CSE 531B: Algorithm Analysis and Design (Spring 2025) NP-Completeness

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NP-Completeness Theory

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

Q: Why do we study negative results?

NP-Completeness Theory

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

Q: Why do we study negative results?

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

Efficient = Polynomial Time

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

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Reason for Efficient = Polynomial Time

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

Outline

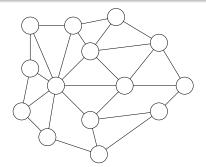
- Some Hard Problems
- P, NP and Co-NF
- 3 Polynomial Time Reductions and NP-Completeness
- MP-Complete Problems
- Dealing with NP-Hard Problems
- **6** Summary
- Summary of Studies 2025 Spring

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

Hamiltonian Cycle (HC) Problem

Input: graph G = (V, E)

Output: whether G contains a Hamiltonian cycle

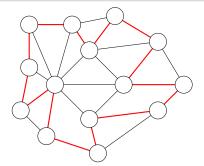


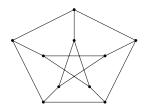
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• The graph is called the Petersen Graph. It has no HC.

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- Better algorithm: $2^{O(n)}$
- Far away from polynomial time

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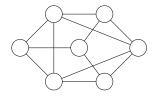
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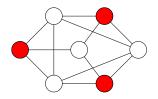
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- Running time: $O(n!m) = 2^{O(n \lg n)}$
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- Far away from polynomial time
- HC is NP-hard: it is unlikely that it can be solved in polynomial time.

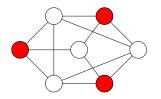
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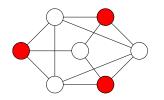


Maximum Independent Set Problem

Input: graph G = (V, E)

Output: the size of the maximum independent set of G

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Maximum Independent Set Problem

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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: $\neg((\neg x_1 \land x_2) \lor (\neg x_1 \land \neg x_3) \lor x_1 \lor (\neg x_2 \land x_3))$ is not satisfiable
- Trivial algorithm: enumerate all possible assignments, and check if each assignment satisfies the formula. The algorithm runs in exponential time.

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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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Maximum Independent Set

Input: a graph G and a bound k

Output: whether there is an independent set of size at least k

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Example: Sorting problem

• Input: (3, 6, 100, 9, 60)

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- Input: (3, 6, 100, 9, 60)
- Binary: (11, 110, 1100100, 1001, 111100)

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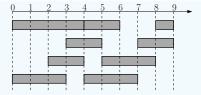
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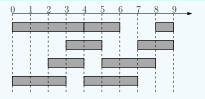
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Example: Interval Scheduling Problem



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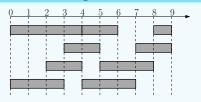
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 $\bullet \ (0,3,0,4,2,4,3,5,4,6,4,7,5,8,7,9,8,9)$

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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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Q: Does it matter how we encode the input instances?

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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.

• $\{0,1\}^*$: the set of all binary strings of any length.

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 $\mbox{\bf Def.}\;$ An algorithm A solves a problem X if, A(s)=X(s) for any binary string s

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

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

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

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

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

The Complexity Class NP

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

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

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

HC (Hamiltonian Cycle) ∈ NP

ullet Input: Graph G

$\mathsf{HC}\ (\mathsf{Hamiltonian}\ \mathsf{Cycle}) \in \mathsf{NP}$

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- $\bullet \ |\mathrm{encoding}(S)| \leq p(|\mathrm{encoding}(G)|)$ for some polynomial function p

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

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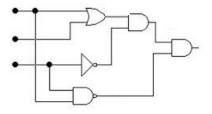
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- ullet Clearly, B runs in polynomial time
- $MIS(G, k) = 1 \iff \exists S, B((G, k), S) = 1$

Circuit Satisfiablity (Circuit-Sat) Problem

Input: a circuit with and/or/not gates

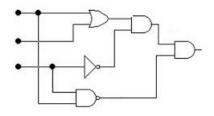
Output: whether there is an assignment such that the output is 1?



Circuit Satisfiablity (Circuit-Sat) Problem

Input: a circuit with and/or/not gates

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Is Circuit-Sat ∈ NP?

