

# Basic Elements of Complexity Theory

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- Basic complexity classes
- Polynomial reductions
- NP-completeness



- A ***polynomial-time algorithm*** is one whose worst-case running time  $T(n)$ , on an input of size  $n$  bits, is  $O(n^k)$  for some *constant*  $k$

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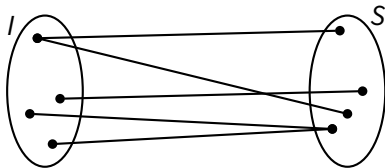
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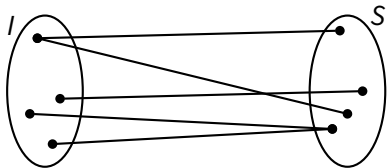
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- A **concrete problem**  $Q$  is one where  $I$  and  $S$  are the set of binary strings  $\{0, 1\}^*$ 
  - ▶ for all practical purposes, instances and solutions can be **encoded** as binary strings (i.e., mapped into  $\{0, 1\}^*$ )
  - ▶ we consider only sensible encodings...





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*Primality Testing*

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- Shortest path in a graph

$$G = (V = \{a, b, c, \dots\}, E = \{(a, c), \dots\}), a, z \longrightarrow a, c, \dots, z$$

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instance                      solution



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- ▶ *input*: a graph  $G$ , a start vertex ( $a$ ), and an end vertex ( $z$ )
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- ▶ *input*: a graph  $G$ , a start vertex ( $a$ ), an end vertex ( $z$ ), and a path length (10)
- ▶ *output*: 1 if there is a path of (at most) the given length

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- An optimization problem is ***not much harder*** than the corresponding decision problem
  - ▶ having a solution to the decision problem does not give an immediate solution to the optimization problem
  - ▶ but we can typically use the decision problem as a subroutine in some kind of (binary) search to solve the corresponding optimization problem

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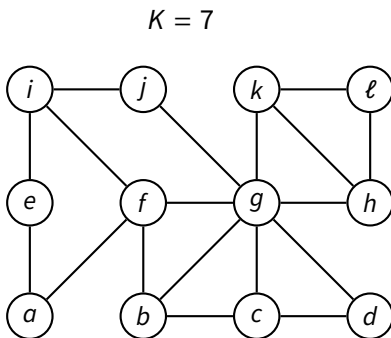
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- ▶ parsing a Java program
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■ **Example:** *Vertex cover* (decision variant)

- ▶ *Input:* A graph  $G = (V, E)$  and a number  $K$
- ▶ *Output:* 1, if there is set  $S$  of at most  $k$  vertices such that for every edge  $e = (u, v) \in E$ ,  $u \in S$  or  $v \in S$  (or both); 0 otherwise

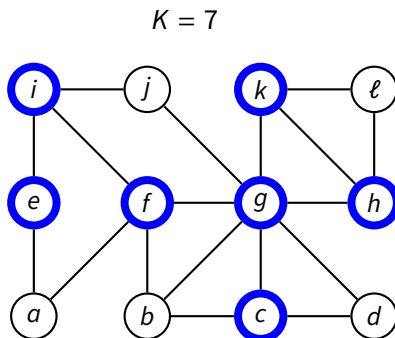
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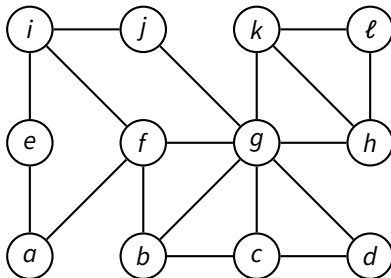
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■ **Example: Vertex cover** (decision variant)

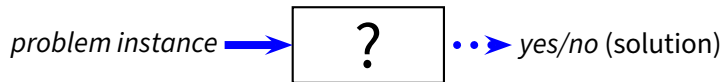
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$K = 6?$



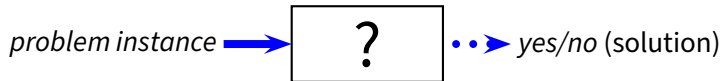
# Polynomial-Time Verification

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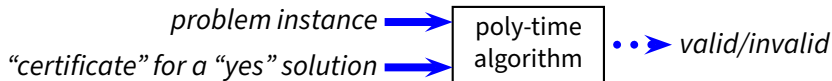


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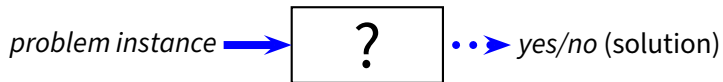
- But we might know how to ***verify a given solution*** in polynomial-time



