算法设计与分析(2026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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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!

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

- For natural problems, if there is an $O(n^k)$-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

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

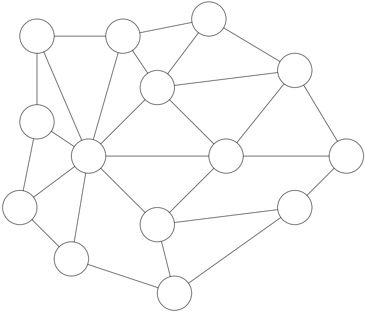
Example: Hamiltonian Cycle Problem

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 $G = (V, E)$

Output: whether G contains a Hamiltonian cycle



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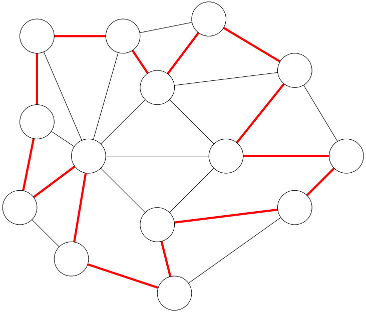

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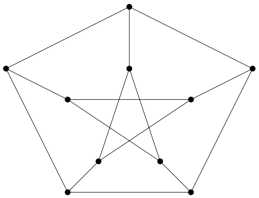

- The graph is called the Petersen Graph. It has no HC.

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- Better algorithm: $2^{O(n)}$
- Far away from polynomial time
- HC is NP-hard: it is unlikely that it can be solved in polynomial time.

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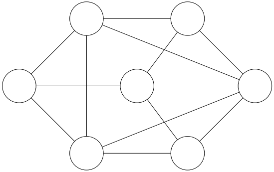

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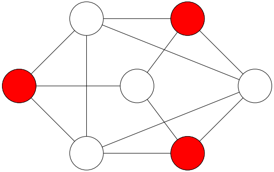

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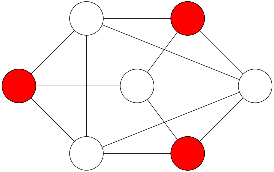

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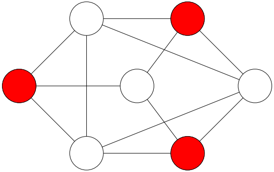

Maximum Independent Set Problem

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

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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.

Optimization to Decision

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

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- Input: (3, 6, 100, 9, 60)
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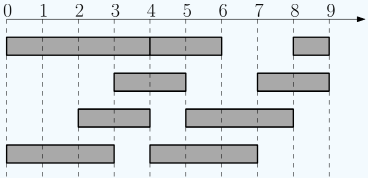

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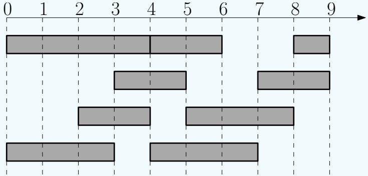

- $(0, 3, 0, 4, 2, 4, 3, 5, 4, 6, 4, 7, 5, 8, 7, 9, 8, 9)$

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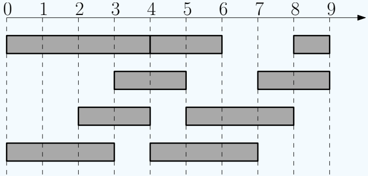

- $(0, 3, 0, 4, 2, 4, 3, 5, 4, 6, 4, 7, 5, 8, 7, 9, 8, 9)$
- Encode the sequence into a binary string as before

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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.

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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- 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

- 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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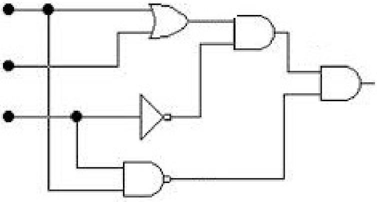
Circuit Satisfiablity (Circuit-Sat) Problem

Input: a circuit with and/or/not gates

Output: whether there is an assignment such that the output is 1?



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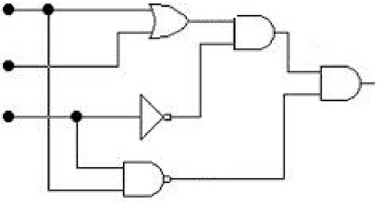

- Is Circuit-Sat $\in$ NP?

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

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. $(\neg x_1 \wedge x_2) \vee (\neg x_1 \wedge \neg x_3) \vee x_1 \vee (\neg x_2 \wedge x_3)$ 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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- The certificate is an empty string
- Thus, $X \in$ NP and P $\subseteq$ NP
- Similarly, P $\subseteq$ Co-NP, thus P $\subseteq$ NP $\cap$ Co-NP

Is P $=$ NP?

Is P = NP?

- A famous, big, and fundamental open problem in computer science

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- Little progress has been made
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- 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 $P = NP$

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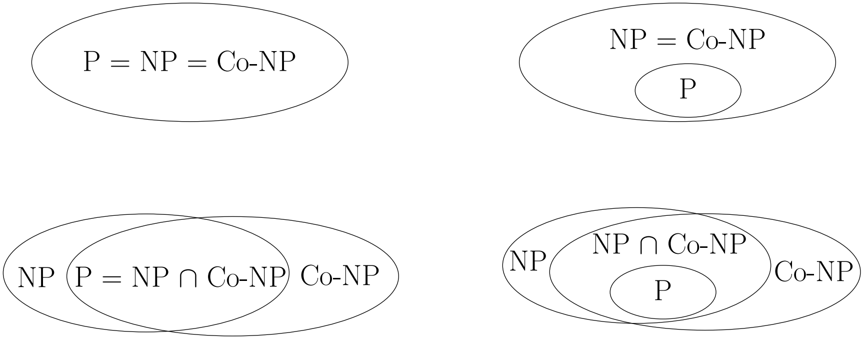
4 Possibilities of Relationships

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



- People commonly believe we are in the 4th scenario

Outline

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 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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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.

Polynomial-Time Reduction: Example

Hamiltonian-Path (HP) problem

Input: $G = (V, E)$ and $s, t \in V$

Output: whether there is a Hamiltonian path from s to t in G

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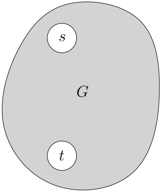

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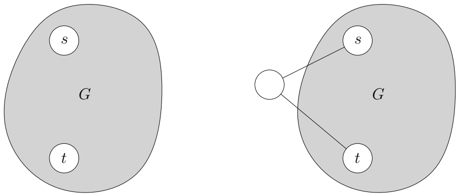

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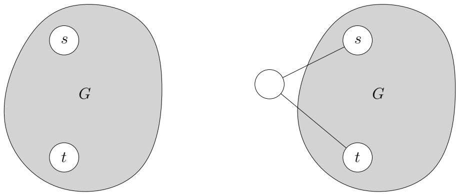

Obs. G has a HP from s to t if and only if graph on right side has a HC.

NP-Completeness

Def. A problem X is called NP-complete if

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

NP-Completeness

Def. A problem X is called NP-hard if

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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)

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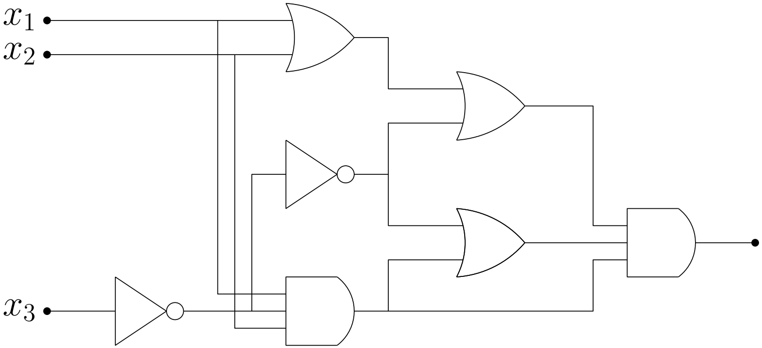
- How can we find a problem $X \in \text{NP}$ such that every problem $Y \in \text{NP}$ is polynomial time reducible to X? Are we asking for too much?
- No! There is indeed a large family of natural NP-complete problems

The First NP-Complete Problem: Circuit-Sat

Circuit Satisfiability (Circuit-Sat)

Input: a circuit

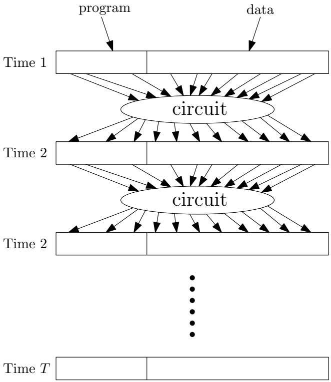
Output: whether the circuit is satisfiable



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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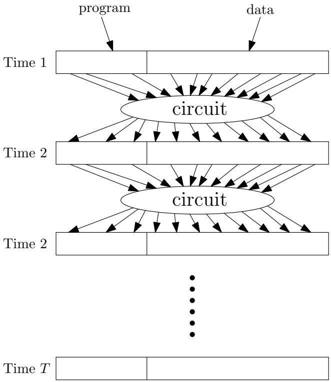

- Then, we can show that any problem $Y \in$ NP can be reduced to Circuit-Sat.
- We prove HC $\leq_P$ Circuit-Sat as an example.

HC $\leq_P$ Circuit-Sat

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 is G and 0 otherwise.

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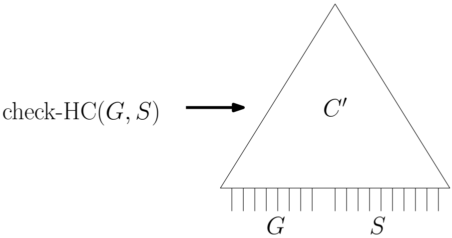

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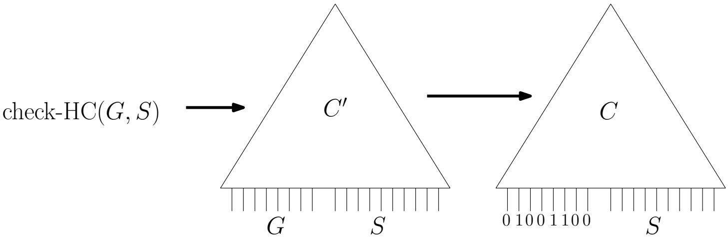

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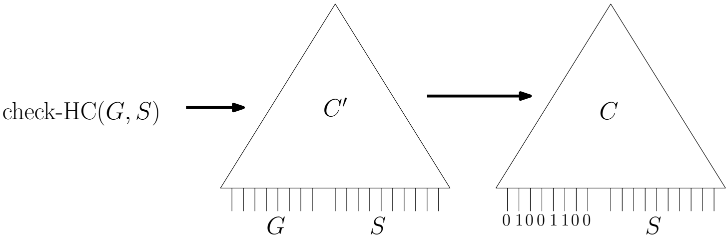

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- Construct a circuit C' for the algorithm check-HC
- hard-wire the instance G to the circuit C' to obtain the circuit C
- G is a yes-instance if and only if C is satisfiable

$Y \leq_P$ Circuit-Sat, For Every $Y \in$NP

- Let check-Y(s,t) be the certifier for problem Y: 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 check-Y(s,t) returns 1

- Construct a circuit C' for the algorithm check-Y
- hard-wire the instance s to the circuit C' to obtain the circuit C
- s is a yes-instance if and only if C is satisfiable $\square$

$Y \leq_P$ Circuit-Sat, For Every $Y \in$NP

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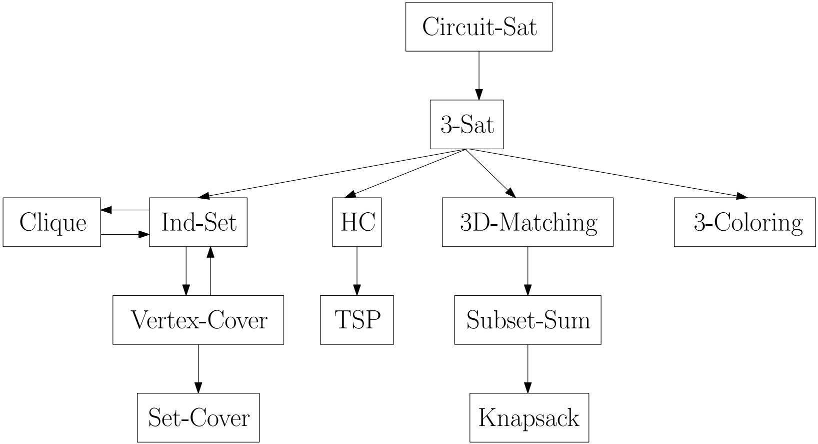
- s is a yes-instance if and only if there is a t such that check-Y(s, t) returns 1
- Construct a circuit C' for the algorithm check-Y
- hard-wire the instance s to the circuit C' to obtain the circuit C
- s is a yes-instance if and only if C is satisfiable □

Theorem Circuit-Sat is NP-complete.