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

The Complexity Class Co-NP

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

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

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

Tautology Problem

Input: a boolean formula

Output: whether the formula is a tautology

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

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- Bob can certify that a formula is not a tautology
- Thus Tautology ∈ Co-NP

$\overline{\mathsf{P}}\subseteq \mathsf{N}\mathsf{P}$

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

$\overline{\mathsf{Is}\;\mathsf{P}=\mathsf{NP?}}$

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- Most researchers believe $P \neq NP$
- ullet It would be too amazing if P = NP: if one can check a solution efficiently, then one can find a solution efficiently

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

Is NP = Co-NP?

• Again, a big open problem

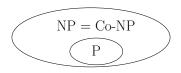
$\overline{\mathsf{Is}\;\mathsf{NP}}=\mathsf{Co-NP}?$

- Again, a big open problem
- Most researchers believe NP \neq Co-NP.

4 Possibilities of Relationships

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

$$P = NP = Co-NP$$







People commonly believe we are in the 4th scenario

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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 $Y \leq_P X$.

Polynomial-Time Reductions

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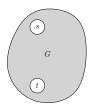
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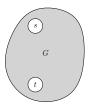


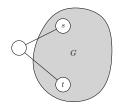
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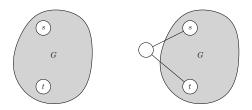


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Def. A problem *X* is called NP-complete if

- ullet $X\in \mathsf{NP}$, and
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Outline

- Some Hard Problems
- P, NP and Co-NP
- 3 Polynomial Time Reductions and NP-Completeness
- 4 NP-Complete Problems
- Dealing with NP-Hard Problems
- **6** Summary
- Summary of Studies 2025 Spring

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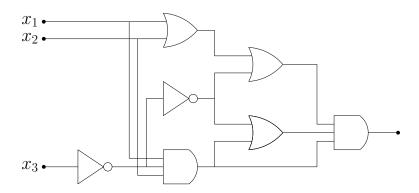
- \bullet $X \in \mathsf{NP}$, and
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 - How can we find a problem $X \in \mathsf{NP}$ such that every problem $Y \in \mathsf{NP}$ is polynomial time reducible to X? Are we asking for too much?
 - No! There is indeed a large family of natural NP-complete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

The First NP-Complete Problem: Circuit-Sat

Circuit Satisfiability (Circuit-Sat)

Input: a circuit

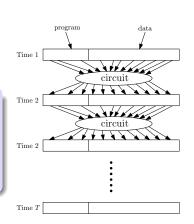
Output: whether the circuit is satisfiable



Circuit-Sat is NP-Complete

 key fact: algorithms can be converted to circuits

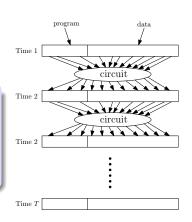
Fact Any algorithm that takes n bits as input and outputs 0/1 with running time T(n) can be converted into a circuit of size p(T(n)) for some polynomial function $p(\cdot)$.



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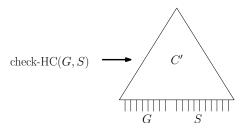
- Then, we can show that any problem $Y \in \mathsf{NP}$ can be reduced to Circuit-Sat.
- We prove HC \leq_P Circuit-Sat as an example.

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

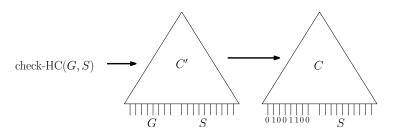
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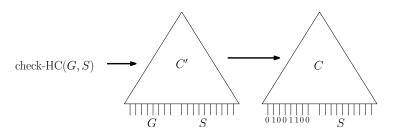


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$\mathsf{HC} \leq_P \mathsf{Circuit} ext{-}\mathsf{Sat}^{\mathsf{l}}$



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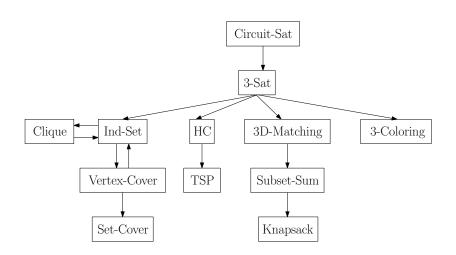
- Let check-Y(s,t) be the certifier for problem Y: check-Y(s,t) returns 1 if t is a valid certificate for s.
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Theorem Circuit-Sat is NP-complete.