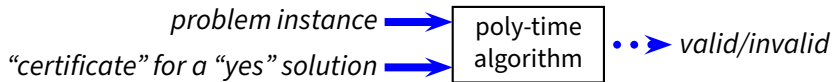


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- But we might know how to ***verify a given solution*** in polynomial-time



- Examples

- ▶ longest path (decision variant)
- ▶ knapsack (decision variant)

# The Complexity Class NP

- A concrete decision problem  $Q$  is **polynomial-time verifiable** if
  - ▶ there is a polynomial-time algorithm  $A$
  - ▶ for each instance  $x \in I$  that has a “yes” solution ( $Q(x) = 1$ )
  - ▶ there is a **certificate**  $y$  of polynomial-size  $|y| = O(|x|^c)$ , for some constant  $c$
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- *polynomial-time solvable*  $\implies$  *polynomial-time verifiable*

$$P \subseteq NP$$



# The Big Open Question

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***Finding a solution to a problem is believed to be inherently more difficult than verifying a given solution (or a proof of a solution)***

***...but nobody has been able to prove that this is the case!***



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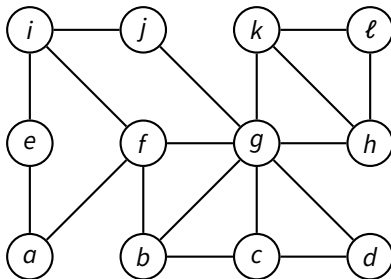
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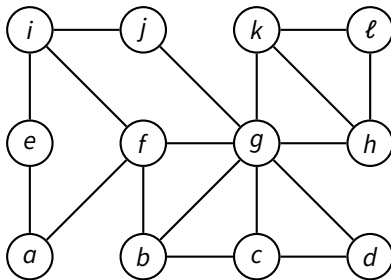


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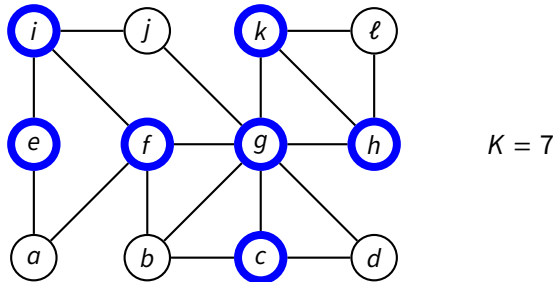
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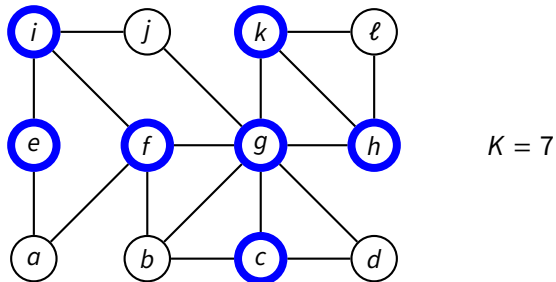


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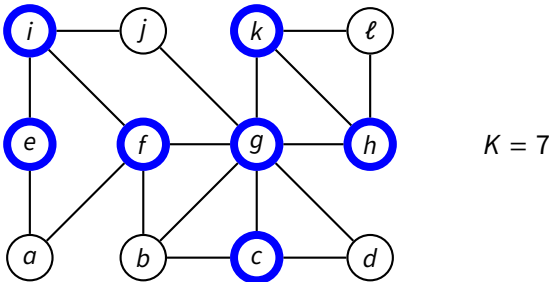
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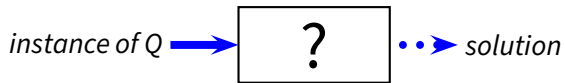
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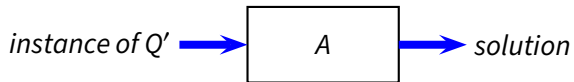
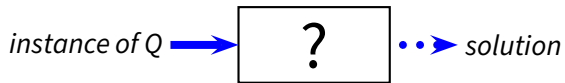