Reductions of NP-Complete Problems



3-Sat

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

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

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Input: a 3-CNF formula

Output: whether the 3-CNF is satisfiable

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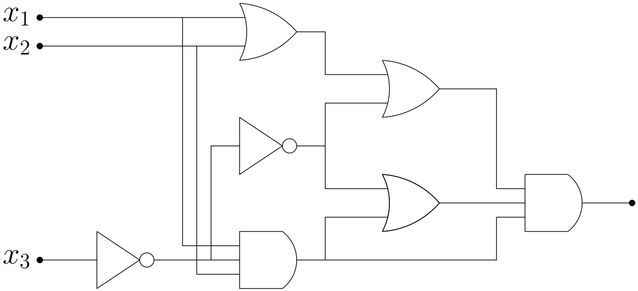
Output: whether the 3-CNF is satisfiable

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

Circuit-Sat $\leq_P$ 3-Sat



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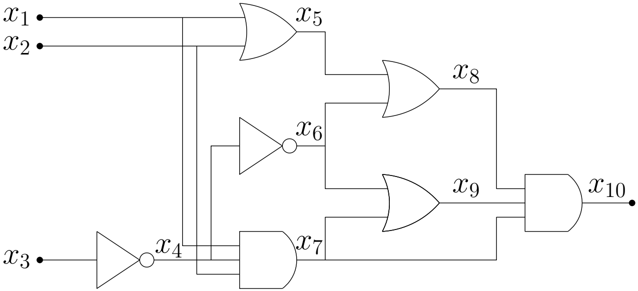

- Associate every wire with a new variable

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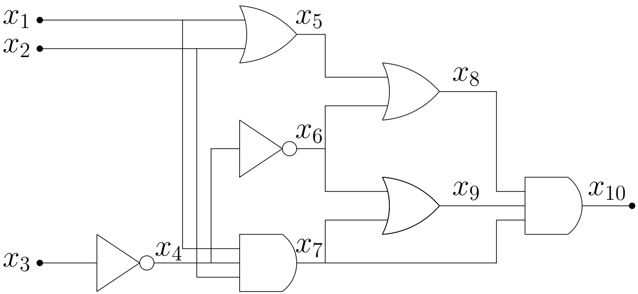

- Associate every wire with a new variable
- The circuit is equivalent to the following formula:

$$
\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}
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1	1	1	1

Circuit-Sat $\leq_P$ 3-Sat

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

Convert each clause to a 3-CNF

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

$$(x_1 \vee x_2 \vee \neg x_5) \quad \wedge$$
$$(x_1 \vee \neg x_2 \vee x_5) \quad \wedge$$
$$(\neg x_1 \vee x_2 \vee x_5) \quad \wedge$$
$$(\neg x_1 \vee \neg x_2 \vee x_5)$$

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

Circuit-Sat $\leq_P$ 3-Sat

- Circuit $\iff$ Formula $\iff$ 3-CNF

Circuit-Sat $\leq_P$ 3-Sat

- Circuit $\Longleftrightarrow$ Formula $\Longleftrightarrow$ 3-CNF
- The circuit is satisfiable if and only if the 3-CNF is satisfiable

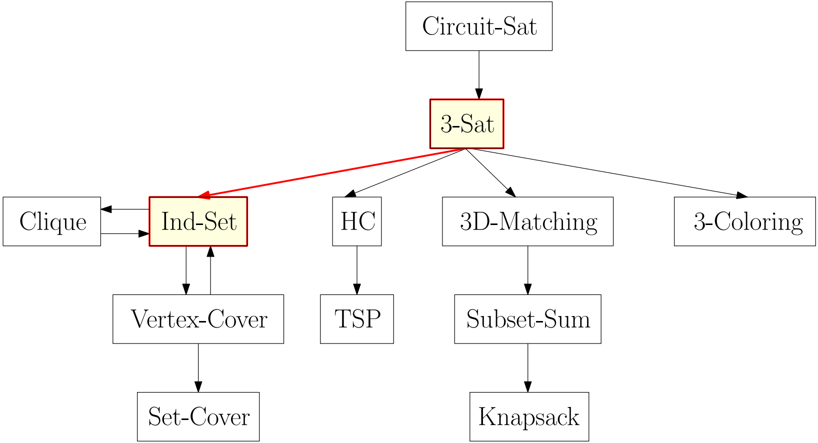
Circuit-Sat $\leq_P$ 3-Sat

- 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

Circuit-Sat $\leq_P$ 3-Sat

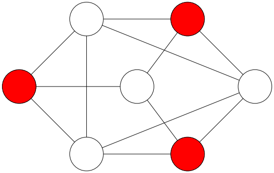
- Circuit $\Longleftrightarrow$ Formula $\Longleftrightarrow$ 3-CNF
- The circuit is satisfiable if and only if the 3-CNF is satisfiable
- The size of the 3-CNF formula is polynomial (indeed, linear) in the size of the circuit
- Thus, Circuit-Sat $\leq_P$ 3-Sat

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

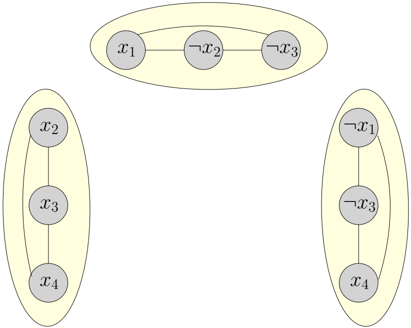
3-Sat $\leq_P$ Ind-Set

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

3-Sat $\leq_P$ Ind-Set

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

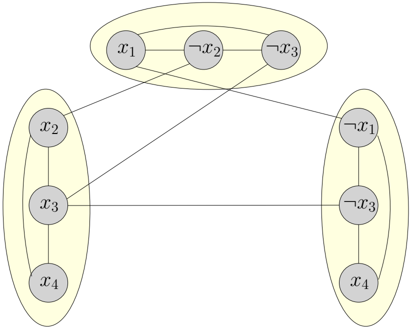
- A clause $\Rightarrow$ a group of 3 vertices, one for each literal
- An edge between every pair of vertices in same group



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



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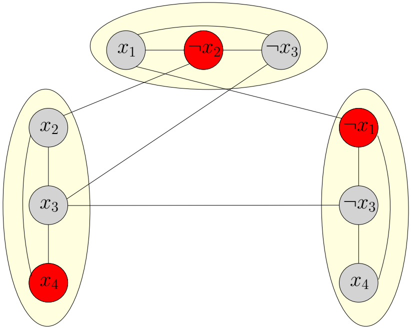
- Problem: whether there is an IS of size $k = \#$clauses



3-Sat $\leq_P$ Ind-Set

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

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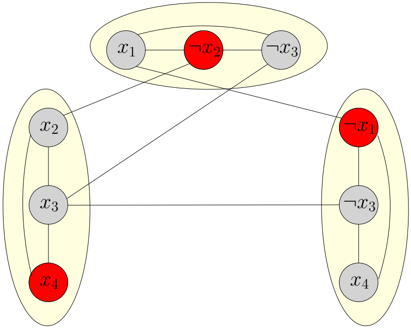

3-Sat instance is yes-instance $\Leftrightarrow$ Ind-Set instance is yes-instance:

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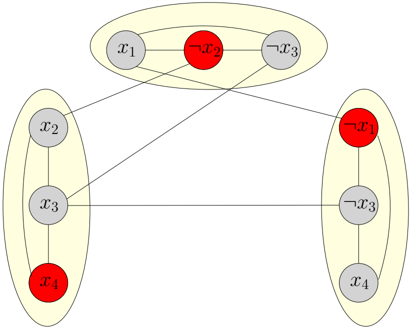
- Problem: whether there is an IS of size $k = \#$clauses

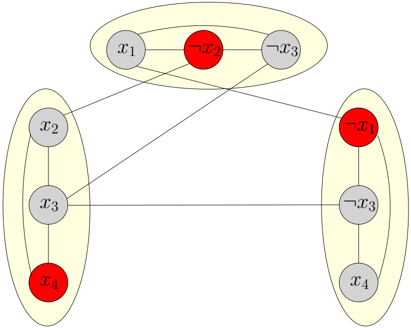


3-Sat instance is yes-instance $\Leftrightarrow$ Ind-Set instance is yes-instance:

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

Satisfying Assignment $\Rightarrow$ IS of Size k

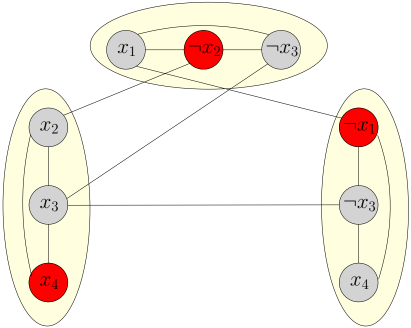
- $(x_1 \vee \neg x_2 \vee \neg x_3) \wedge (x_2 \vee x_3 \vee x_4) \wedge (\neg x_1 \vee \neg x_3 \vee x_4)$



Satisfying Assignment $\Rightarrow$ IS of Size k

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

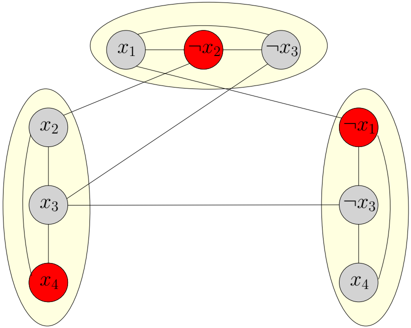
- For every clause, at least 1 literal is satisfied



Satisfying Assignment $\Rightarrow$ IS of Size k

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

- For every clause, at least 1 literal is satisfied
- Pick the vertex correspondent the literal



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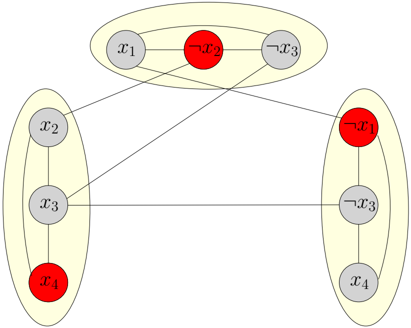
- $(x_1 \vee \neg x_2 \vee \neg x_3) \wedge (x_2 \vee x_3 \vee x_4) \wedge (\neg x_1 \vee \neg x_3 \vee x_4)$

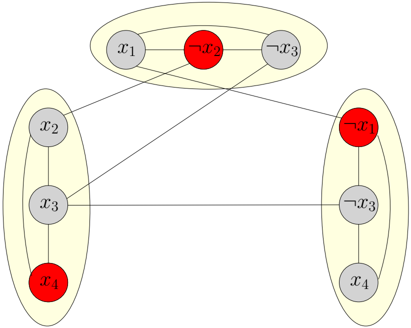
- For every clause, at least 1 literal is satisfied
- Pick the vertex correspondent the literal
- So, 1 literal from each group



Satisfying Assignment $\Rightarrow$ IS of Size k

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

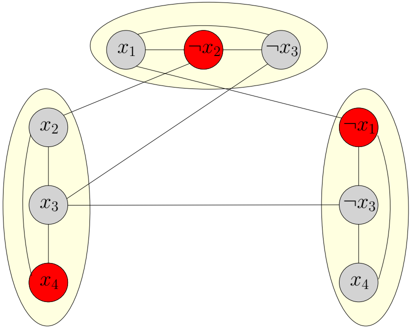
- For every clause, at least 1 literal is satisfied
- Pick the vertex correspondent the literal
- So, 1 literal from each group
- No contradictions among the selected literals



