Basic Elements of Complexity Theory

Antonio Carzaniga

Faculty of Informatics
Università della Svizzera italiana

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Outline

- Basic complexity classes
- Polynomial reductions
- NP-completeness

Polynomial Time

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- 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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polynomial ≡ ***good***

super-polynomial ≡ ***bad***

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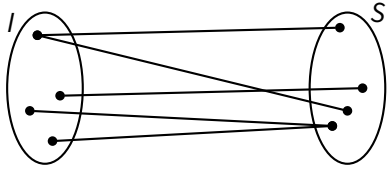

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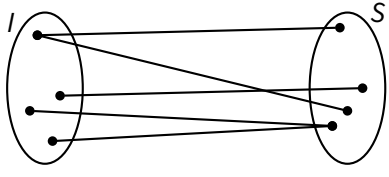

- A ***concrete problem*** Q is one where I and S are the set of binary strings $\{0, 1\}^*$
  - for all practical purposes, instances and solutions can be ***encoded*** as binary strings (i.e., mapped into $\{0, 1\}^*$)
  - we consider only sensible encodings…

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Primality Testing

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

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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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- A concrete decision problem Q is ***polynomial-time solvable*** if there is a polynomial-time algorithm A that solves it

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  - parsing a Java program
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  - *Input:* A graph $G = (V, E)$ and a number K
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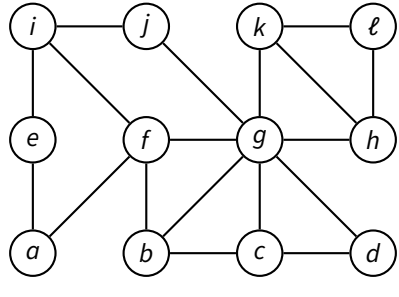

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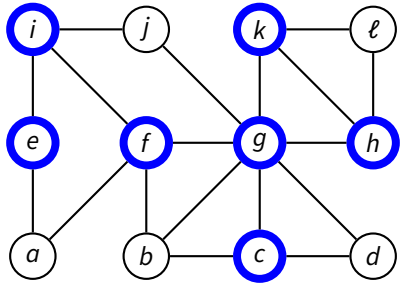

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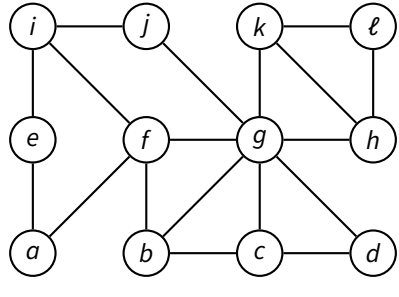

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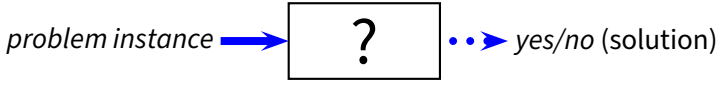

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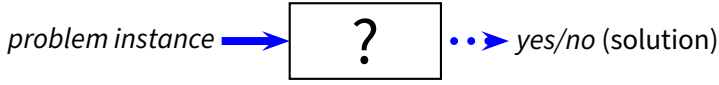

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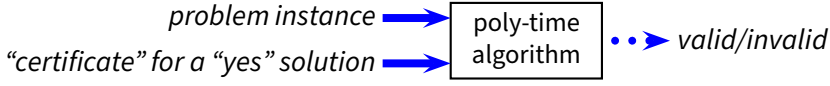

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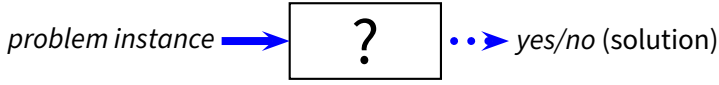

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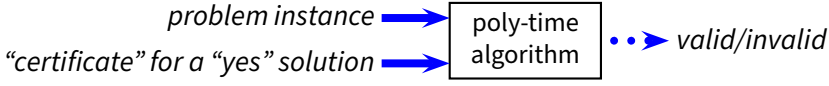

- Examples
  - longest path (decision variant)
  - knapsack (decision variant)

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$$\mathrm{P} \subseteq \mathrm{NP}$$