Reductions of NP-Complete Problems



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

3-Sat

Input: a 3-CNF formula

Output: whether the 3-CNF is satisfiable

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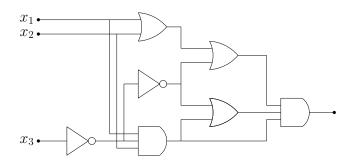
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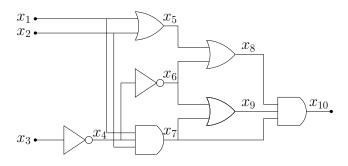
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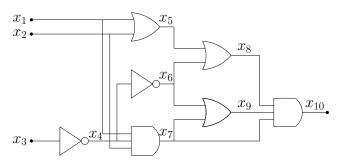
Output: whether the 3-CNF is satisfiable

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





• Associate every wire with a new variable



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

$$(x_4 = \neg x_3) \land (x_5 = x_1 \lor x_2) \land (x_6 = \neg x_4)$$

$$\land (x_7 = x_1 \land x_2 \land x_4) \land (x_8 = x_5 \lor x_6)$$

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| x_1 | x_2 | x_5 | $x_5 \leftrightarrow x_1 \lor x_2$ |
|-------|-------|-------|------------------------------------|
| 0 | 0 | 0 | 1 |
| 0 | 0 | 1 | 0 |
| 0 | 1 | 0 | 0 |
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| | | | 1 |
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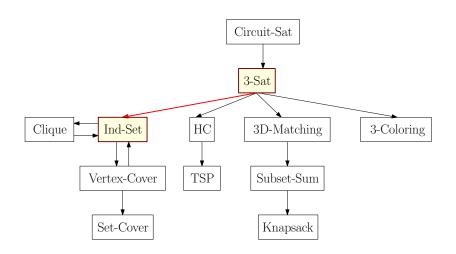
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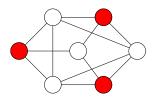
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- The circuit is satisfiable if and only if the 3-CNF is satisfiable
- The size of the 3-CNF formula is polynomial (indeed, linear) in the size of the circuit
- Thus, Circuit-Sat \leq_P 3-Sat

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

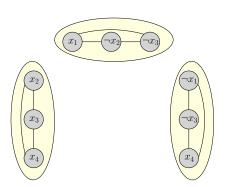
Input: G = (V, E), k

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

|3-Sat $\leq_P \mathsf{Ind}$ -Set

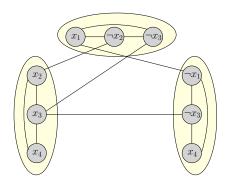
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- A clause ⇒ a group of 3 vertices, one for each literal
- An edge between every pair of vertices in same group

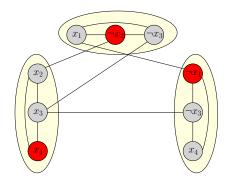


3-Sat $\leq_P \mathsf{Ind}$ -Set

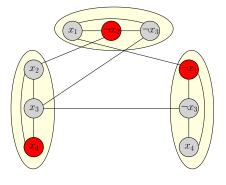
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- Problem: whether there is an IS of size k = #clauses

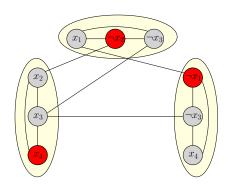


- $\bullet \ (x_1 \vee \neg x_2 \vee \neg x_3) \wedge (x_2 \vee x_3 \vee x_4) \wedge (\neg x_1 \vee \neg x_3 \vee x_4)$
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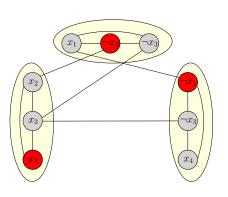
3-Sat instance is yes-instance ⇔ Ind-Set instance is yes-instance:

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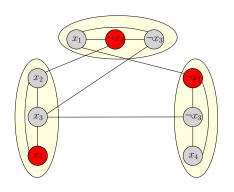


- 3-Sat instance is yes-instance ⇔ Ind-Set instance is yes-instance:
- ullet satisfying assignment \Rightarrow independent set of size k
- independent set of size $k \Rightarrow$ satisfying assignment