Satisfying Assignment $\Rightarrow$ IS of Size k

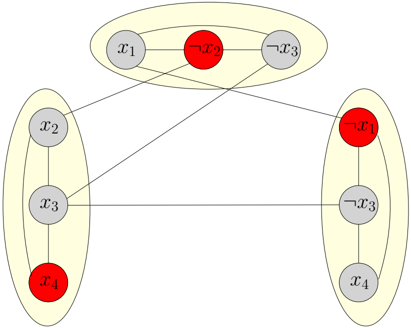
- $(x_1 \vee \neg x_2 \vee \neg x_3) \wedge (x_2 \vee x_3 \vee x_4) \wedge (\neg x_1 \vee \neg x_3 \vee x_4)$

- For every clause, at least 1 literal is satisfied
- Pick the vertex correspondent the literal
- So, 1 literal from each group
- No contradictions among the selected literals
- An IS of size k



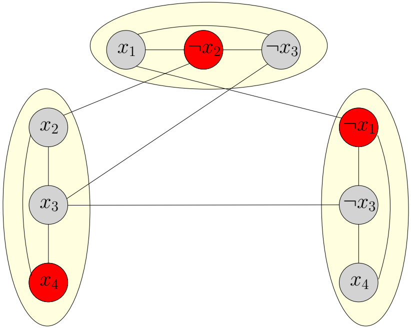
IS of Size $k \Rightarrow$ Satisfying Assignment

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



IS of Size $k \Rightarrow$ Satisfying Assignment

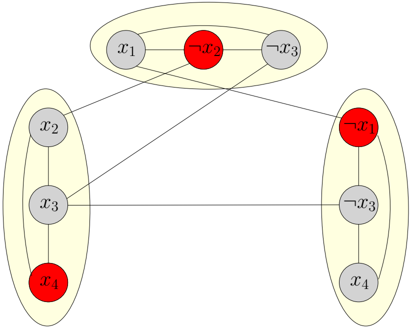
- $(x_1 \vee \neg x_2 \vee \neg x_3) \wedge (x_2 \vee x_3 \vee x_4) \wedge (\neg x_1 \vee \neg x_3 \vee x_4)$
- For every group, exactly one literal is selected in IS



IS of Size $k \Rightarrow$ Satisfying Assignment

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

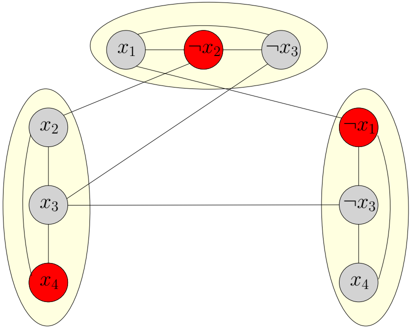
- For every group, exactly one literal is selected in IS
- No contradictions among the selected literals



IS of Size $k \Rightarrow$ Satisfying Assignment

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

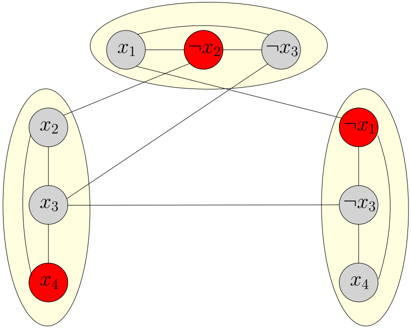
- For every group, exactly one literal is selected in IS
- No contradictions among the selected literals
- If x_i is selected in IS, set $x_i = 1$



IS of Size $k \Rightarrow$ Satisfying Assignment

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

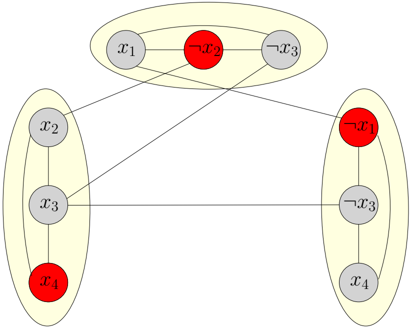
- For every group, exactly one literal is selected in IS
- No contradictions among the selected literals
- If x_i is selected in IS, set $x_i = 1$
- If $\neg x_i$ is selected in IS, set $x_i = 0$



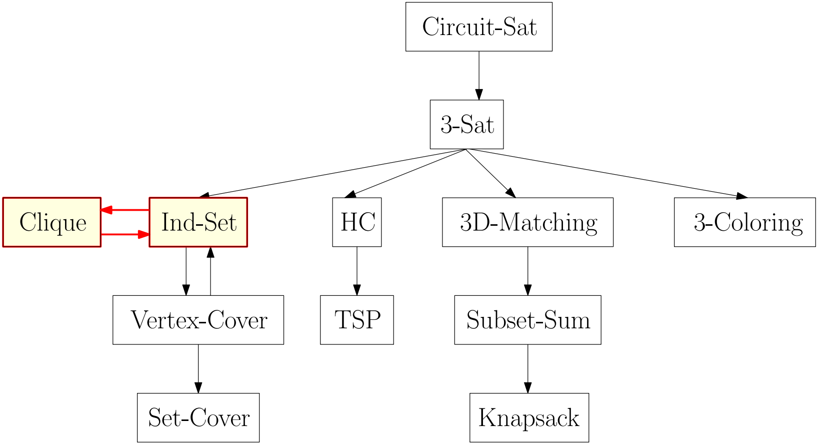
IS of Size $k \Rightarrow$ Satisfying Assignment

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

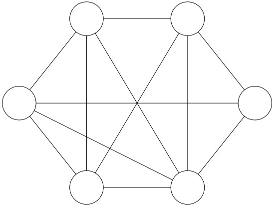
- For every group, exactly one literal is selected in IS
- No contradictions among the selected literals
- If x_i is selected in IS, set $x_i = 1$
- If $\neg x_i$ is selected in IS, set $x_i = 0$
- Otherwise, set x_i arbitrarily



Reductions of NP-Complete Problems



Def. A clique in an undirected graph $G = (V, E)$ is a subset $S \subseteq V$ such that $\forall u, v \in S$ we have $(u, v) \in E$



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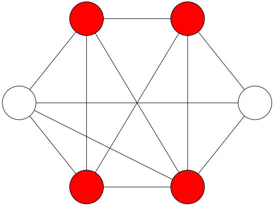

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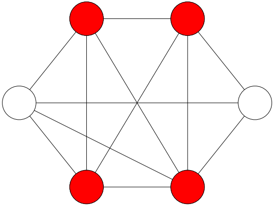

Clique Problem

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

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

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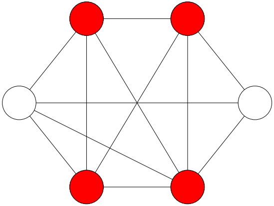


Clique Problem

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

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

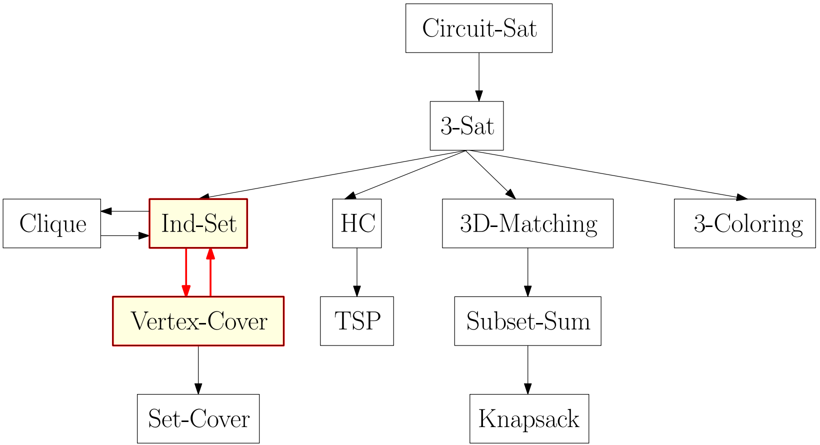
- What is the relationship between Clique and Ind-Set?

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 $(u, v) \notin E$.

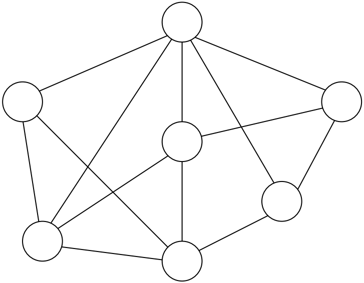
Obs. S is an independent set in G if and only if S is a clique in $\overline{G}$.

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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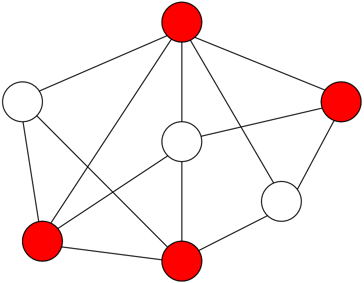

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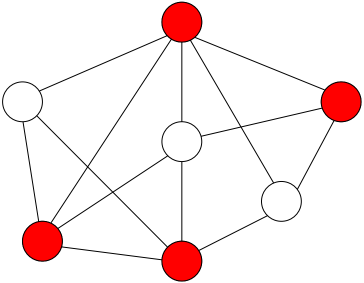


Vertex-Cover Problem

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

Vertex-Cover $=_P$ Ind-Set

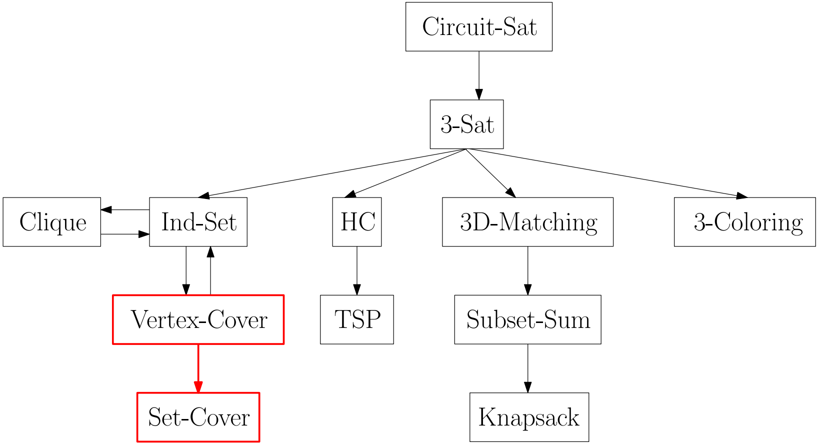
Q: What is the relationship between Vertex-Cover and Ind-Set?

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

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

Set Cover

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

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

- decision version: given t, does there exist a solution I with $|I| \leq t$?

Set Cover

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

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

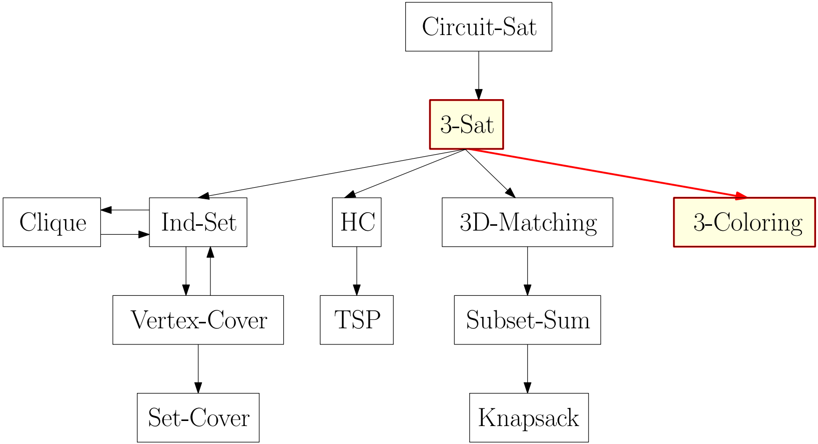
- decision version: given t, does there exist a solution I with $|I| \leq t$?

Vertex Cover $\leq_P$ Set Cover

- m edges $\Leftrightarrow$ N elements
- n vertices $\Leftrightarrow$ M sets
- vertex is incident to edge e $\Leftrightarrow$ set contains element

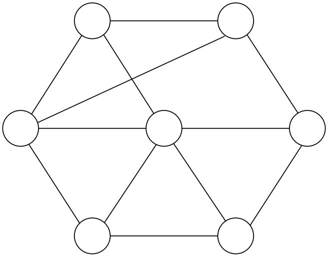
- Vertex cover is the special case of set cover where each element appears in exactly two sets.

