P_{i+1}$
- $x_i = 1 \iff$  traverse  $P_i$  from left to right
- e.g.  $x_1 = 1, x_2 = 1, x_3 = 0, x_4 = 0$

# 3-Sat $\leq_P$ Directed-HC



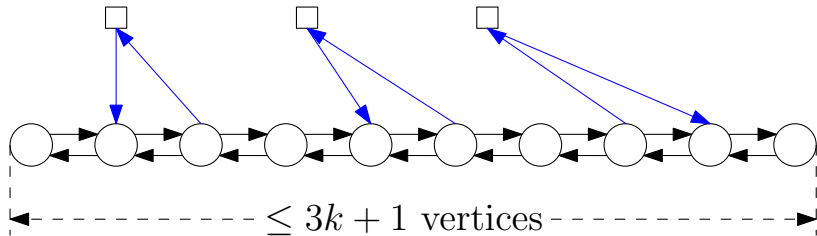
- There are exactly  $2^n$  different Hamiltonian cycles, each correspondent to one assignment of variables

# 3-Sat $\leq_P$ Directed-HC



- There are exactly  $2^n$  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.

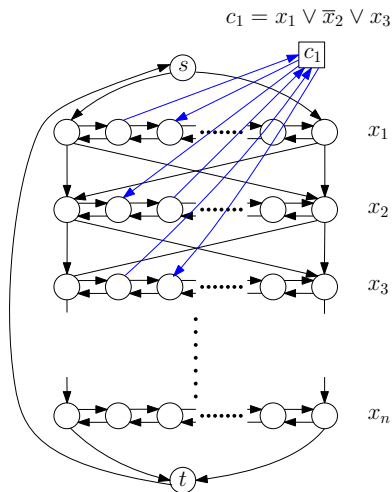
# A Path Should Be Long Enough



- $k$ : number of clauses

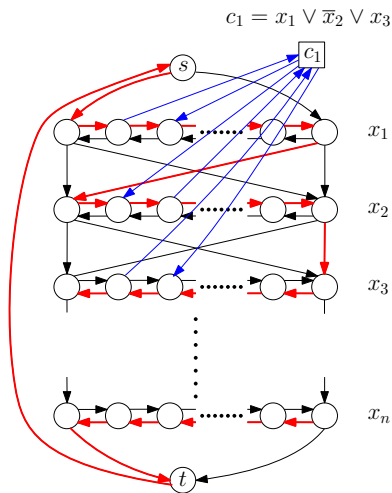


# Yes-Instance for 3-Sat $\Rightarrow$ Yes-Instance for Di-HC



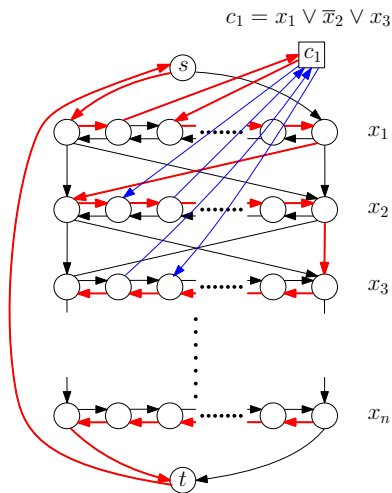
- In base graph, construct an HC according to the satisfying assignment

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



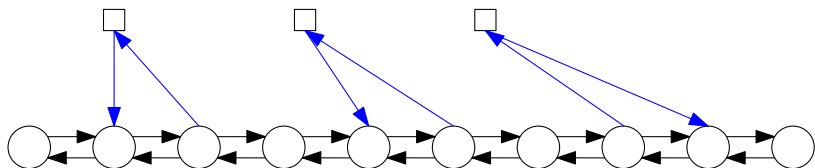
- In base graph, construct an HC according to the satisfying assignment
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# Yes-Instance for 3-Sat $\Rightarrow$ Yes-Instance for Di-HC



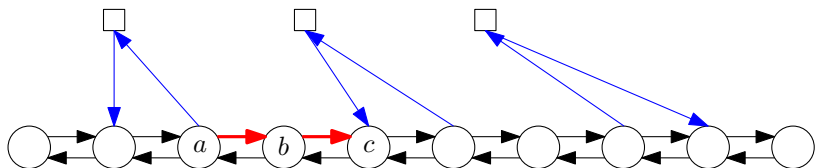
- In base graph, construct an HC according to the satisfying assignment
- For every clause, one literal is satisfied
- Visit the vertex for the clause by taking a “detour” from the path for the literal

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



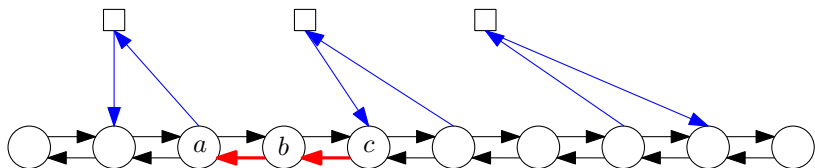
- Idea: for each path  $P_i$ , must follow the left-to-right or right-to-right pattern.