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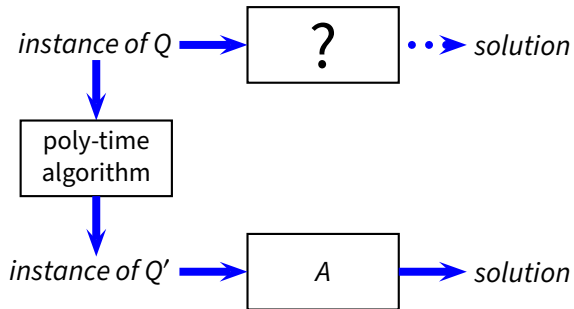
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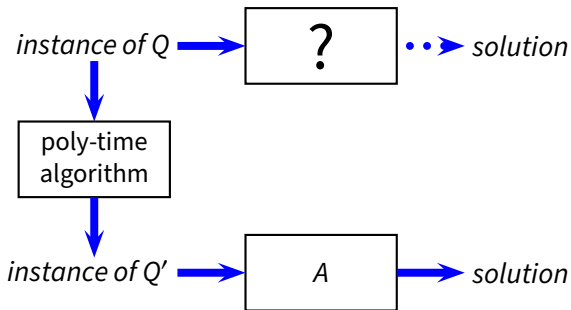
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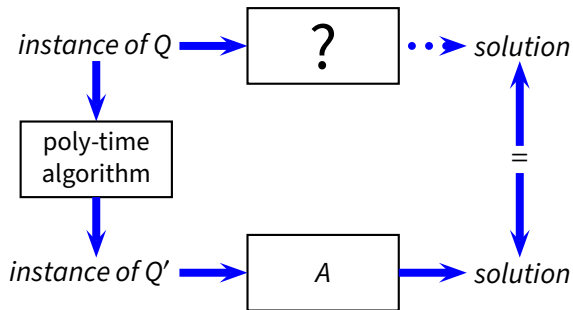


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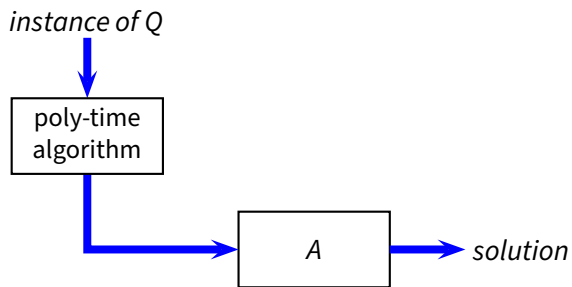
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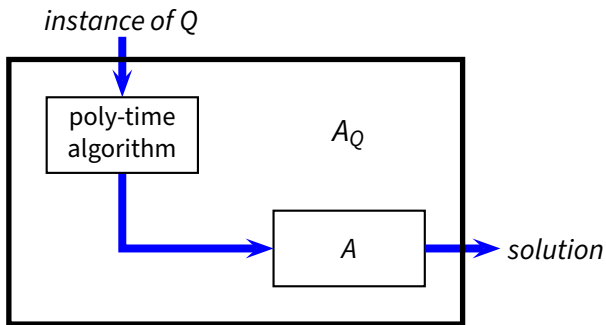


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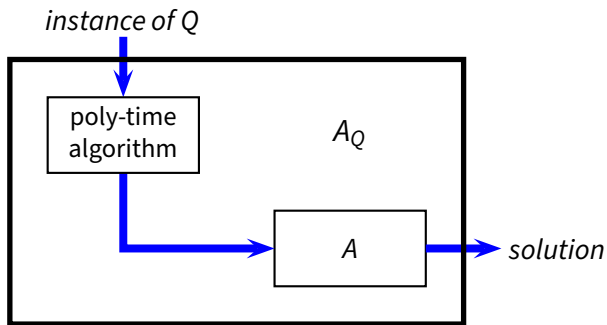




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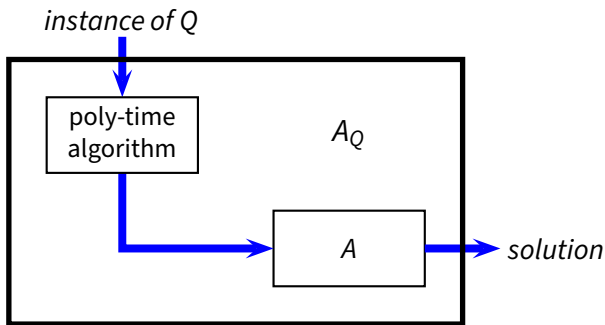


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- ▶ if  $A$  is polynomial-time, then  $A_Q$  is also polynomial time
- ▶ therefore if  $Q' \in P$ , then  $Q \in P$



## ■ 2-CNF-SAT problem

### Input:

- ▶  $f$  is a Boolean formula of  $n$  (Boolean) variables  $x_1, x_2, \dots, x_n$
- ▶  $f$  is in *conjunctive normal form (CNF)*, so  $f = C_1 \wedge C_2 \wedge \dots \wedge C_k$
- ▶ every *clause*  $C_i$  of  $f$  contains exactly *two* literals (a variable or its negation)