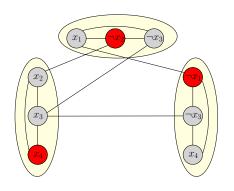
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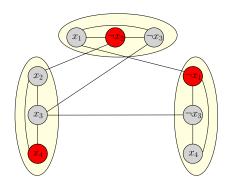
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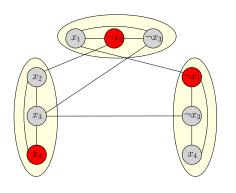
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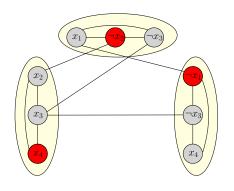
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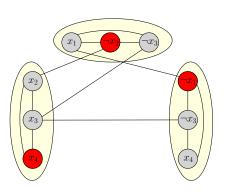
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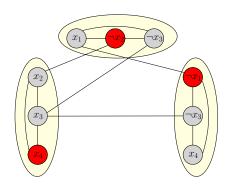
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- An IS of size k



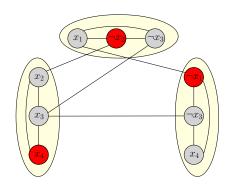
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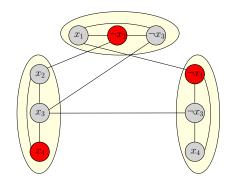
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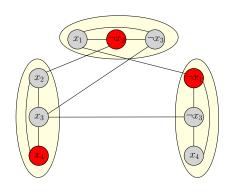
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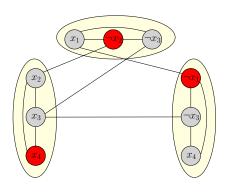
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- If x_i is selected in IS, set $x_i = 1$



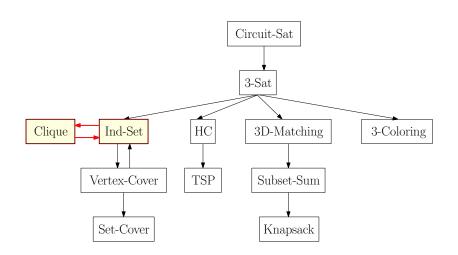
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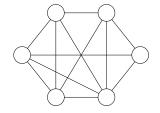


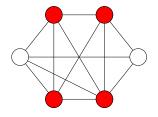
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- No contradictions among the selected literals
- If x_i is selected in IS, set $x_i = 1$
- If $\neg x_i$ is selected in IS, set $x_i = 0$
- Otherwise, set x_i arbitrarily

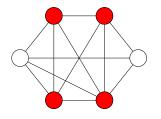


Reductions of NP-Complete Problems





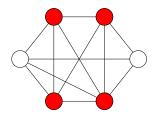




Clique Problem

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

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



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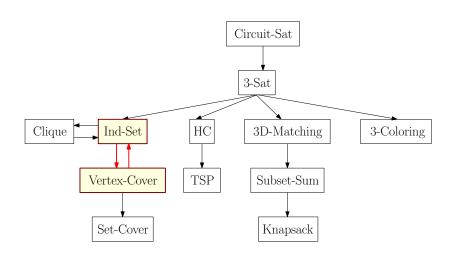
• What is the relationship between Clique and Ind-Set?

$Clique =_P Ind-Set$

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

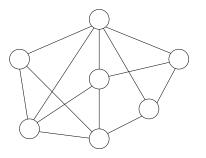
Obs. S is an independent set in G if and only if S is a clique in \overline{G} .

Reductions of NP-Complete Problems



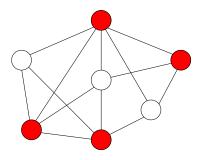
Vertex-Cover

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



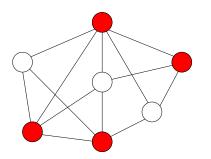
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Vertex-Cover Problem

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

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

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

$Vertex-Cover =_P Ind-Set$

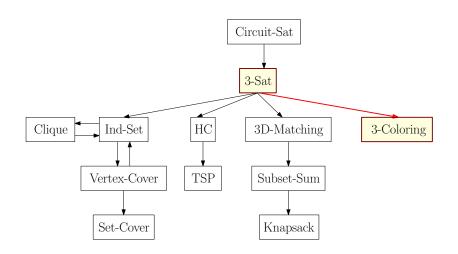
Q: What is the relationship between Vertex-Cover and Ind-Set?

$Vertex-Cover =_P Ind-Set$

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

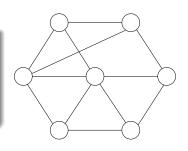
A: S is a vertex-cover of G=(V,E) if and only if $V\setminus S$ is an independent set of G.