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



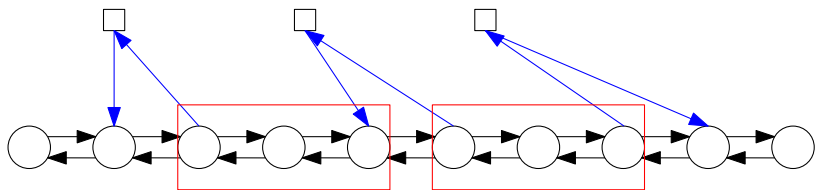
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# Yes-Instance for Di-HC $\Rightarrow$ Yes-Instance for 3-Sat



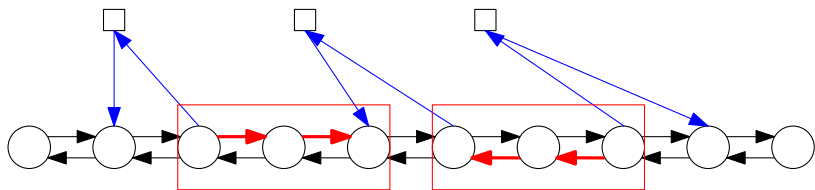
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- Idea: for each path  $P_i$ , must follow the left-to-right or right-to-right pattern.
- To visit vertex  $b$ , can either go  $a-b-c$  or  $b-c-a$
- Created “chunks” of 3 vertices.

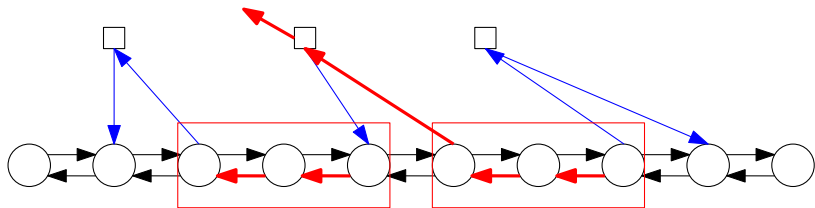
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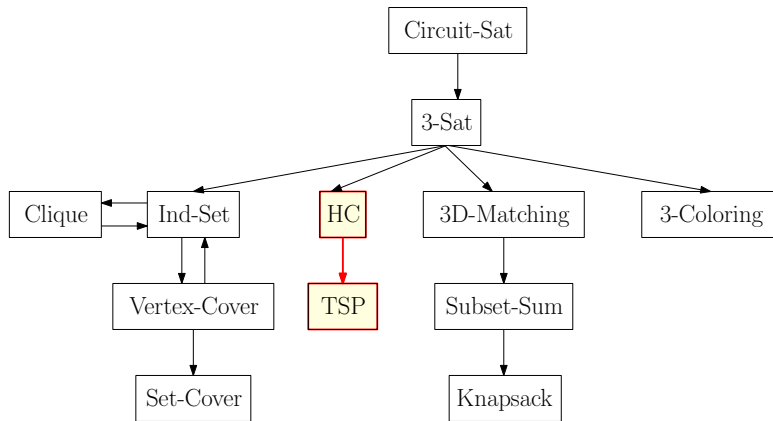


# Yes-Instance for Di-HC $\Rightarrow$ Yes-Instance for 3-Sat



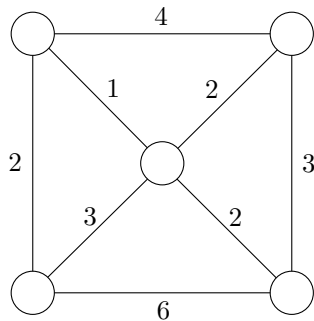
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- Created “chunks” of 3 vertices.
- Directions of the chunks must be the same
- Can not take a detour to some other path