### Output: 1 iff $f$ is satisfiable

- ▶ there is an assignment of variables that satisfies  $f$

### Example:

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

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

is equivalent to

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## 2-CNF-SAT to Graph Reachability

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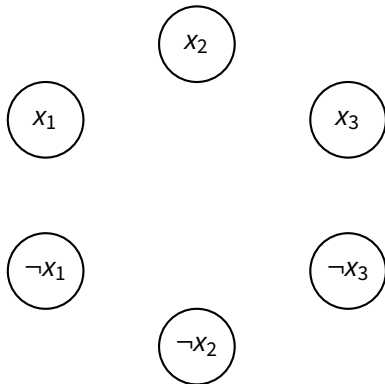
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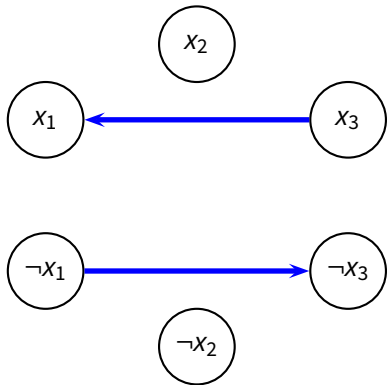


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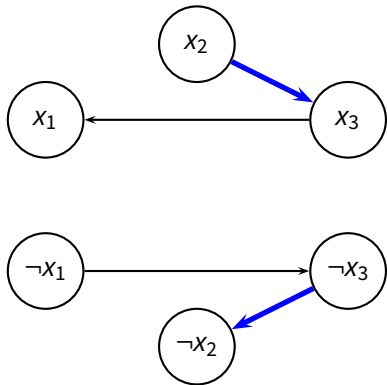


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$$(x_1 \vee \neg x_3) \wedge (\neg x_2 \vee x_3) \wedge (\neg x_1 \vee \neg x_3) \wedge (x_1 \vee x_2)$$

↓↑

$$(\neg x_1 \Rightarrow \neg x_3) \wedge (x_3 \Rightarrow x_1) \wedge (x_2 \Rightarrow x_3) \wedge (\neg x_3 \Rightarrow \neg x_2)$$
$$(x_1 \Rightarrow \neg x_3) \wedge (x_3 \Rightarrow \neg x_1) \wedge (\neg x_1 \Rightarrow x_2) \wedge (\neg x_2 \Rightarrow x_1)$$



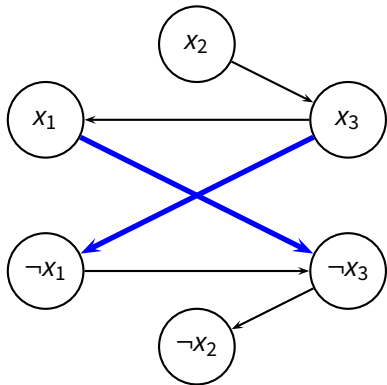
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$\Downarrow \Uparrow$

$$(\neg x_1 \Rightarrow \neg x_3) \wedge (x_3 \Rightarrow x_1) \wedge (x_2 \Rightarrow x_3) \wedge (\neg x_3 \Rightarrow \neg x_2) \wedge$$

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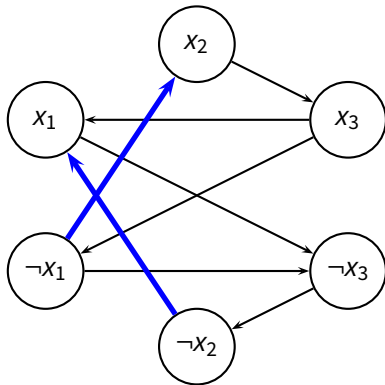


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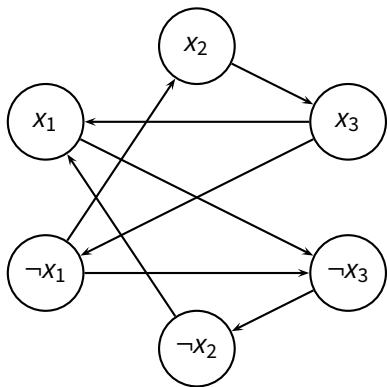


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*not satisfiable*  
if and only if  
 $x_i \rightsquigarrow \neg x_i \rightsquigarrow x_i$   
for some  $i$