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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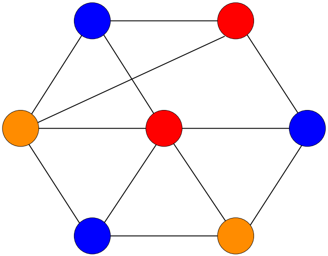

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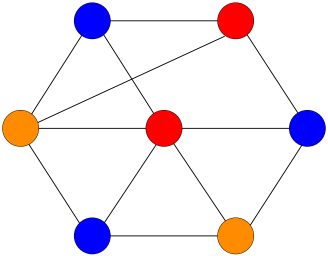


k-coloring problem

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.

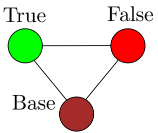
Q: How do we check if a graph G is 2-colorable?

A: We check if G is bipartite.

3-SAT $\leq_P$ 3-Coloring

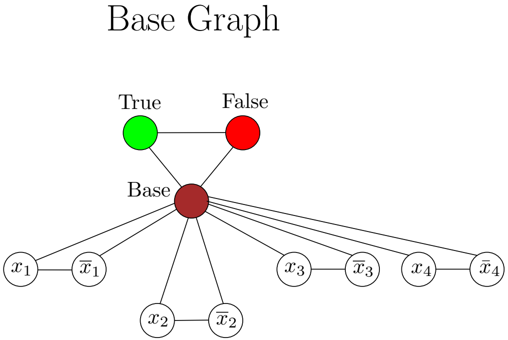
- Construct the base graph

Base Graph



3-SAT $\leq_P$ 3-Coloring

- Construct the base graph

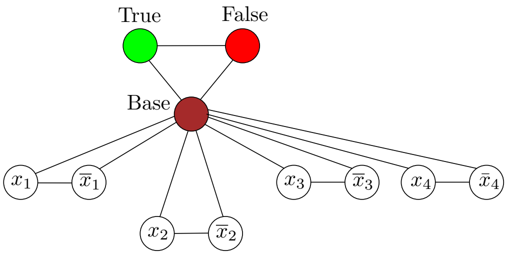


3-SAT $\leq_P$ 3-Coloring

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

Base Graph

$x_1 \vee \neg x_2 \vee x_3$



3-SAT $\leq_P$ 3-Coloring

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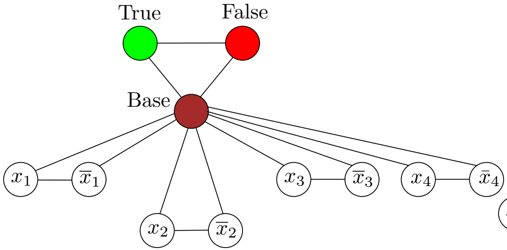

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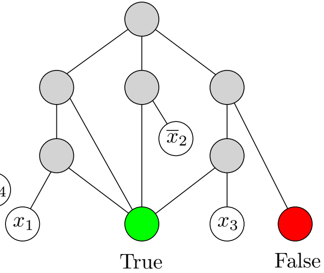

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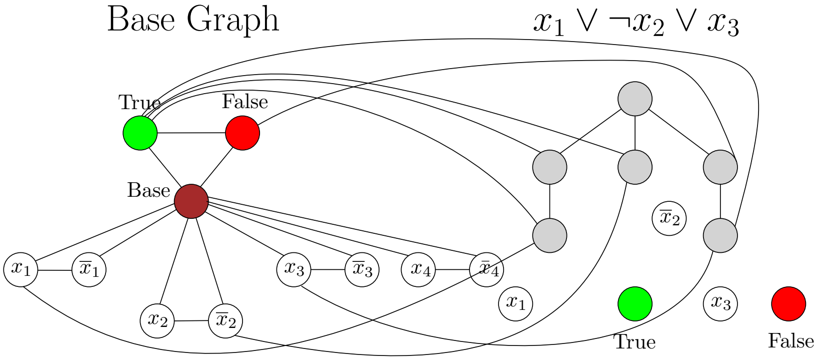

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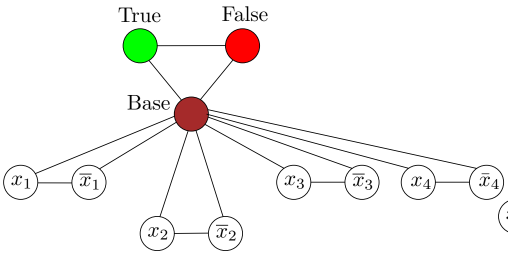

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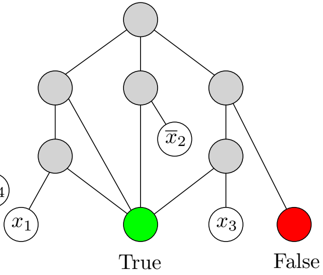

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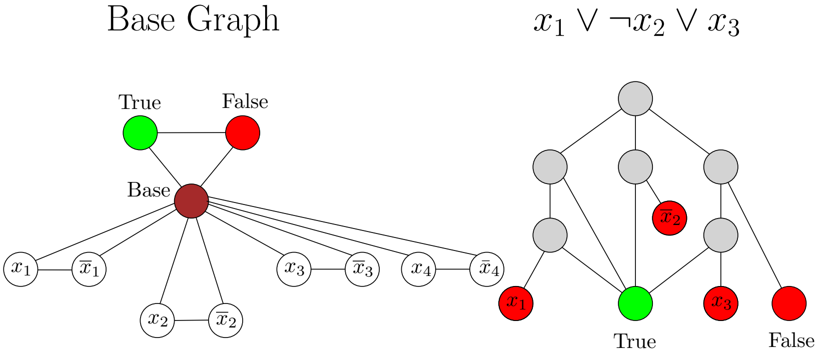

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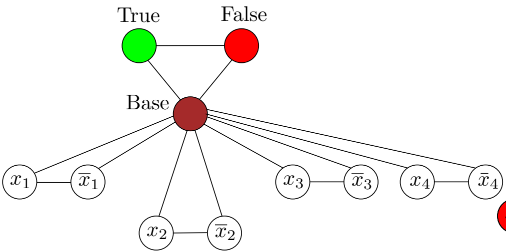

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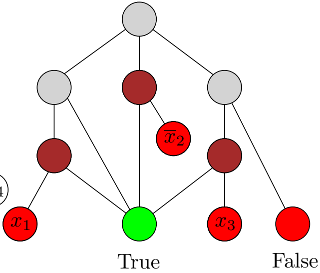

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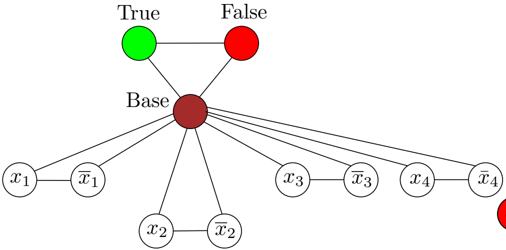

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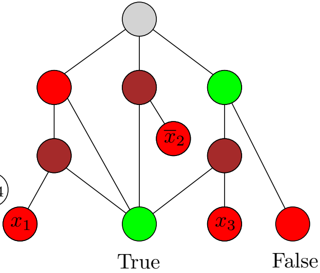

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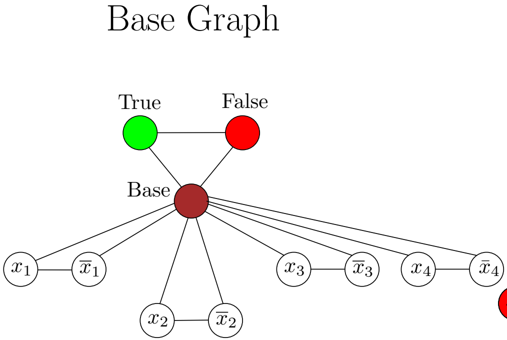

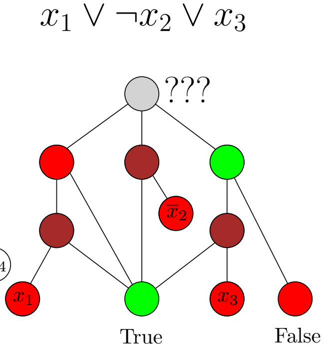

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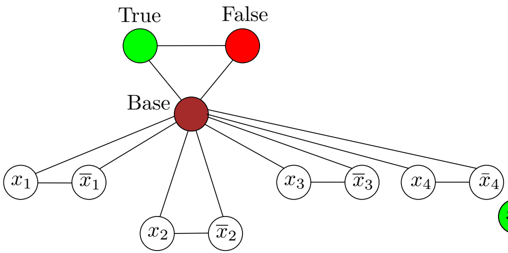

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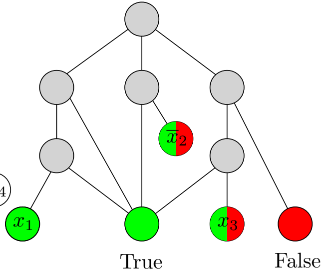

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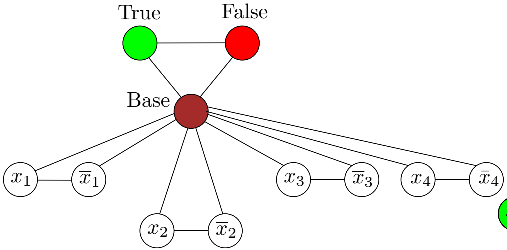

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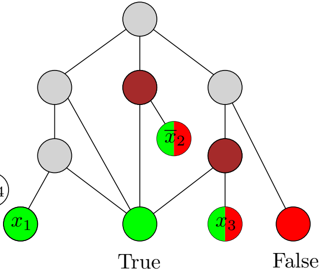

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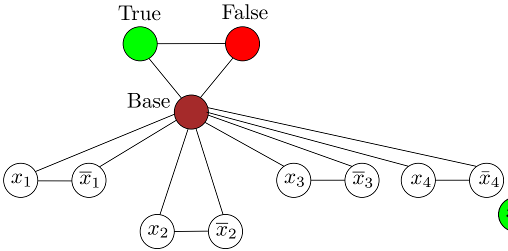

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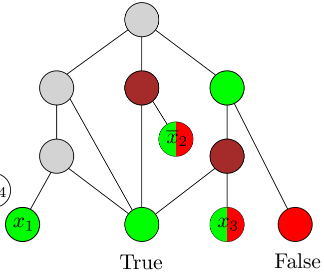

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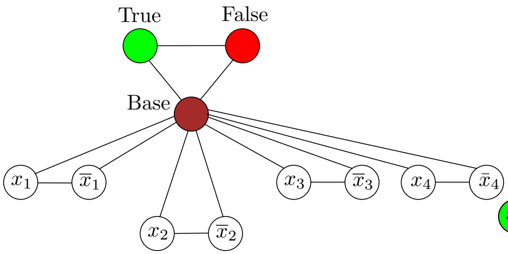

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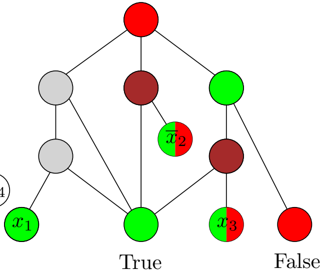

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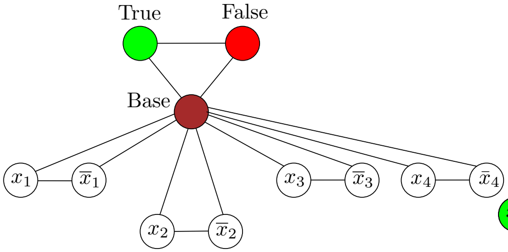

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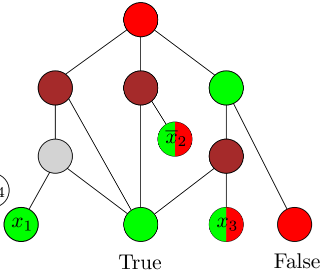

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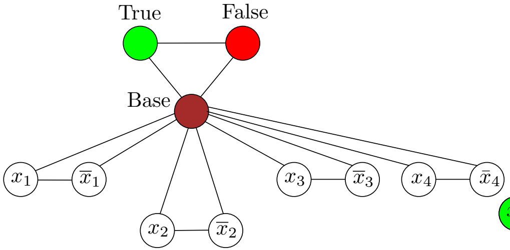