# Reductions of NP-Complete Problems



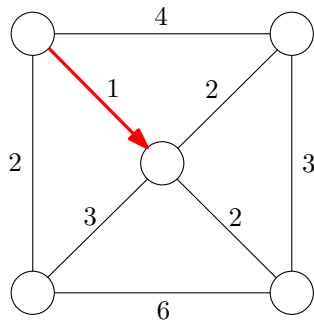
# Traveling Salesman Problem

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



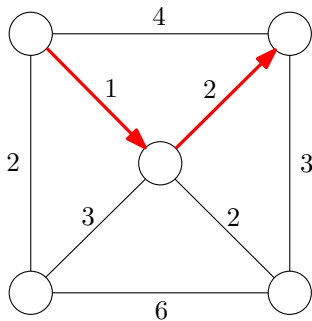
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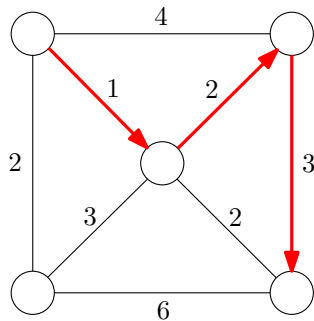
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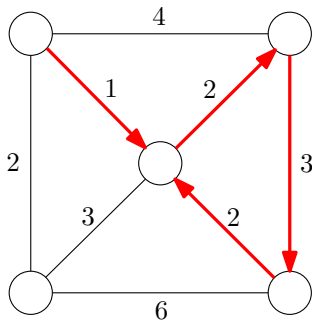
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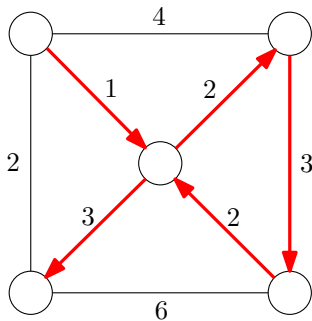
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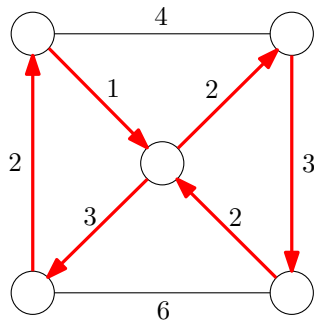
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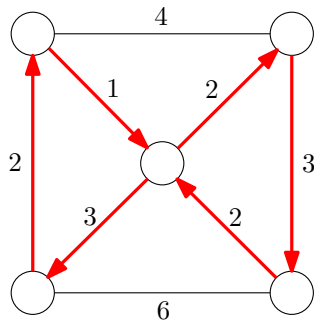
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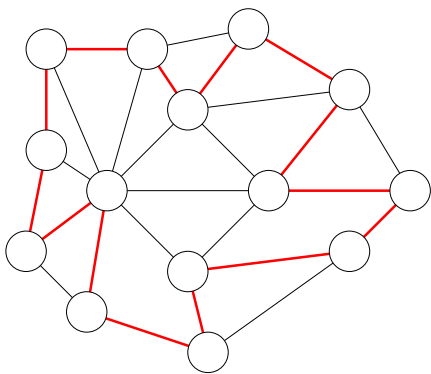
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## Travelling Salesman Problem (TSP)

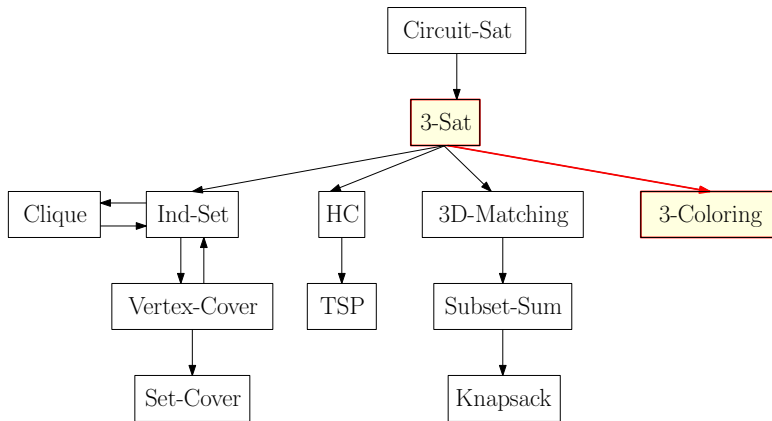
**Input:** a graph  $G = (V, E)$ , weights  $w : E \rightarrow \mathbb{R}_{\geq 0}$ , and  $L > 0$

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



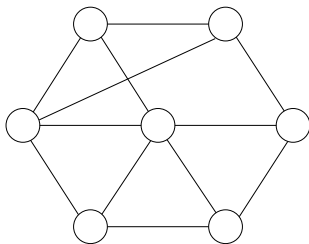
**Obs.** There is a Hamilton cycle in  $G$  if and only if there is a tour for the salesman of length  $n = |V|$ .

# Reductions of NP-Complete Problems



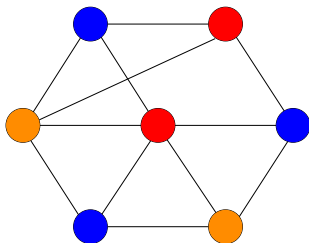
# $k$ -coloring problem

**Def.** A  $k$ -coloring of  $G = (V, E)$  is a function  $f : V \rightarrow \{1, 2, 3, \dots, k\}$  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  $G$ .



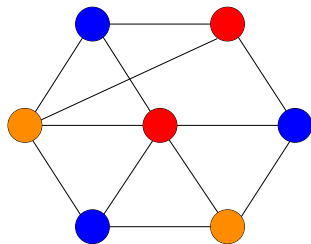
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## $k$ -coloring problem

**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.

- There is an  $O(m + n)$ -time algorithm to decide if a graph  $G$  is 2-colorable



## 2-Coloring Problem

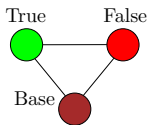
**Obs.** A graph  $G$  is 2-colorable if and only if it is bipartite.

