# **Basic Elements of Complexity Theory**

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### Outline

- Basic complexity classes
- Polynomial reductions
- NP-completeness

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

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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...

A *decision problem* Q is one where the set of solutions is  $S = \{0, 1\}$ 

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 Example:

• • •

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. . .

$$1 \longrightarrow 0$$

$$10 \longrightarrow 1$$

$$11 \longrightarrow 1$$

$$100 \longrightarrow 0$$

$$101 \longrightarrow 1$$

$$110 \longrightarrow 0$$

$$111 \longrightarrow 1$$

$$1000 \longrightarrow 0$$

$$1001 \longrightarrow 0$$

$$1010 \longrightarrow 0$$

$$1011 \longrightarrow 1$$

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**Example:** shortest path in a graph

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

- ▶ *input:* a graph *G*, a start vertex (*a*), and an end vertex (*z*)
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Shortest path as a decision problem

$$G = (V = \{a, b, c, \ldots\}, E = \{(a, c), \ldots\}), a, z, 10 \longrightarrow 1$$

- ▶ *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

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

The *complexity class P* is the set of all concrete decision problems that are *polynomial-time solvable* 

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  - Neeraj Kayal and Nitin Saxena were Bachelor students!

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- parsing a Java program

#### **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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$$K = 6?$$



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*problem instance* poly-time *solution or "certificate" valid/invalid* 

Examples

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

■ A concrete decision problem *Q* is *polynomial-time verifiable* if there is a polynomial-time algorithm *A* and a constant *c* such that, for each instance  $x \in I$ , there is a *certificate y* of polynomial-size  $|y| = O(|x|^c)$  such that A(x, y) = 1

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• polynomial-time solvable  $\implies$  polynomial-time verifiable

 $\mathsf{P}\subseteq\mathsf{NP}$
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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

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Examples

•  $\neg x \land (\neg y \lor \neg z) \land \neg z \land (x \lor y)$ 

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Examples

$$\neg x \land (\neg y \lor \neg z) \land \neg z \land (x \lor y) \longrightarrow 1 \quad (x = 0, y = 1, z = 0)$$

$$(x \lor y \lor z) \land (x \lor \neg y) \land (y \lor \neg z) \land (z \lor \neg x) \land (\neg x \lor \neg y \lor \neg z) \longrightarrow 0$$

■ SAT  $\in$  NP?

yes: given an assignment that satisfies the formula, it is easy (poly-time) to verify that the formula is satisfiable

#### ■ SAT $\in$ P?

we don't know

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instance of 
$$Q' \longrightarrow A \longrightarrow$$
 solution

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Solution by polynomial-time reductions to a solvable problem



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Solution by polynomial-time reductions to a solvable problem



- ► if *A* is polynomial-time, then of *A*<sub>Q</sub> is also polynomial time
- therefore if  $Q' \in P$ , then  $Q \in P$

# Example: 2-CNF-SAT

## Example: 2-CNF-SAT

#### 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  $f = C_1 \land C_2 \land \cdots \land C_k$
- every clause C<sub>i</sub> 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:

$$(x_1 \lor \neg x_3) \land (\neg x_2 \lor x_3) \land (\neg x_1 \lor \neg x_3) \land (x_1 \lor x_2)$$

## 2-CNF-SAT to Implicative Form

#### 2-CNF-SAT to Implicative Form

Consider each clause *C<sub>i</sub>* 

$$(a \lor b) \equiv (\neg a \Rightarrow b) \equiv (\neg b \Rightarrow a)$$

so we can rewrite a 2-CNF-SAT formula *f* into another formula in *implicative normal form* 

#### Example:

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

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so we can rewrite a 2-CNF-SAT formula *f* into another formula in *implicative normal form* 

Example:

$$(x_1 \lor \neg x_3) \land (\neg x_2 \lor x_3)$$

is equivalent to

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

#### 2-CNF-SAT to Graph Reachability

 $(x_1 \lor \neg x_3) \land (\neg x_2 \lor x_3) \land (\neg x_1 \lor \neg x_3) \land (x_1 \lor x_2)$ 

## 2-CNF-SAT to Graph Reachability

$$(x_{1} \lor \neg x_{3}) \land (\neg x_{2} \lor x_{3}) \land (\neg x_{1} \lor \neg x_{3}) \land (x_{1} \lor x_{2})$$

$$\Downarrow \uparrow$$

$$(\neg x_{1} \Rightarrow \neg x_{3}) \land (x_{3} \Rightarrow x_{1}) \land (x_{2} \Rightarrow x_{3}) \land (\neg x_{3} \Rightarrow \neg x_{2}) \land$$

$$(x_{1} \Rightarrow \neg x_{3}) \land (x_{3} \Rightarrow \neg x_{1}) \land (\neg x_{1} \Rightarrow x_{2}) \land (\neg x_{2} \Rightarrow x_{1})$$






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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
  - ► i.e., most researchers believe that there is no such *Q*′

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- *Circuit satisfiability (SAT)* was the first problem that was proved NP-hard and, since SAT ∈ NP, also NP-complete
- Many other problems were then proved NP-complete through polynomial reductions
  - e.g., SAT is polynomial-time reducible to the *longest path* problem
  - therefore, the *longest path* problem is also NP-complete