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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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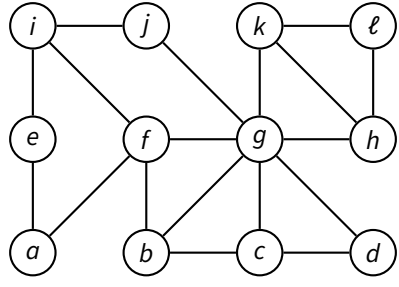

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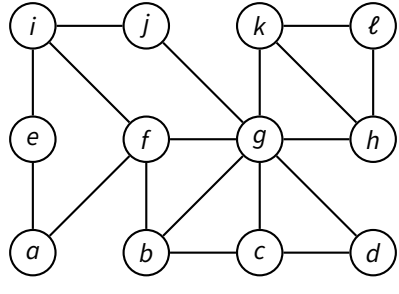

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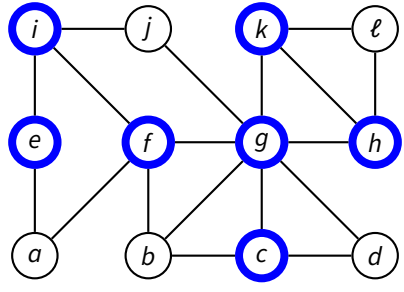

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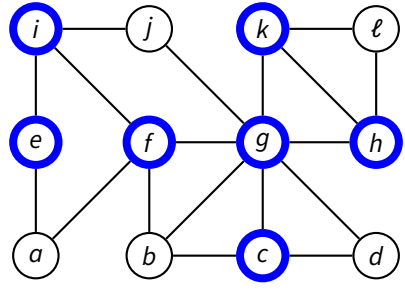

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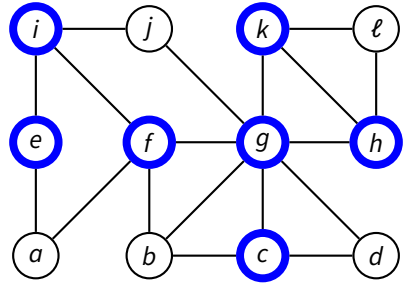

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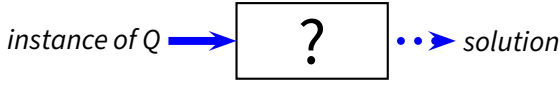

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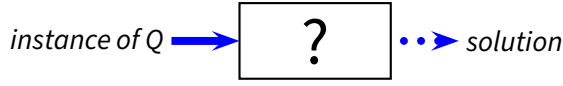

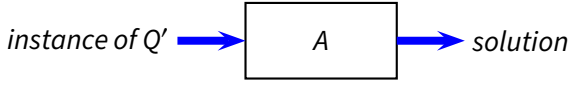

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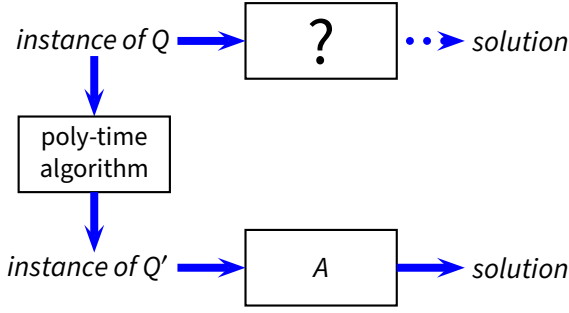

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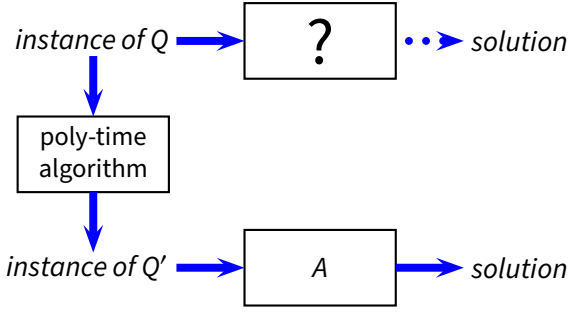