Reductions of NP-Complete Problems



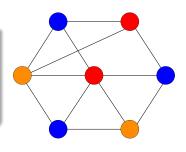
k-coloring problem

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



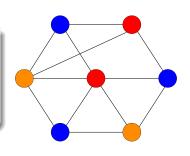
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k-coloring problem

Input: a graph G = (V, E)

Output: whether G is k-colorable or not

2-Coloring Problem

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

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

2-Coloring Problem

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

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

A: We check if *G* is bipartite.

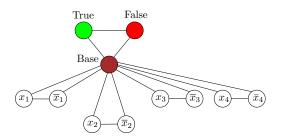
• Construct the base graph

Base Graph



Construct the base graph

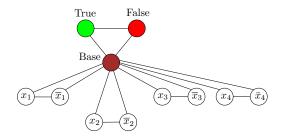
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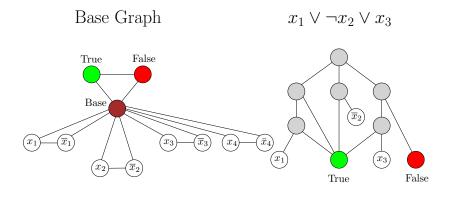
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- Construct a gadget from each clause: gadget is 3-colorable if and only if the clause is satisfied.