- There is an  $O(m + n)$ -time algorithm to decide if a graph  $G$  is 2-colorable
- Idea: suppose  $G$  is connected. If we fix the color of one vertex in  $G$ , then the colors of all other vertices are fixed.

# 3-SAT $\leq_P$ 3-Coloring

- Construct the base graph

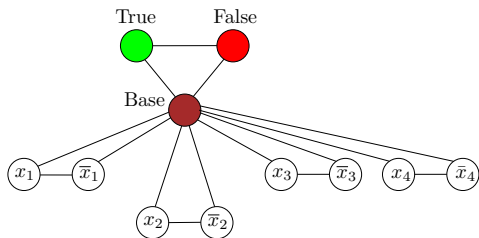
Base Graph



# 3-SAT $\leq_P$ 3-Coloring

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Base Graph

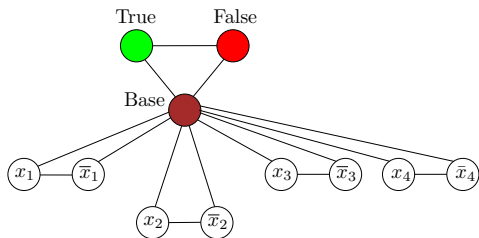


# 3-SAT $\leq_P$ 3-Coloring

- Construct the base graph
- Construct a gadget from each clause: gadget is 3-colorable if and only if the clause is satisfied.

Base Graph

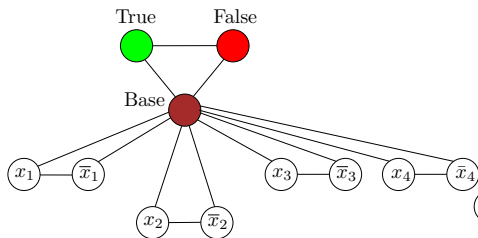
$$x_1 \vee \neg x_2 \vee x_3$$



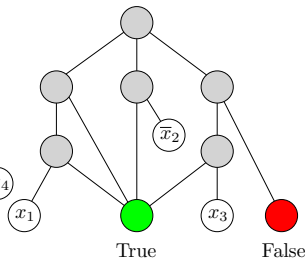
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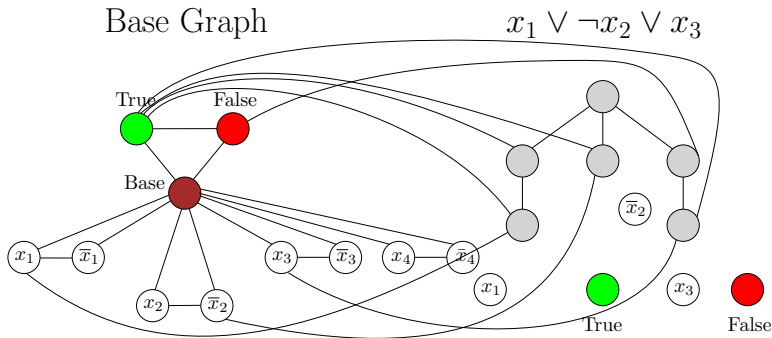


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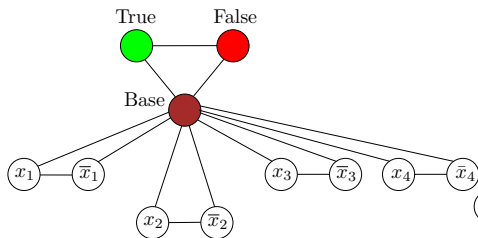
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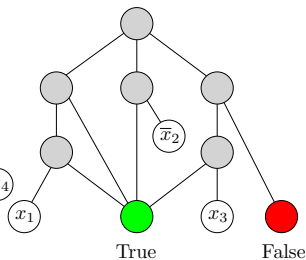
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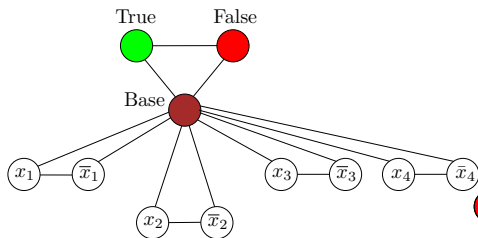
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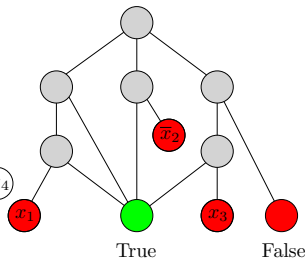
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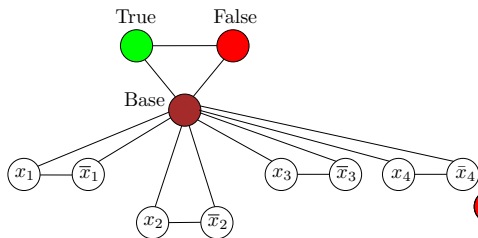