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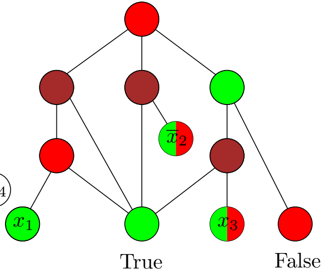

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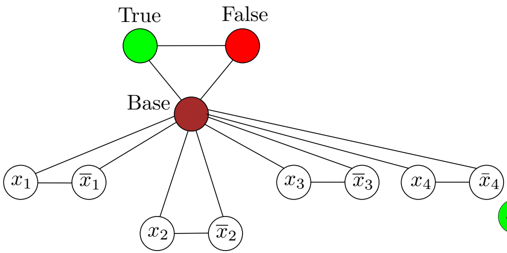

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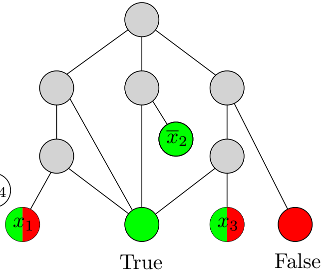

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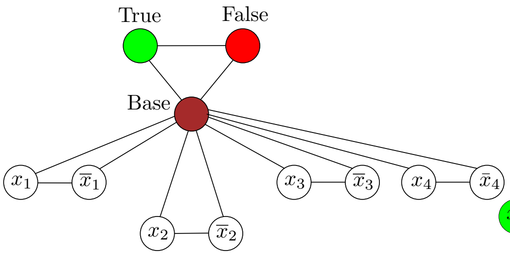

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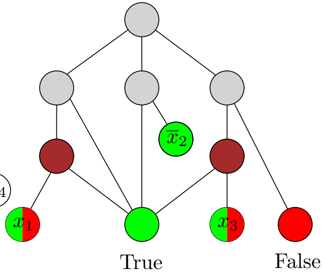

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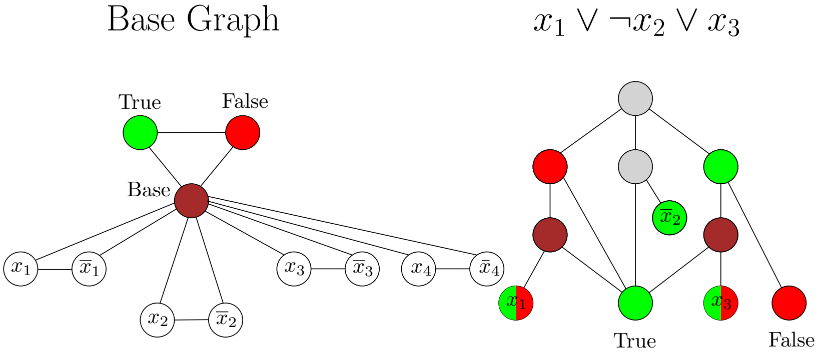

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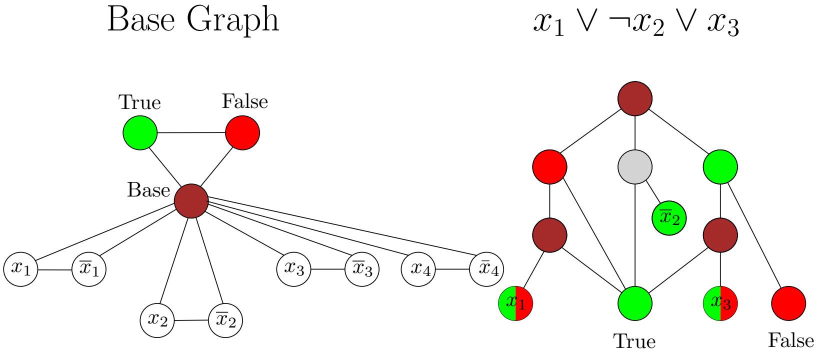

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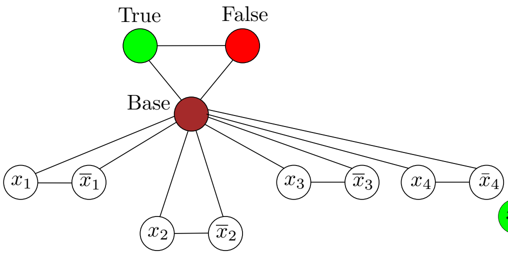

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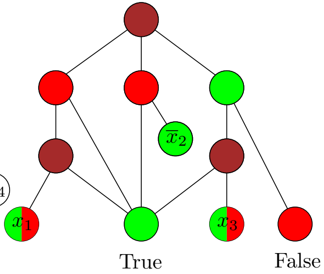

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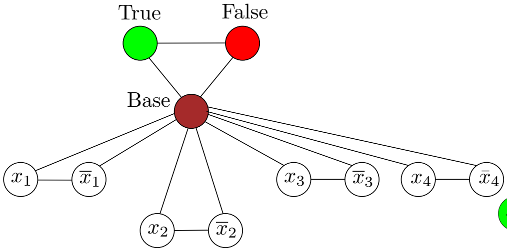

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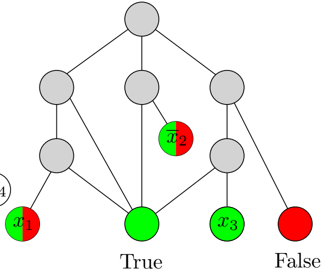

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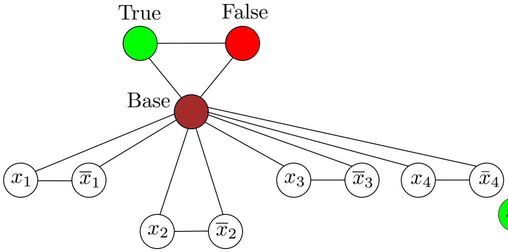

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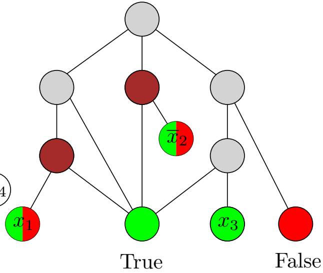

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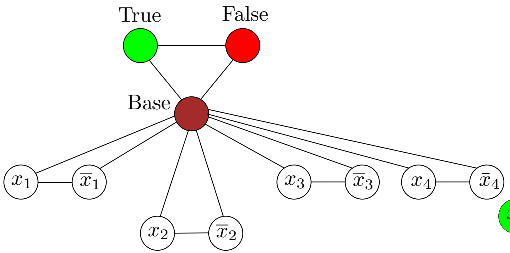

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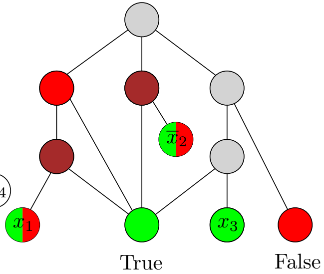

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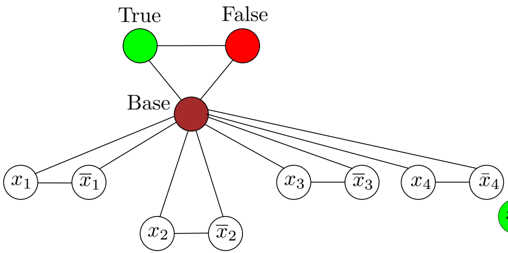

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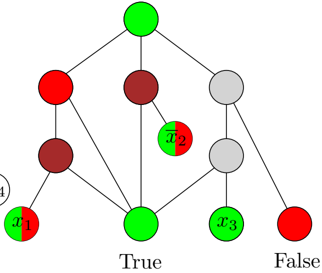

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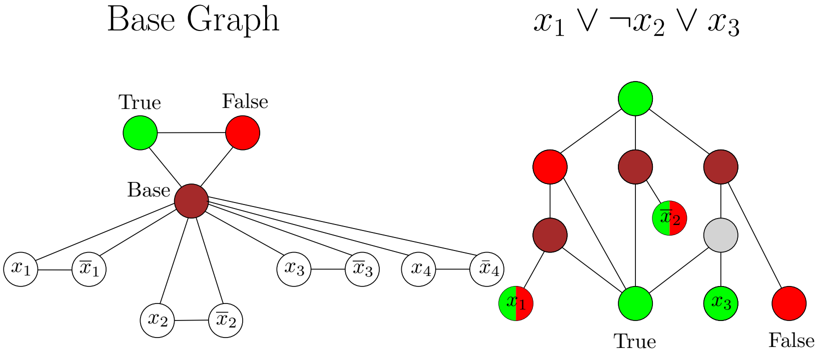

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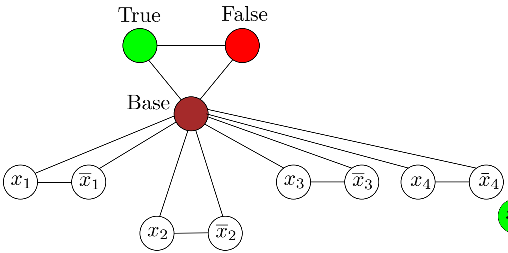

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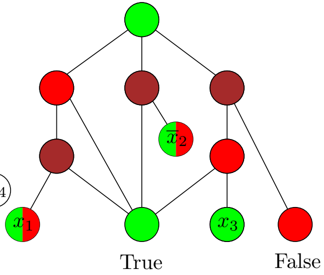
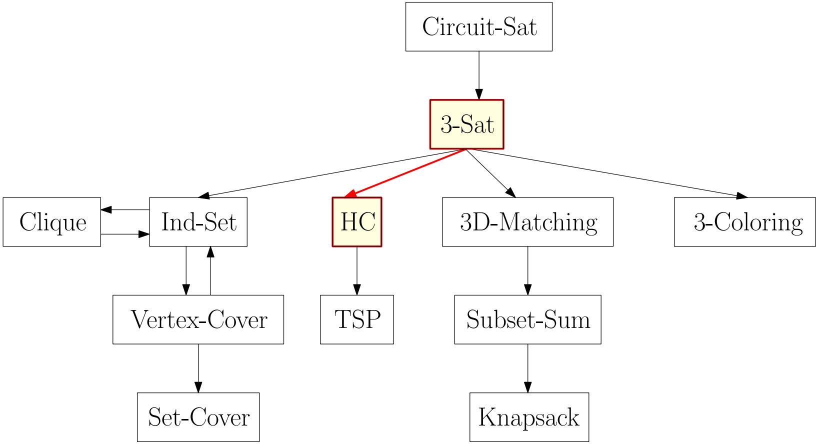


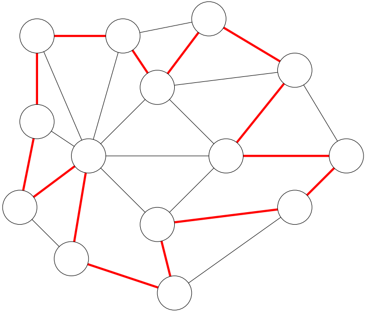
Reductions of NP-Complete Problems



Recall: Hamiltonian Cycle (HC) Problem

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

Output: whether G contains a Hamiltonian cycle



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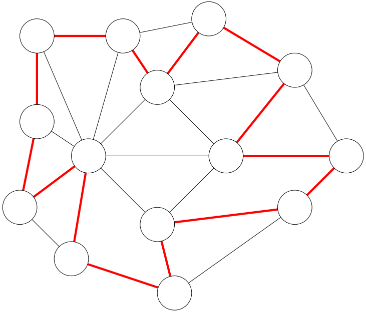

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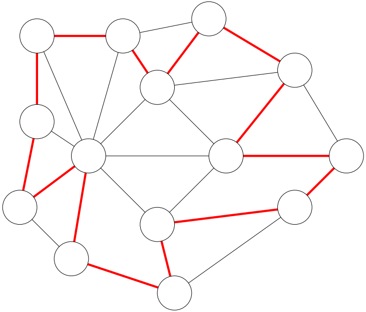
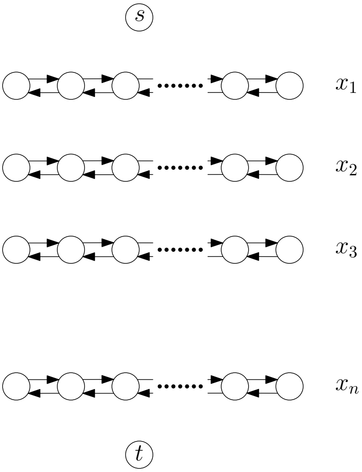