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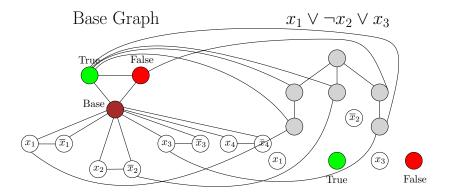
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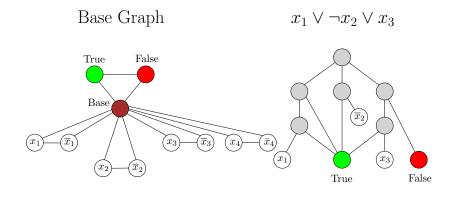
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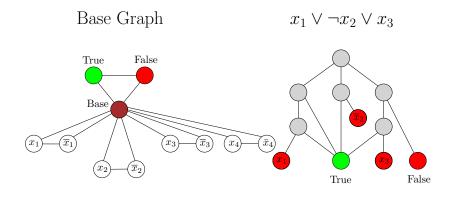
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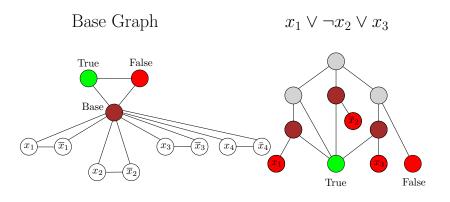
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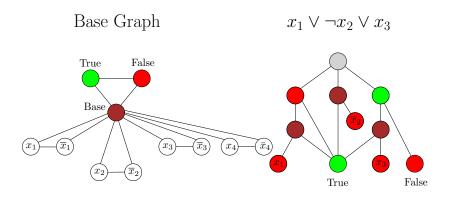
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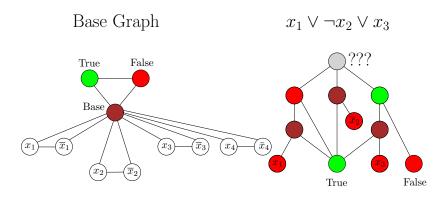
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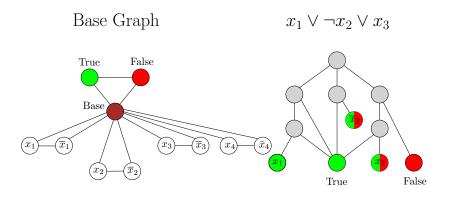
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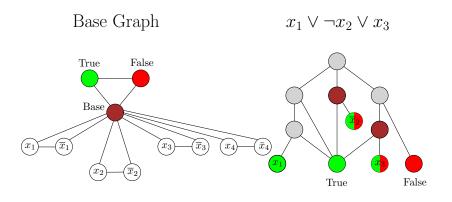
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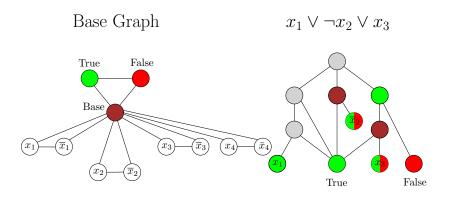
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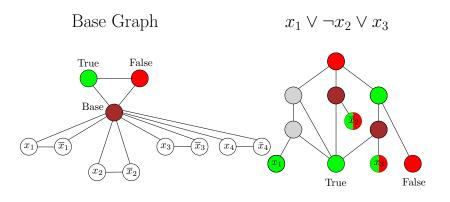
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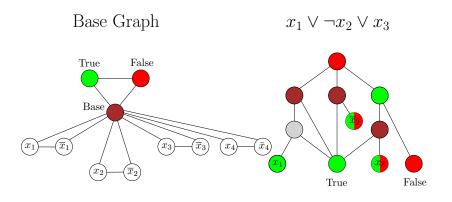
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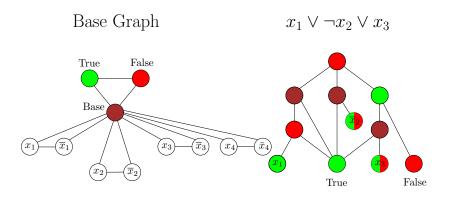
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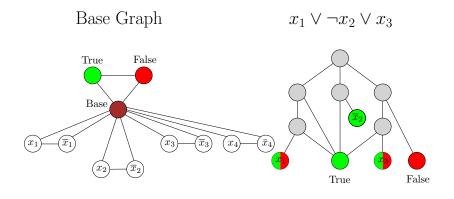
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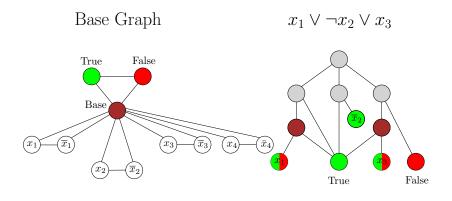
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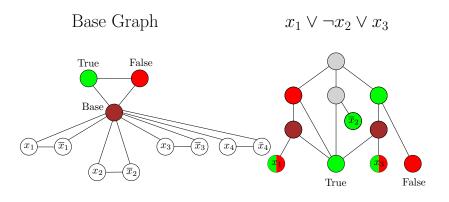
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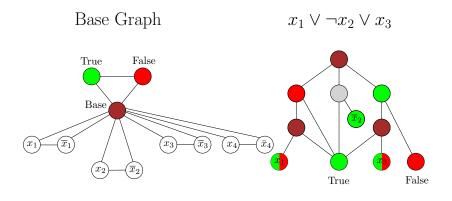
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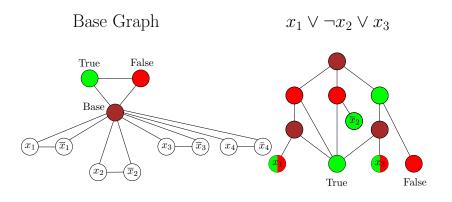
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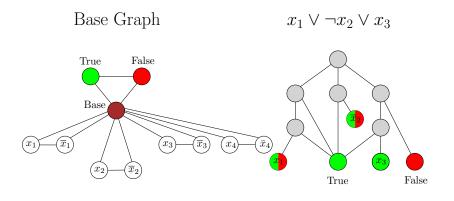
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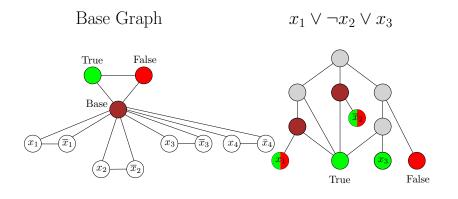
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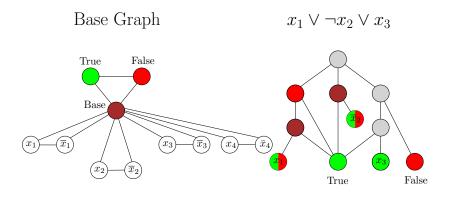
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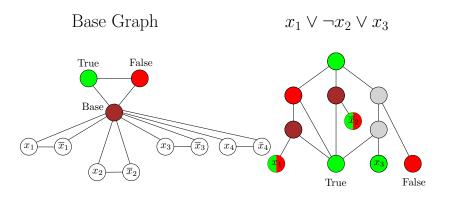
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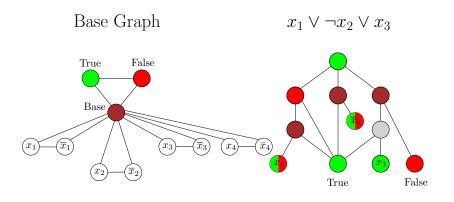
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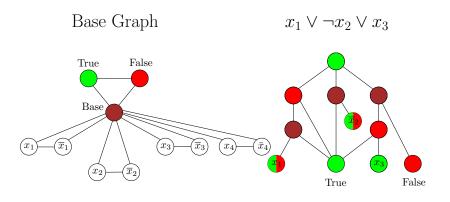
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A Strategy of Polynomial Reduction