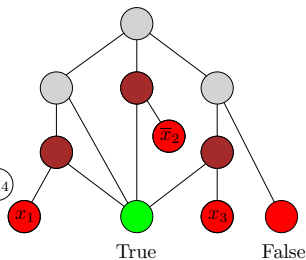
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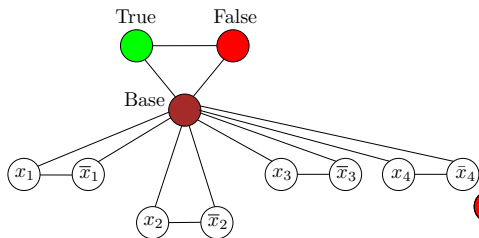
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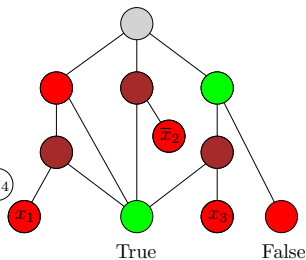
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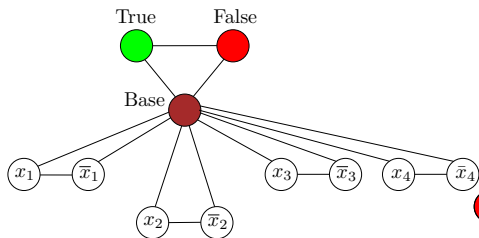
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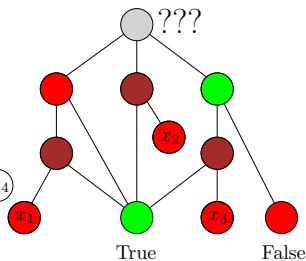
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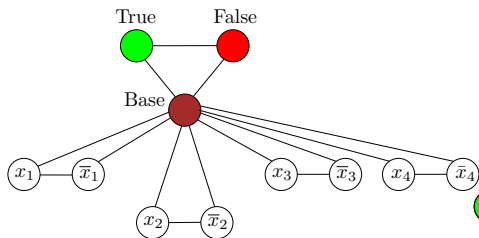
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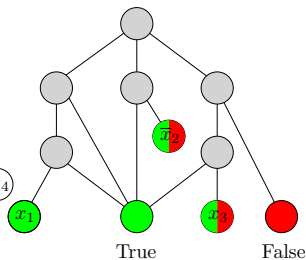
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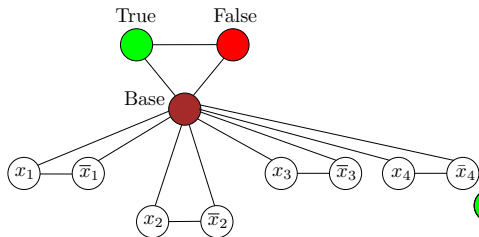
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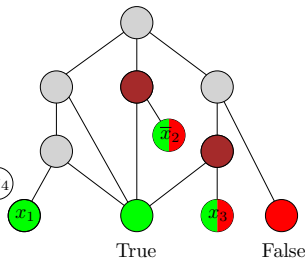
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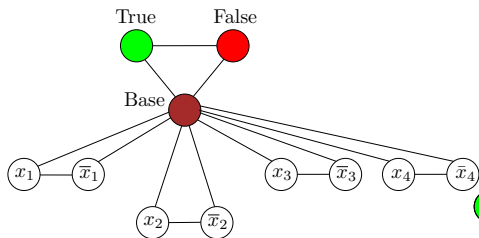
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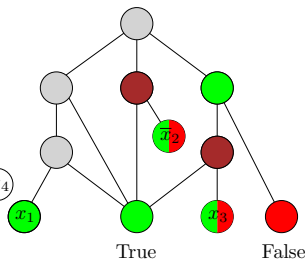
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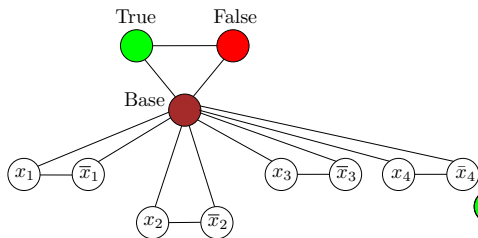
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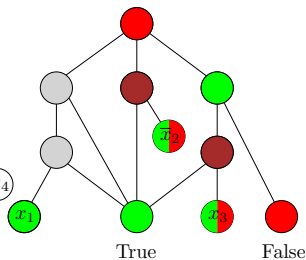
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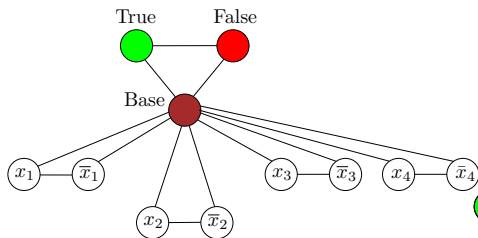
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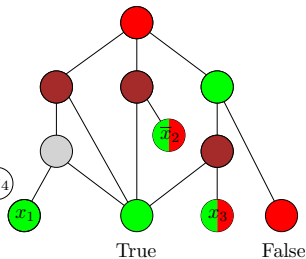
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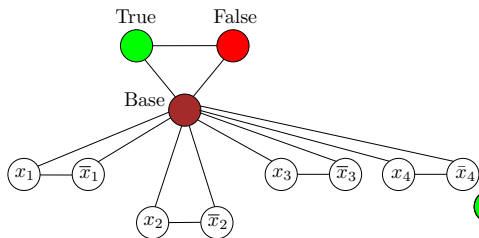