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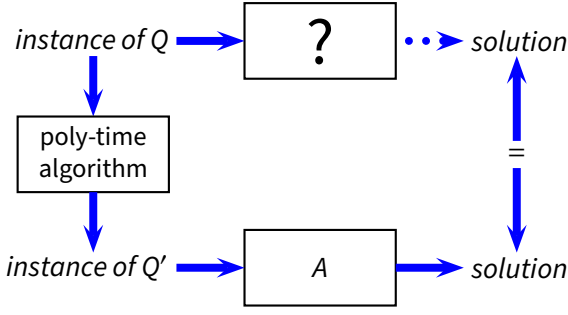

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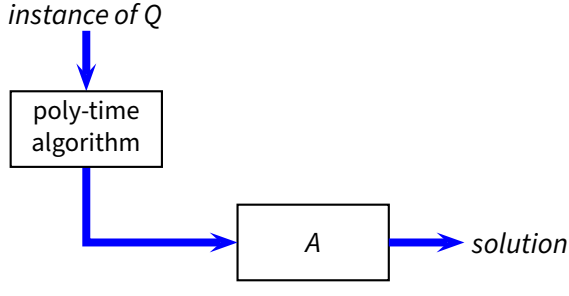

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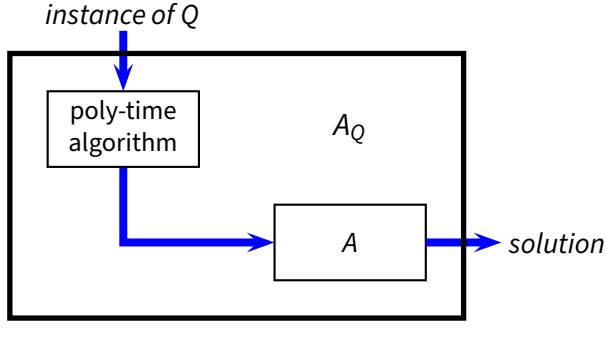

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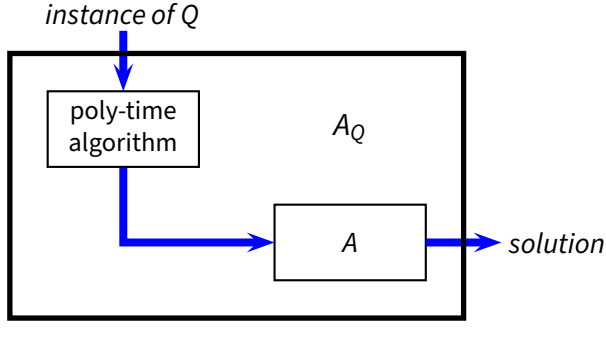

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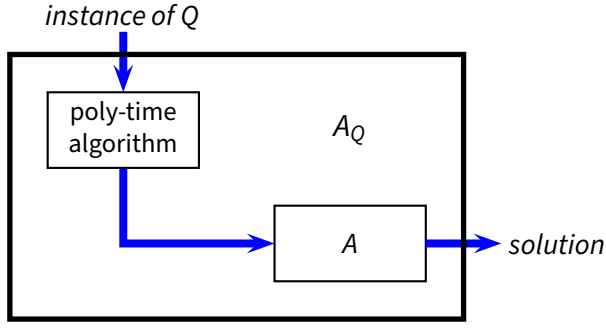

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  - therefore if $Q' \in P$, then $Q \in P$

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2-CNF-SAT problem

Input:

- f is a Boolean formula of n (Boolean) variables $x_1, x_2, \ldots, x_n$
- f is in *conjunctive normal form (CNF)*, so $f = C_1 \wedge C_2 \wedge \cdots \wedge C_k$
- 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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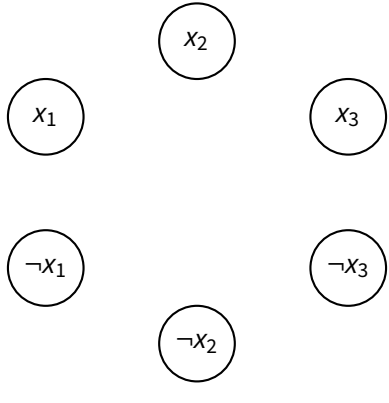
$$(x_1 \Rightarrow \neg x_3) \wedge (x_3 \Rightarrow \neg x_1) \wedge (\neg x_1 \Rightarrow x_2) \wedge (\neg x_2 \Rightarrow x_1)$$