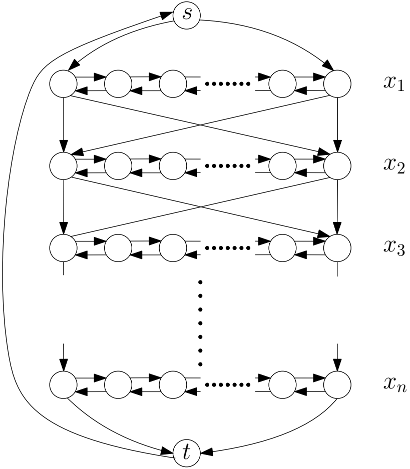
- We consider Hamiltonian Cycle Problem in directed graphs
- Exercise: HC-directed $\leq_P$ HC

3-Sat $\leq_P$ Directed-HC



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

3-Sat $\leq_P$ Directed-HC



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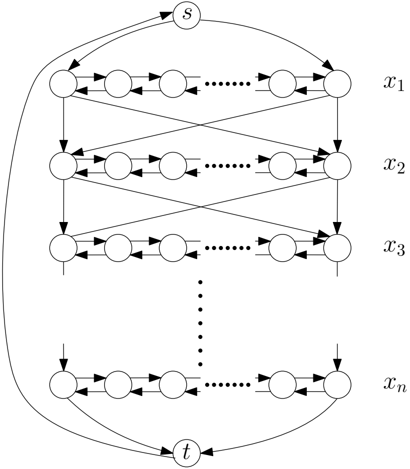

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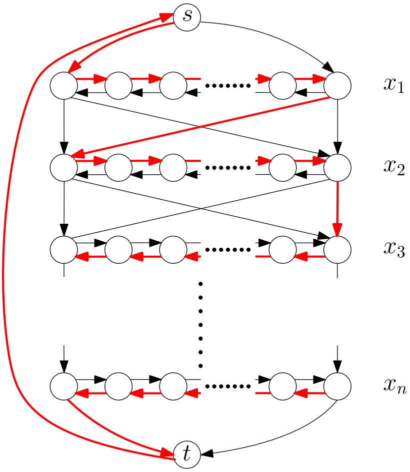

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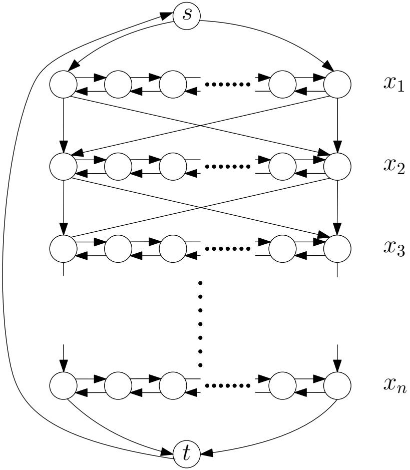

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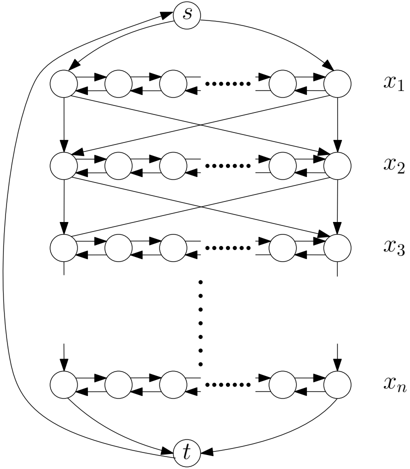

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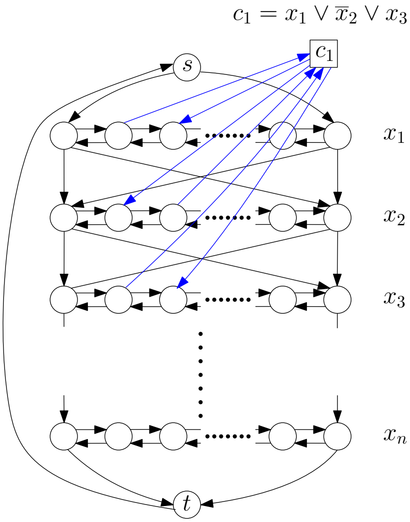
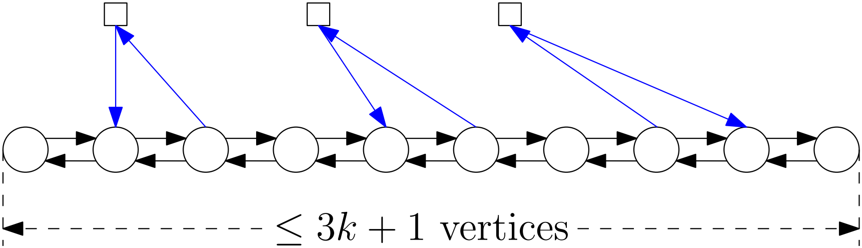


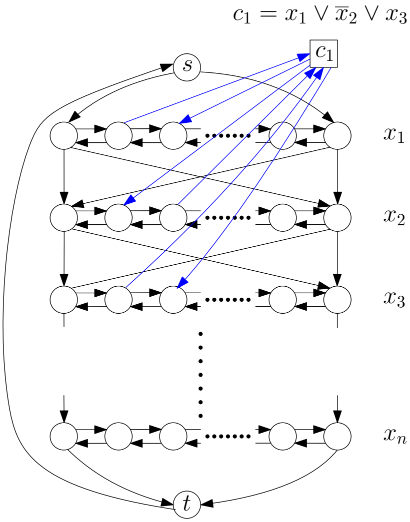
- There are exactly 2^n different Hamiltonian cycles, each correspondent to one assignment of variables
- Add a vertex for each clause, so that the vertex can be visited only if one of the literals is satisfied.

A Path Should Be Long Enough



- k: number of clauses

Yes-Instance for 3-Sat ⇒ Yes-Instance for Di-HC



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

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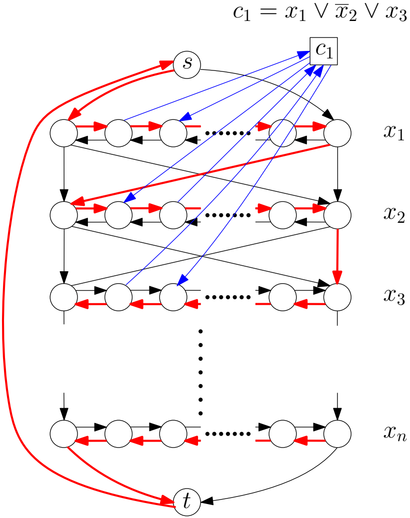

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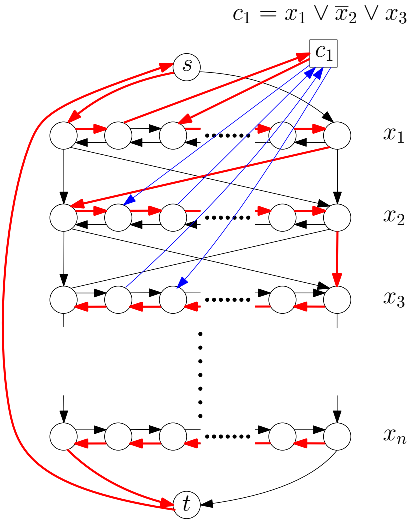

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- Visit the vertex for the clause by taking a “detour” from the path for the literal

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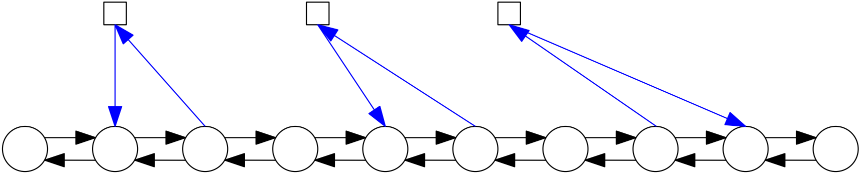

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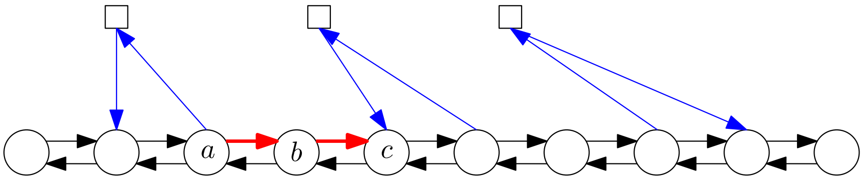

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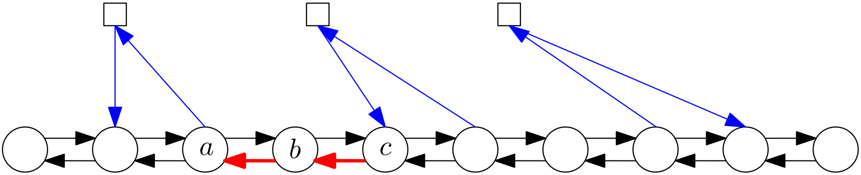

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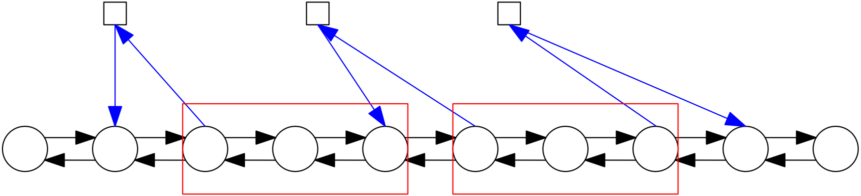

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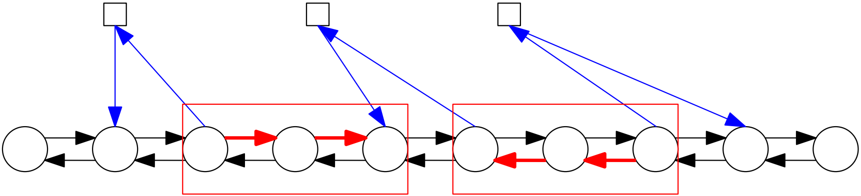

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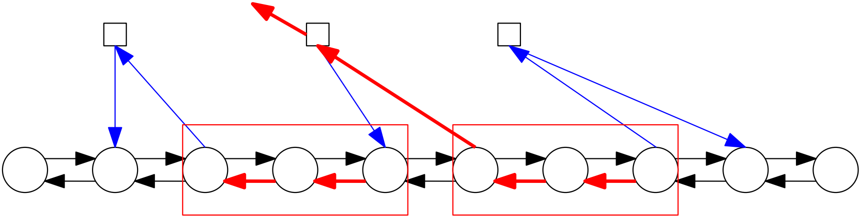

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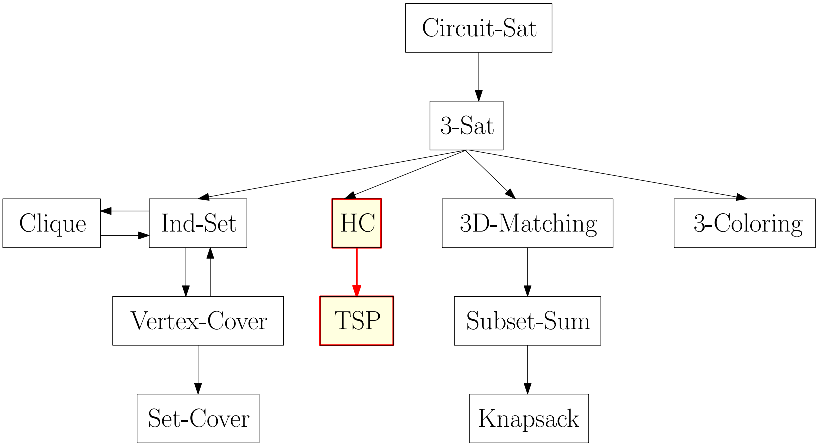
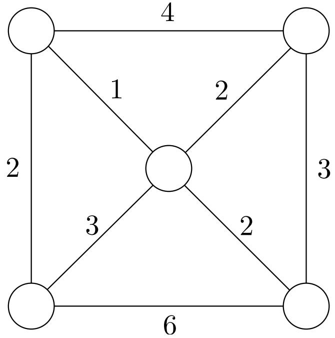
Reductions of NP-Complete Problems