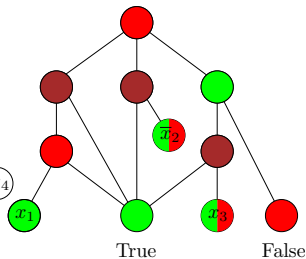
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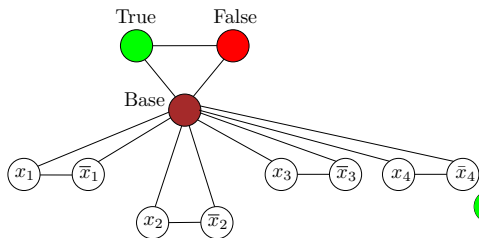
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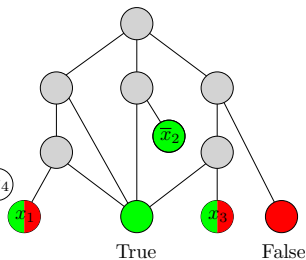
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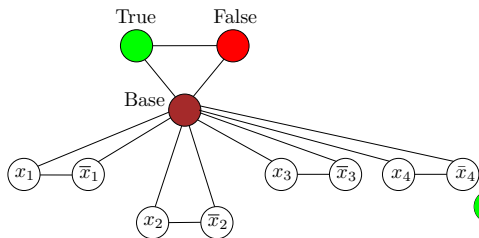
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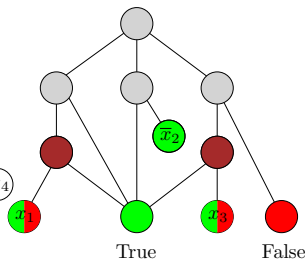
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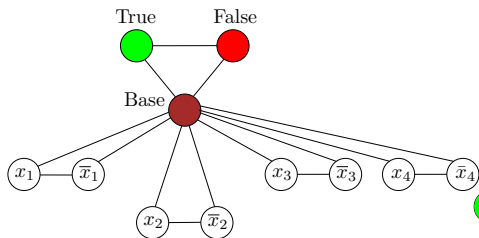
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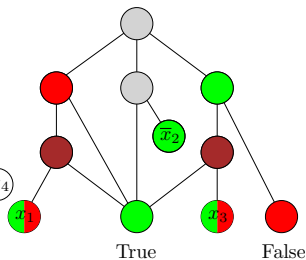
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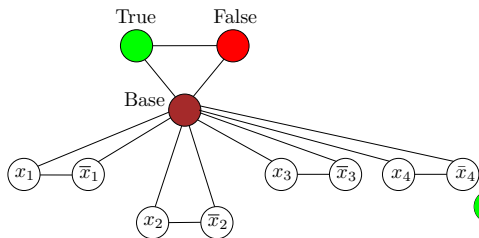
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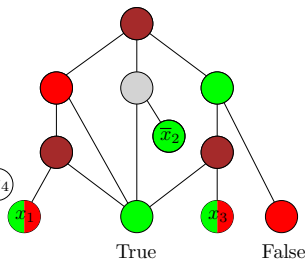
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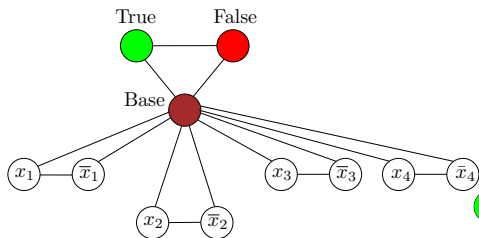
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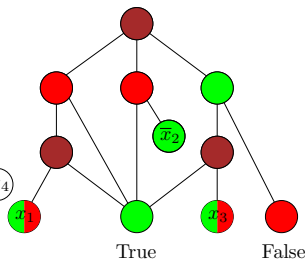
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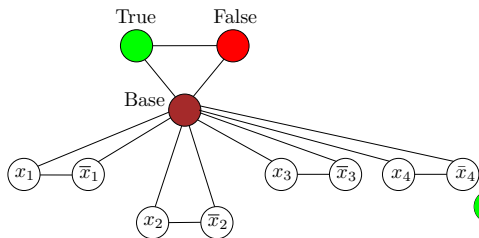
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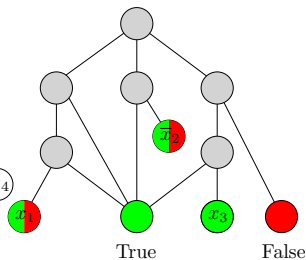
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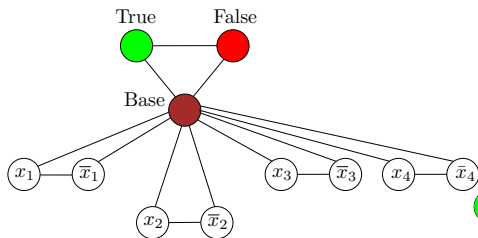
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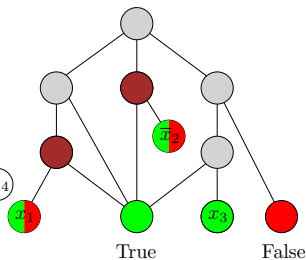
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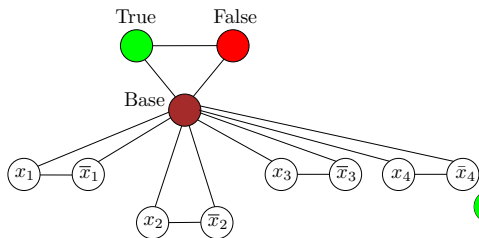