2-CNF-SAT to Graph Reachability

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

$$\Downarrow\Uparrow$$

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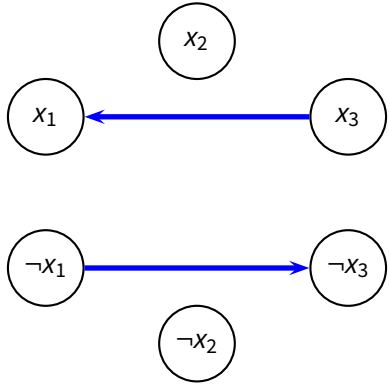

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$$(\neg x_1 \Rightarrow \neg x_3) \wedge (x_3 \Rightarrow x_1) \wedge (x_2 \Rightarrow x_3) \wedge (\neg x_3 \Rightarrow \neg x_2) \wedge$$
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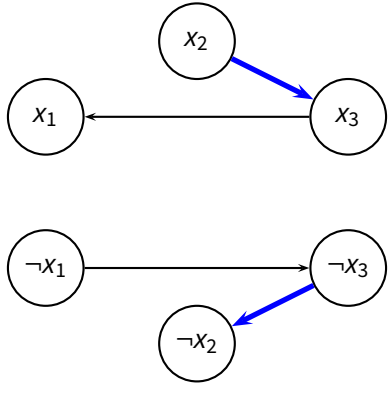

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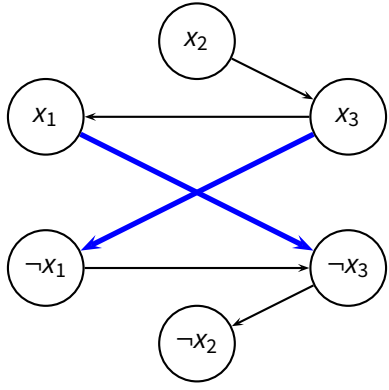
$$(x_1 \vee \neg x_3) \wedge (\neg x_2 \vee x_3) \wedge \boxed{(\neg x_1 \vee \neg x_3)} \wedge (x_1 \vee x_2)$$

$$\Downarrow\Uparrow$$

$$(\neg x_1 \Rightarrow \neg x_3) \wedge (x_3 \Rightarrow x_1) \wedge (x_2 \Rightarrow x_3) \wedge (\neg x_3 \Rightarrow \neg x_2) \wedge$$
$$\boxed{(x_1 \Rightarrow \neg x_3) \wedge (x_3 \Rightarrow \neg x_1)} \wedge (\neg x_1 \Rightarrow x_2) \wedge (\neg x_2 \Rightarrow x_1)$$



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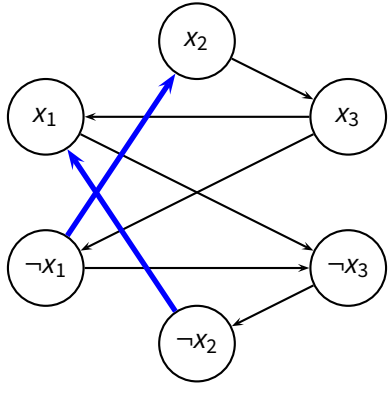

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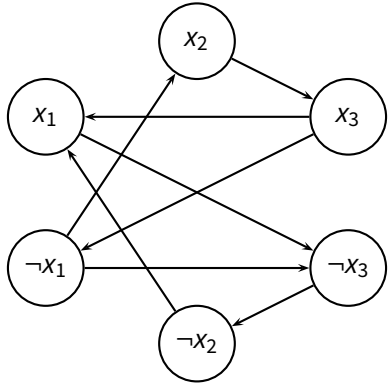

not satisfiable
if and only if
$x_i \rightsquigarrow \neg x_i \rightsquigarrow x_i$
for some i

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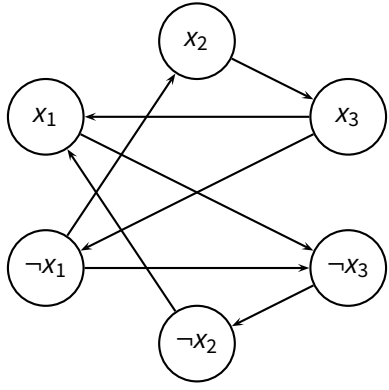