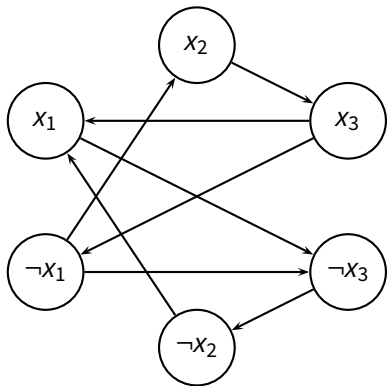


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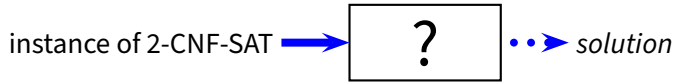
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**depth-first search**

# Reduction of 2-CNF-SAT

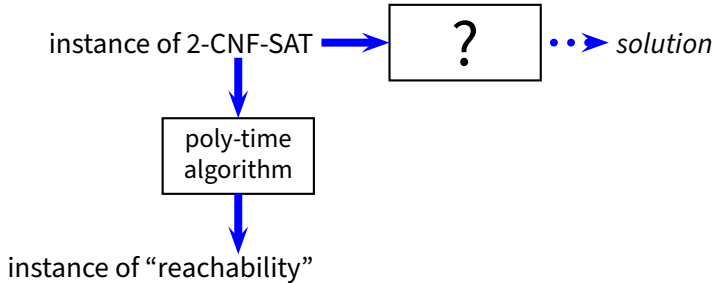
# Reduction of 2-CNF-SAT

- 2-CNF-SAT  $\in P$



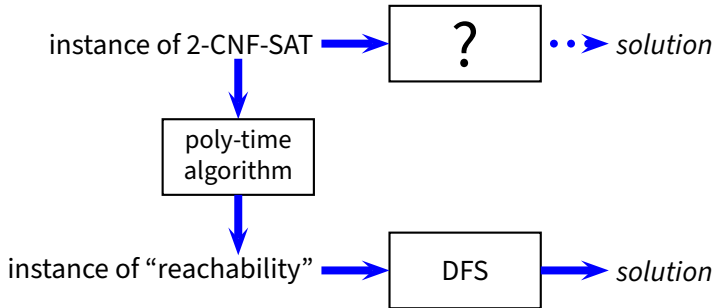
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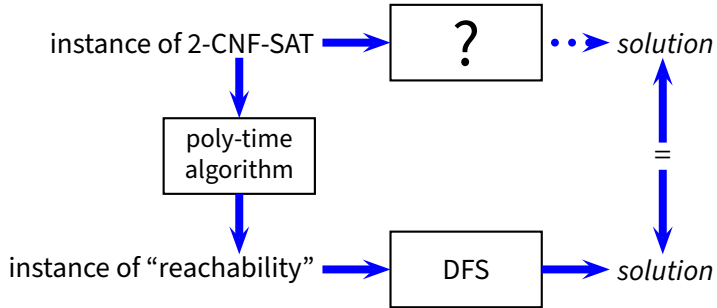
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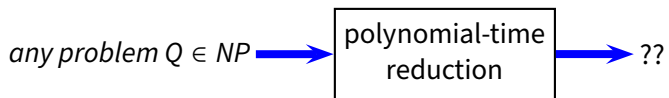
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- If  $Q'$  is NP-hard and *polynomial-time solvable*, then  $P = NP$ 
  - ▶ most researchers believe that there is no such  $Q'$

# The First NP-Complete Problem

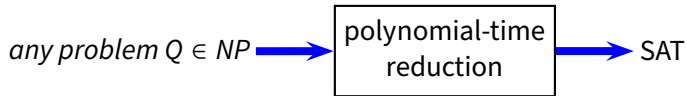
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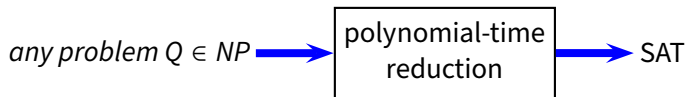


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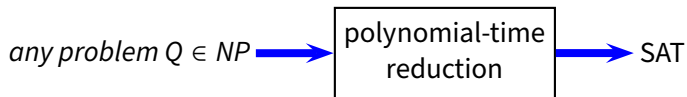
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  - ▶ e.g., SAT is polynomial-time reducible to Vertex Cover (and VC is in NP)
  - ▶ therefore, Vertex Cover is also NP-complete
- If a problem is NP-Hard (or NP-Complete) you should not feel so bad for not finding an efficient solution algorithm