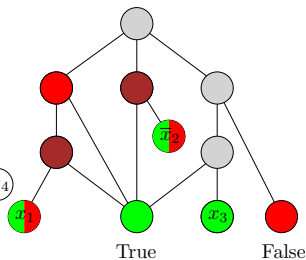
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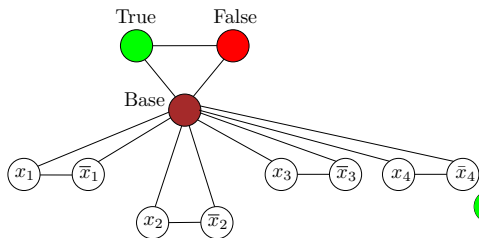
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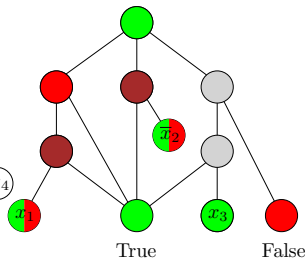
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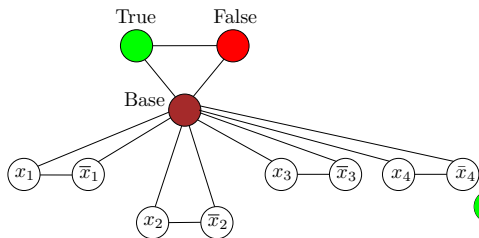
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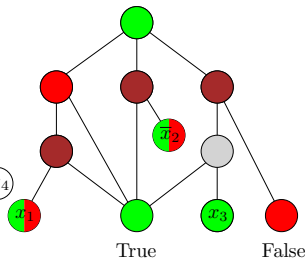
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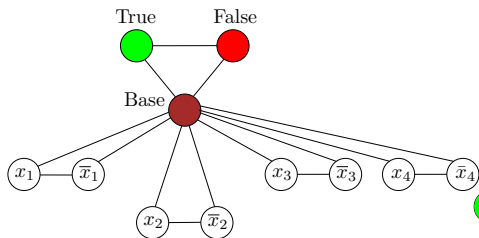
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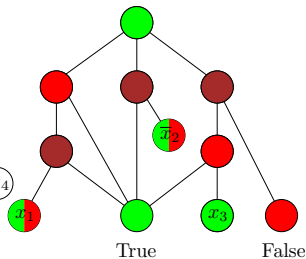
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3.36pt

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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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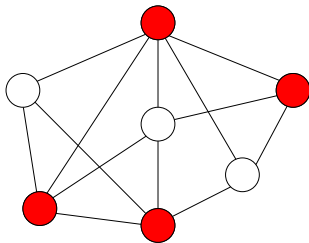
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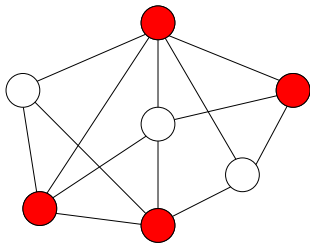
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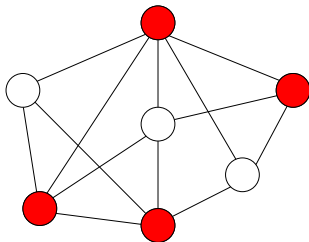
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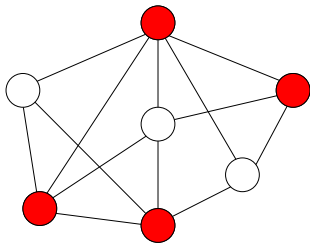
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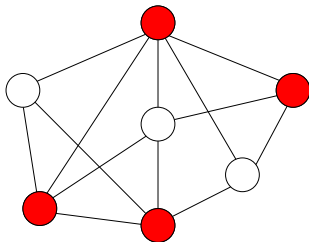
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# Summary

- We consider decision problems
- 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

# Summary

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

- $B$  is a polynomial-time algorithm that takes two input strings  $s$  and  $t$
- there is a polynomial function  $p$  such that,  $s \in X$  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.