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depth-first search

Reduction of 2-CNF-SAT

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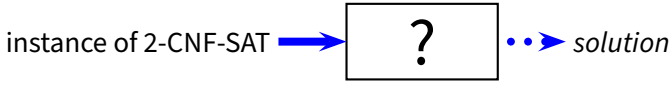
- 2-CNF-SAT $\in P$



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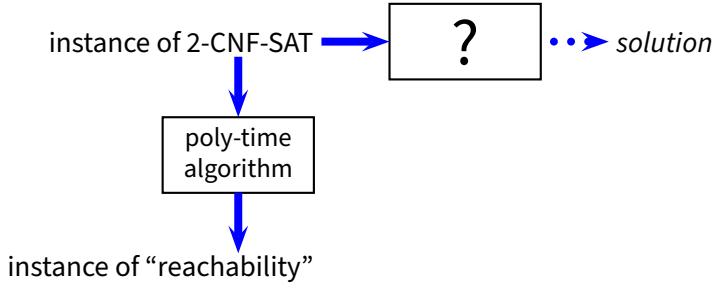

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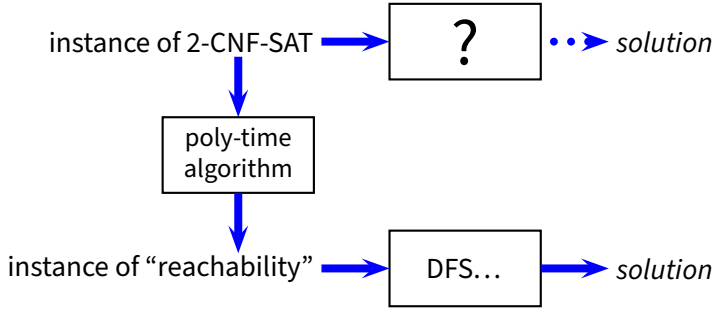

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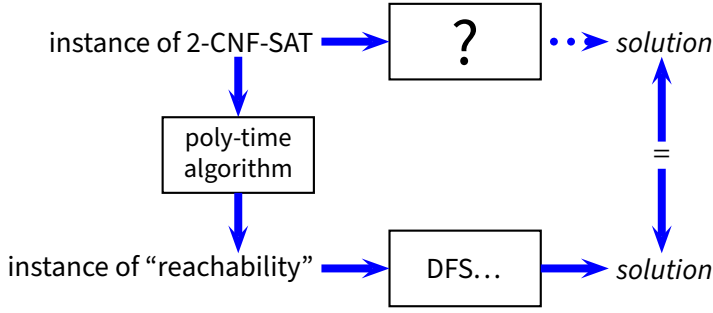

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- If Q' is NP-hard and *polynomial-time reducible* to Q'', then Q'' is NP-hard
- If Q' is NP-hard and *polynomial-time solvable*, then P $=$ NP
  - most researchers believe that there is no such Q'

The First NP-Complete Problem

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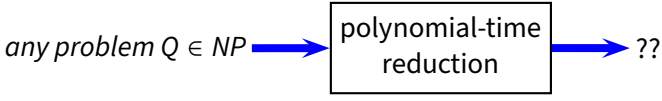
- Is there any NP-complete problem?



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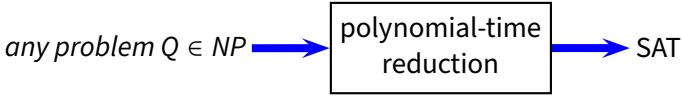

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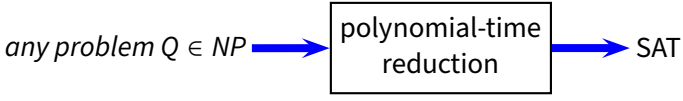

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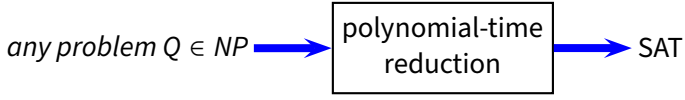

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- If a problem is NP-Hard (or NP-Complete) you should not feel so bad for not finding an efficient solution algorithm