Traveling Salesman Problem

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



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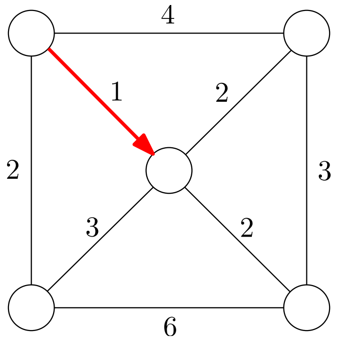

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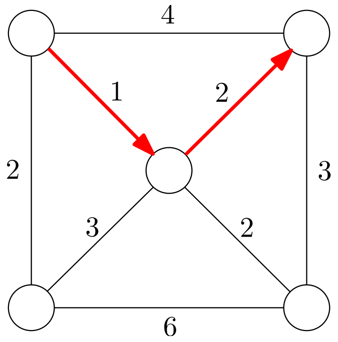

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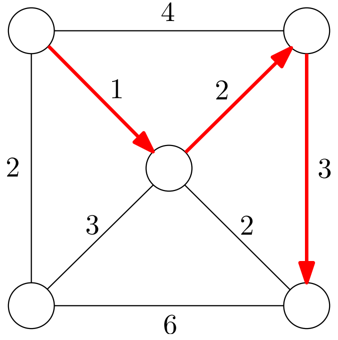

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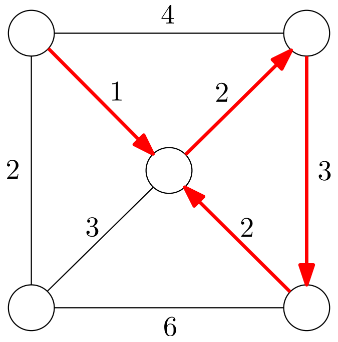

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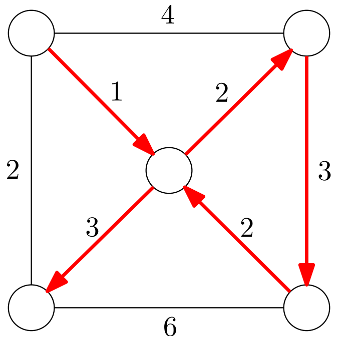

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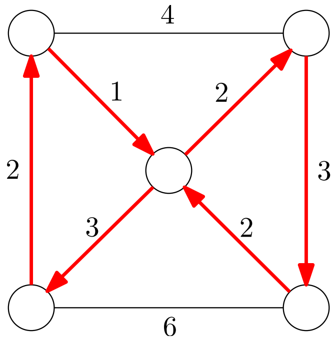

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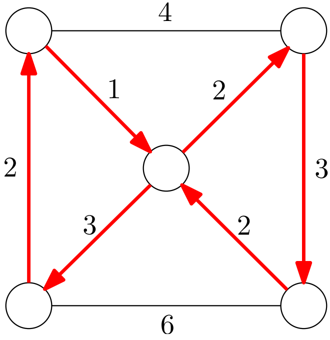
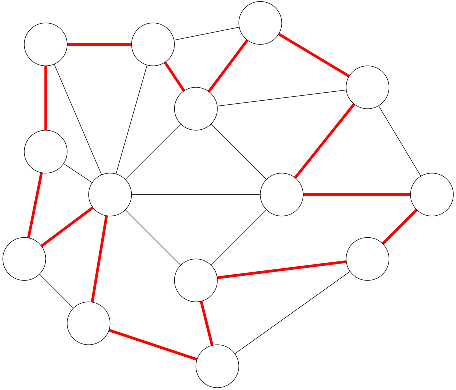


Travelling Salesman Problem (TSP)

Input: a graph $G = (V, E)$, weights $w : E \to \mathbb{R}_{\geq 0}$, 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 $n = |V|$.

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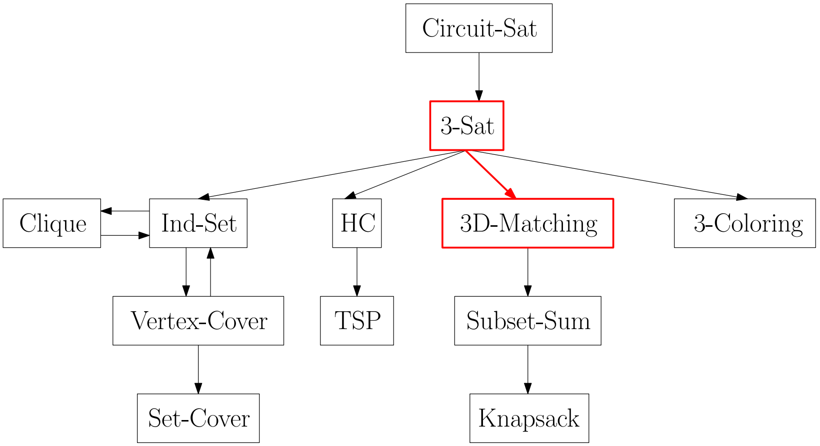

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Application: Matching between Teachers and Courses

- n teachers and n courses
- a teacher may or may not be able to teach a course
- find a way to match the n teachers and n courses.

3D-Matching

Input: $|X| = |Y| = |Z| = n$, $E \subseteq X \times Y \times Z, |E| = m$

Output: whether there exists a perfect 3-dimensional matching M, i.e., a set $M \subseteq E$ of size n such that

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X	Y	Z
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②	Ⓑ	ⓑ
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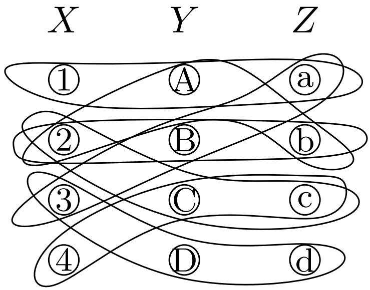

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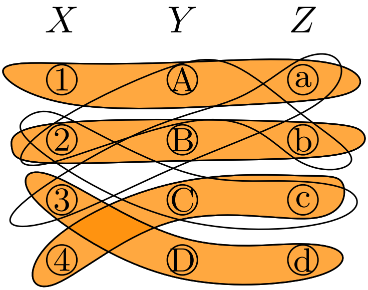

Application: Matching among Teachers, Courses and Resources

- n teachers, n courses and n resources
  - e.g., resource = (location, time) pair
- $(x, y, z) \in E$ teacher x can teach a course y using resource z
- find a way to match the teachers, courses and resources

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Remark

- The tuples can be arbitrary: the relationship is 3-dimensional.
- It is not a concatenation of two bipartite matching problems: If a teacher x can teach a course y, and resource z is available for teacher x, it does not necessarily mean $(x, y, z) \in E$

3D-Matching = Colorful Bipartite Matching

Colorful Bipartite Matching

Input: a bipartite multi-graph $G = (X \cup Y, E)$ with
$|X| = |Y| = n$ each edge in E has a color $c \in [n]$

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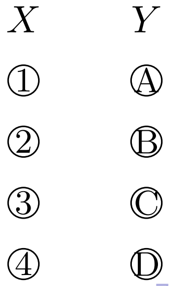

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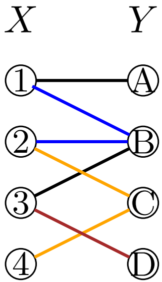

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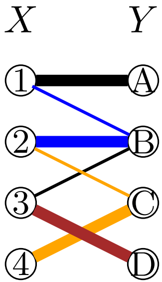

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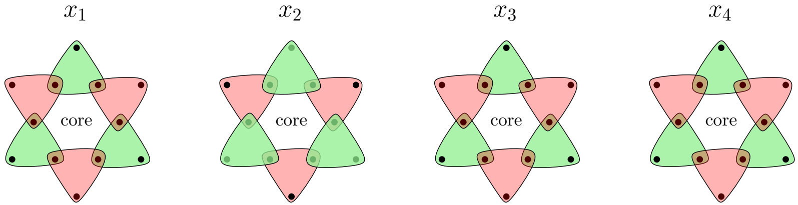

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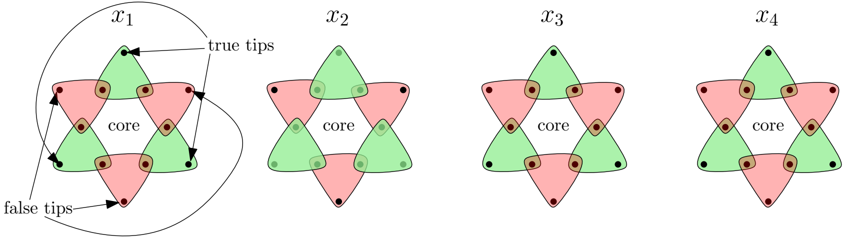

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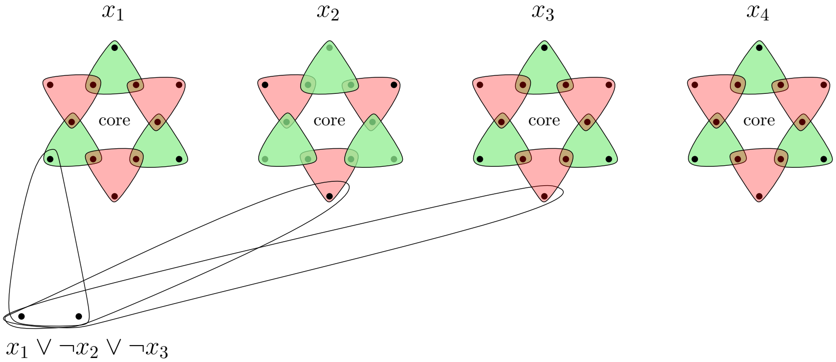

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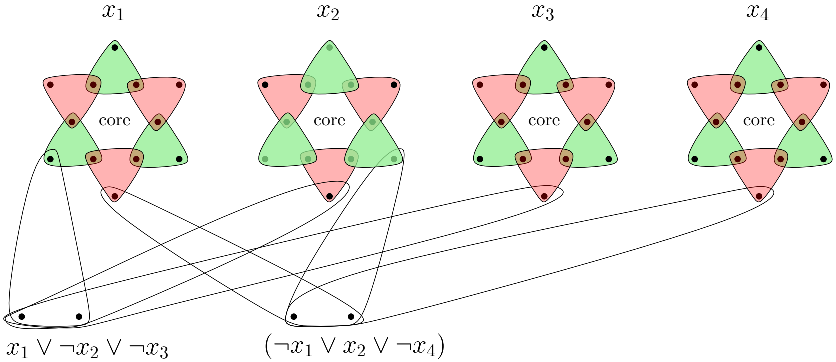

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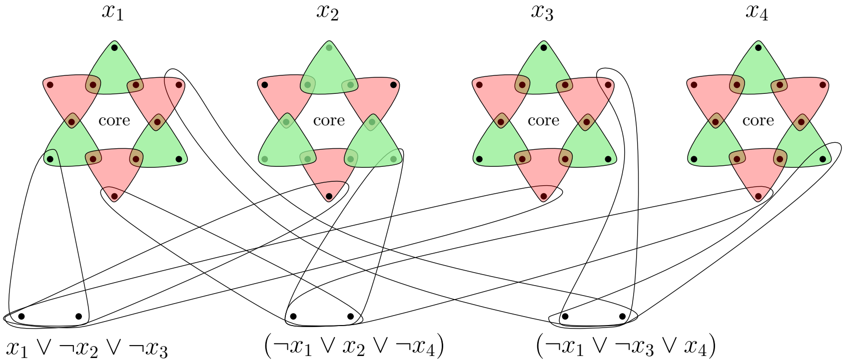