# Summary

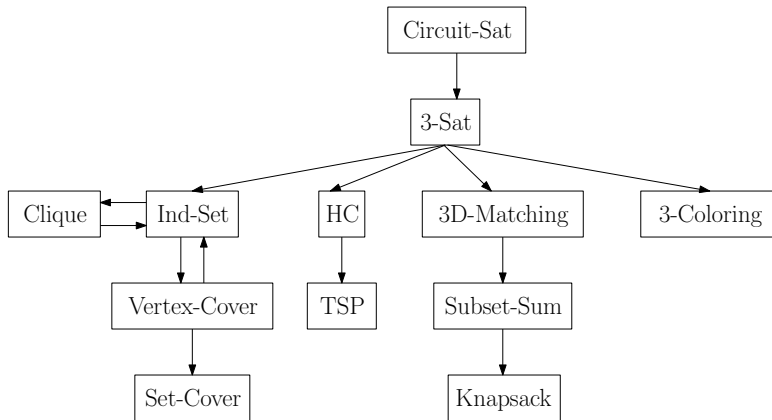
**Def.** Given a black box algorithm  $A$  that solves a problem  $X$ , if any instance of a problem  $Y$  can be solved using a polynomial number of standard computational steps, plus a polynomial number of calls to  $A$ , then we say  $Y$  is polynomial-time reducible to  $X$ , denoted as  $Y \leq_P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

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

- 1  $X \in \text{NP}$ , and
- 2  $Y \leq_P X$  for every  $Y \in \text{NP}$ .

- If any NP-complete problem can be solved in polynomial time, then  $P = \text{NP}$
- Unless  $P = \text{NP}$ , a NP-complete problem can not be solved in polynomial time

# Summary

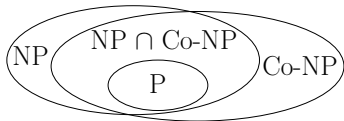
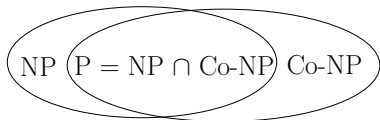
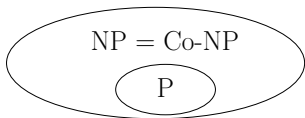
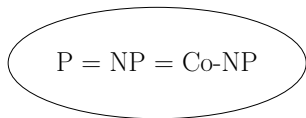


## Proof of NP-Completeness for Circuit-Sat

- 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  $X \in \text{NP}$ , let  $B(s, t)$  be the certifier
  - Convert  $B(s, t)$  to a circuit and hard-wire  $s$  to the input gates
  - $s$  is a yes-instance if and only if the resulting circuit is satisfiable
- 
- Proof of NP-Completeness for other problems by reductions

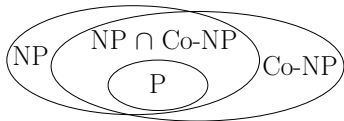
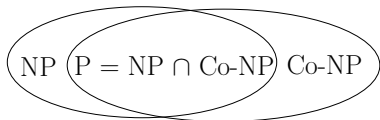
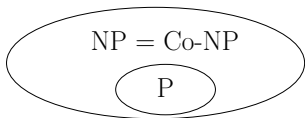
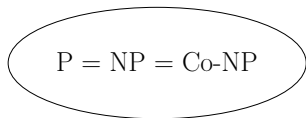
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Recall the 4 scenarios:



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- Prove:  $P = NP$  if and only if  $P = \text{CO-NP}$

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For each of the following problem  $X$ , answer: whether (1)  $X \in \text{NP}$ , (2)  $X \in \text{CO-NP}$ . Each answer is either “yes” or “we do not know”.

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- 3 Given a directed graph  $G = (V, E)$ , with weights  $w : E \rightarrow \mathbb{R}_{>0}$ ,  $s, t \in V$ , and a number  $L > 0$ , whether the length of the shortest path from  $s$  to  $t$  in  $G$  is at most  $L$ .



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- 4 Given two boolean formulas, whether they are equivalent. For example,  $(x_1 \vee x_2) \wedge (\neg x_1 \vee x_3)$  and  $(\neg x_1 \wedge x_2) \vee (x_1 \wedge x_3)$  are equivalent since they give the same value for every assignment of  $(x_1, x_2, x_3)$ .

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- 3 Given a graph  $G = (V, E)$ , the degree-3 spanning tree (D3ST) problem asks whether  $G$  contains a spanning tree  $T$  of degree at most 3. Prove Hamiltonian-Path  $\leq_P$  D3ST.