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

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

Outline

- Some Hard Problems
- P, NP and Co-NP
- 3 Polynomial Time Reductions and NP-Completeness
- 4 NP-Complete Problems
- 5 Dealing with NP-Hard Problems
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- For 3-Sat problem:
 - Assume the number of clauses is $\Theta(n)$, n = number variables
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 - Best lower bound is $\Omega(n)$
- Essentially we have no techniques for proving lower bound for running time

Dealing with NP-Hard Problems

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

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Travelling Salesman Problem:

- Brute-force: $O(n! \cdot poly(n))$
- Better algorithm: $O(2^n \cdot \mathsf{poly}(n))$
- In practice: TSP Solver can solve Euclidean TSP instances with more than 100,000 vertices

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

• trees (Quiz 11)

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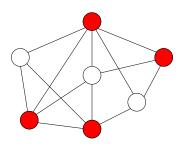
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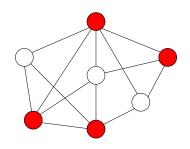
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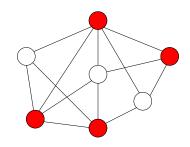
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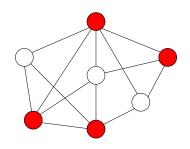
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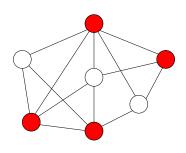
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- $\bullet \ \, {\rm Running \ time \ is} \ f(k)n^c \ \, {\rm for \ some} \ \, c \\ {\rm independent \ of} \ \, k \\$
- Vertex-Cover is fixed-parameter tractable.



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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

2-Approximation Algorithm for Vertex Cover

VertexCover(G)

- 1: $C \leftarrow \emptyset$
- 2: while $E \neq \emptyset$ do
- 3: select an edge $(u, v) \in E$, $C \leftarrow C \cup \{u, v\}$
- 4: Remove from E every edge incident on either u or v
- 5: return C
- Let the set C and C^* be the sets output by above algorithm and an optimal alg, respectively. Let S be the set of edges selected.
- Since no two edge in S are covered by the same vertex (Once an edge is picked in line 3, all other edges that are incident on its endpoints are removed from E in line 4), we have $|C^*| \geq |S|$;
- As we have added both vertices of edge (u,v), we get |C|=2|S| but C^* have to add one of the two, thus, $|C|/|C^*| \leq 2$.

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

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

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

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

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

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

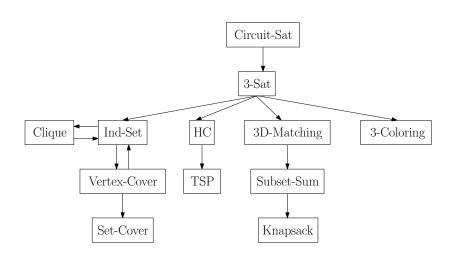
The string t such that B(s,t)=1 is called a certificate.

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

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

Def. A problem X is called NP-complete if

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



Proof of NP-Completeness for Circuit-Sat

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

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- HW 2, Quiz 5-6, P1, Mid Exam I
- Quiz 6: Job scheduling with deadline, clustering problem,
 Weighted scheduling problem

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- Quiz 8: Modular Exponentiation Problem, Finding Substring 101, Median of Mountain Problem, Missing Number Problem

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- HW 3-4, Quiz 9, P2, Mid Exam II

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- HW 3-4, Quiz 9, P2, Mid Exam II
- Quiz 11: Longest Increasing Subsequence, Maximum Total Weight Independent Set, Shortest Path With Even Number of Vertices, Counting number of inverted 5-tuples

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- HW 4, Quiz 10, P2

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