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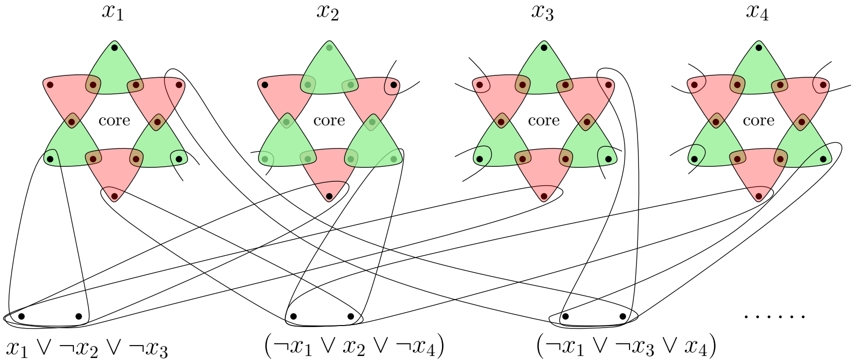

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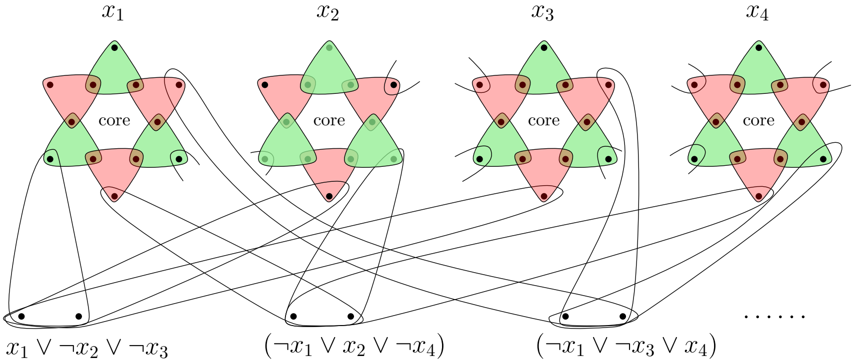

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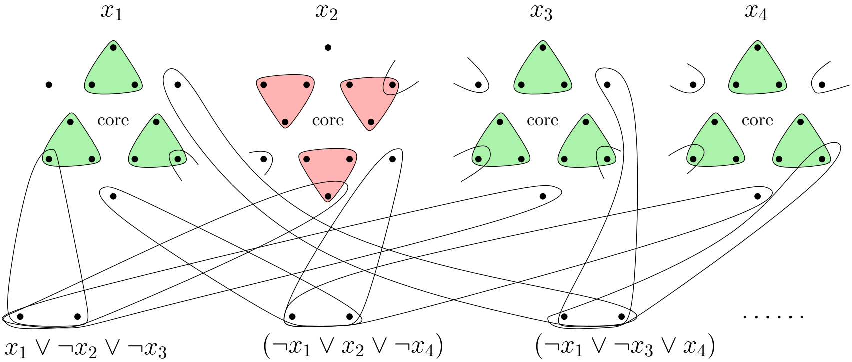

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- $(x_1 \vee \neg x_2 \vee \neg x_3) \wedge (\neg x_1 \vee x_2 \vee \neg x_4) \wedge (\neg x_1 \vee \neg x_3 \vee x_4) \wedge$ $(x_1 \vee \neg x_3 \vee \neg x_4) \wedge (\neg x_2 \vee x_3 \vee \neg x_4) \wedge (x_2 \vee x_3 \vee x_4)$
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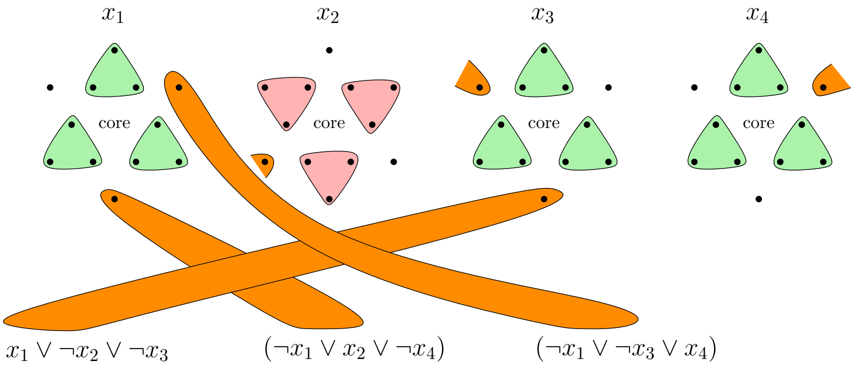

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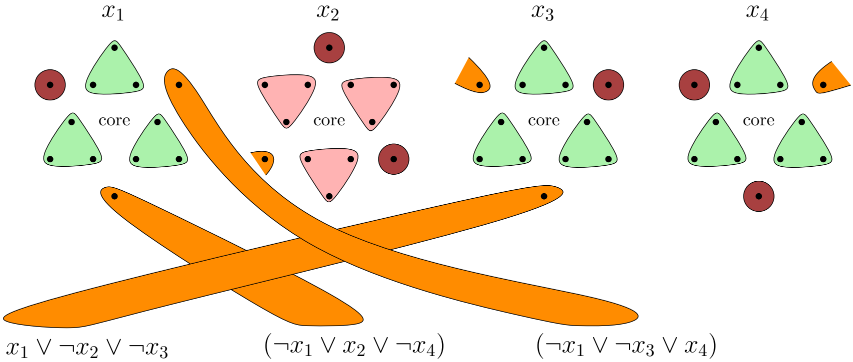

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- n: number of variables m: number of clauses
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Construction of 3D-Matching Instance

for each $x_i, i \in [n]$ **do**
    create a core with k true tips and k false tips
for each clause **do**
    create two private vertices u, v for the clause
    for each of the 3 literals in clause **do**
        create a tuple containing u, v and a tip for the literal
Repeat $kn - m$ times:
    create a dummy vertex pair (u, v)
    for every tip w **do**: add a tuple (u, v, w) for each tip w

3-SAT $\leq_P$ 3D-Matching

- Check: the hyper-graph constructed is indeed tripartite.

Yes-Instance for 3-SAT $\implies$ Yes-Instance for 3D-Matching

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- All vertices are covered; every vertex is covered once.

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- Contradiction.

Subset-Sum Problem

Subset Sum Problem

Input: an integer bound $W > 0$

a set of n items, each with an integer weight $w_i > 0$

Output: a subset S of items that

$$\text{maximizes} \sum_{i \in S} w_i \qquad \text{s.t.} \sum_{i \in S} w_i \le W.$$

- Decision version: decide if there is an S with $\sum_{i \in S} w_i = W$.

3D-Matching $\leq_P$ Subset-Sum

Example

- $X = \{1, 2, 3, 4\}$ $Y = \{\mathsf{A}, \mathsf{B}, \mathsf{C}, \mathsf{D}\}$ $Z = \{\mathsf{a}, \mathsf{b}, \mathsf{c}, \mathsf{d}\}$

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- $(1, \mathsf{A}, \mathsf{a}), (2, \mathsf{A}, \mathsf{b}), (2, \mathsf{B}, \mathsf{b}), (2, \mathsf{C}, \mathsf{c}), (3, \mathsf{B}, \mathsf{a}), (3, \mathsf{D}, \mathsf{d}), (4, \mathsf{C}, \mathsf{c})$

	1	2	3	4	A	B	C	D	a	b	c	d
(1, A, a)	0 0 1	0 0 0	0 0 0	0 0 0	0 0 1	0 0 0	0 0 0	0 0 0	0 0 1	0 0 0	0 0 0	0 0 0
(2, A, b)	0 0 0	0 0 1	0 0 0	0 0 0	0 0 1	0 0 0	0 0 0	0 0 0	0 0 0	0 0 1	0 0 0	0 0 0
(2, B, b)	0 0 0	0 0 1	0 0 0	0 0 0	0 0 0	0 0 1	0 0 0	0 0 0	0 0 0	0 0 1	0 0 0	0 0 0
(2, C, c)	0 0 0	0 0 1	0 0 0	0 0 0	0 0 0	0 0 0	0 0 1	0 0 0	0 0 0	0 0 0	0 0 1	0 0 0
(3, B, a)	0 0 0	0 0 0	0 0 1	0 0 0	0 0 0	0 0 1	0 0 0	0 0 0	0 0 1	0 0 0	0 0 0	0 0 0
(3, D, d)	0 0 0	0 0 0	0 0 1	0 0 0	0 0 0	0 0 0	0 0 0	0 0 1	0 0 0	0 0 0	0 0 0	0 0 1
(4, C, c)	0 0 0	0 0 0	0 0 0	0 0 1	0 0 0	0 0 0	0 0 1	0 0 0	0 0 0	0 0 0	0 0 1	0 0 0
sum=	0 0 1	0 0 1	0 0 1	0 0 1	0 0 1	0 0 1	0 0 1	0 0 1	0 0 1	0 0 1	0 0 1	0 0 1

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

Outline

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

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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

Faster Exponential Time Algorithms

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Travelling Salesman Problem:

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- In practice: TSP Solver can solve Euclidean TSP instances with more than 100,000 vertices

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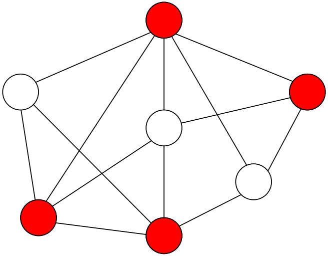
- Problem: whether there is a vertex cover of size k, for a small k (number of nodes is n, number of edges is $\Theta(n)$.)



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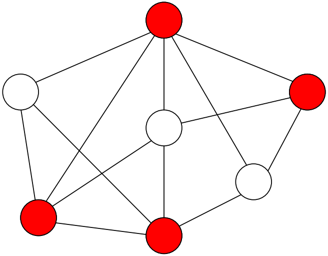

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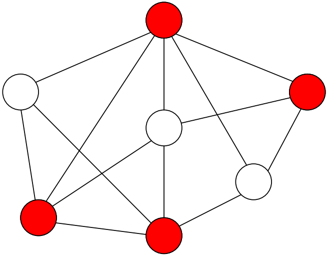

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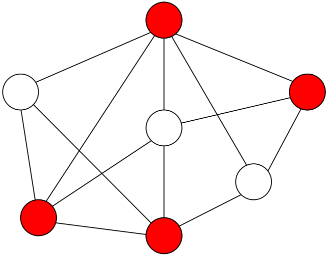

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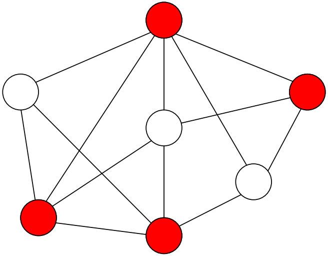
- Vertex-Cover is fixed-parameter tractable.



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- We want to make the approximation ratio as small as possible, while maintaining the property that the algorithm runs in polynomial time
- 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

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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, $X(s) = 1$ 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.

Summary

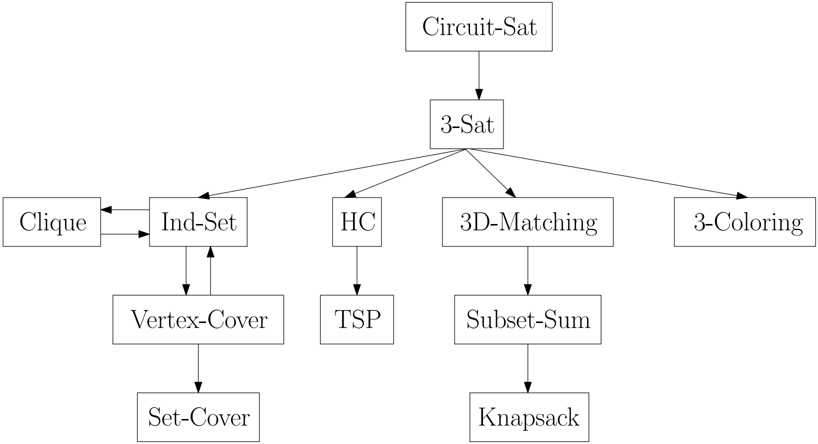
Def. Given a black box algorithm A that solves a problem X, if any instance of a problem Y can be solved using a polynomial number of standard computational steps, plus a polynomial number of calls to A, then we say Y is polynomial-time reducible to X, denoted as $Y \leq_P X$.

Def. A problem X is called NP-complete if

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

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

Summary



Circuit-Sat
3-Sat
Clique
Ind-Set
HC
3D-Matching
3-Coloring
Vertex-Cover
TSP
Subset-Sum
Set-Cover
Knapsack

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 $X \in$ 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