NP Completeness

Tao Hou

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- In this topic, we are turning our attention to *problems* themselves
- Previously, for different problems we consider, we were trying to show how we can design efficient algorithms for solving them
- Now, we are going to show for certain problems, how we *cannot* design efficient algorithms

- "Efficient" algorithms: *polynomial-time* algorithms, i.e., ones with worst-case time complexity being *O*(*n*^{*k*}) for some constant *k*
- You might wonder whether all problems can be solved in polynomial time the answer is *no*:

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 - There are also problems that can be solved in finite steps (e.g., in exponential time), but not in polynomial time
- Generally, we think of problems that are solvable by polynomial-time algorithms as being *tractable*, or "easy", and problems that require superpolynomial time as being *intractable*, or "hard"

NP-Complete problems

- The subject of this chapter, however, is an interesting class of problems called the "NP-complete" problems, whose status is unknown:
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 - No polynomial-time algorithm have ever been discovered for an NP-complete problem, nor has anyone been able to prove that no polynomial-time algorithm can exist for any one of them
- This so-called $P \neq NP$ question has been one of the deepest, most perplexing open research problems in theoretical computer science since it was first posed in 1971
- Notice that NP-complete problems are still in general considered "hard" problems as most people believe you cannot find polynomial time algorithms for them

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- Whether a problem is hard or easy can be very elusive
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Ex.: Shortest vs. longest simple paths

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Euler tour vs. Hamiltonian cycle:

- An *Euler tour* of an undirected graph is a cycle that traverses each edge of the graph exactly once (it is allowed to visit vertices more than once)
- A *Hamiltonian cycle* of an undirected graph is a simple cycle that traverses each vertex exactly once
- We can determine whether a graph has an Euler tour in only O(|E|) time
- Determining whether an undirected graph has a Hamiltonian cycle is NP-complete

P, NP, NPC

Throughout this topic, we shall consider three classes of problems:

- P: Problems that are solvable in polynomial time
- NP: Problems that are "verifiable" in polynomial time
 - We have $P \subseteq NP$
- NPC: NP-complete problems, those problems that are as hard as *any* problems in the class NP (you can also say is the hardest problem in NP)

Why do we study it?

Understanding NP-completeness theory is critical to algorithm designers:

- If you can find that a problem is NP-complete, you would then do better to spend your time finding an approximation algorithm or solving a tractable special case
- Many natural and interesting problems that on the surface seem no harder than sorting, graph searching, or network flow are in fact NP-complete

Why do we care polynomial time?

We focus on polynomial time algorithms for certain reasons:

- Although a polynomial running time of $\Theta(n^{100})$ is completely disastrous in practice, the polynomial-time algorithms we actually encountered *typically require much less time*
- Experience has shown that once the first polynomial-time algorithm for a problem has been discovered, more efficient algorithms often follow

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- Most importantly, the class of polynomial-time solvable problems has nice *closure* properties, since polynomials are closed under addition, multiplication, and composition
 - E.g., if we apply a polynomial-time algorithm for polynomially many times, we still have a polynomial-time algorithm

Decision Problems vs. Optimization Problems

- Many problems of interest are optimization problems: each legal solution has an associated value, and we wish to find a legal solution with the best value
- (Example) SHORTEST-PATH-OPTMZ: given an undirected graph *G* and vertices *u* and *v*, we wish to find a path from *u* to *v* with the fewest edges

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- However, the theory of NP-Completeness focuses only on *decision* problems: given an input, a program should produce "yes" or "no"
- (Example) SHORTEST-PATH: given an undirected graph G, two vertices u and v, and an integer k, is there a path from u to v with ≤ k edges?

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- The decision problem is typically "easier" than the optimization problem: we can *simply invoke the algorithm for the optimization problem* and have an algorithms for the decision problem
 - ► E.g., given an instance (G, u, v, k) of SHORTEST-PATH, we can find the length ℓ of the shortest path of (G, u, v) using an algorithm for the optimization problem, and then check if $k \ge \ell$

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- Implication: if we show that a decision problem is "hard", we also show that its related optimization problem is hard
 - If we can find a polynomial-time algorithm for the optimization problem, we can definitely find a polynomial-time algorithm for the decision problem
 - Equivalently, if we *cannot* find a polynomial-time algorithm for the decision problem, we *also cannot* find a polynomial-time algorithm for the optimization problem
- Thus, though NP-completeness theory restricts attention to decision problems, it often has implications for optimization problems

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- An instance for the problem is a triple (G, u, v)
- A solution is a sequence of vertices in *G* encoding the shortest path from *u* to *v*, with perhaps the empty sequence denoting that no path exists
- Notice: a given problem instance may be associated with more than one solution

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- An instance for the problem is a triple (G, u, v, k)
- Return ...

Polynomial-time solvable problem

A problem is said to be *polynomial-time solvable* if there exist an algorithm such that:

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Complexity class **P**

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

Consider two problems:

Hamiltonian cycle problem (HAM-CYCLE)

Given an undirected graph G = (V, E), does G contain a *Hamiltonian* cycle, i.e., a simple cycle containing each vertex in V?

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Left dodecahedron graph (taken from [K&T] slides) has a Hamiltonian cycle while the right bipartite graph (taken from Wikipedia) does not have one

Satisfiability problem (SAT)

Given a boolean formula with *n* boolean variables x_1, \ldots, x_n , is there an assignment (of true/false values) to x_1, \ldots, x_n making the whole formula true?

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A boolean formula is made up of the boolean variables x_1, \ldots, x_n , operators including \land (AND), \lor (OR), \neg (NOT), \rightarrow (implication), \leftrightarrow (if and only if), and composite (combinations) of them possibly with parenthesis. E.g.,:

$$((x_1 \rightarrow x_2) \lor \neg ((\neg x_1 \leftrightarrow x_3) \lor x_4)) \land \neg x_2.$$

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- Let's consider an easier version for such a problem by solving it "*indirectly*" (HAM-CYCLE as an example)
- Suppose that someone tells you a given graph G is Hamiltonian and offers to prove it by giving you a sequence of vertices which this person claims to be a Hamiltonian cycle
- It would then be easy to verify this: simply verify whether the sequence contain all the vertices and whether each two consecutive vertices form an edge

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- It would then be easy to verify this: simply verify whether the sequence contain all the vertices and whether each two consecutive vertices form an edge
- The "verification" process can definitely be done in polynomial time in terms of the size of G
- Formally speaking, the algorithm used for the "verification" is termed as a verification algorithm, and the sequence of vertices you used for verification is called a certificate

Verification algorithm

For a problem Q, a *verification algorithm* (or simply *verifier*), denoted C(x, y), is an algorithm satisfying:

- C(x, y) returns "yer"/"no"
- input *x* is an instance of *Q*
- input $y \in \{0, 1\}^*$ (a binary string) is a *certificate*
- *x* is an "yes"-instance of $Q \Leftrightarrow$ there exist a certificate *y* making C(x, y) return "yes"

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Notice:

- For a "yes"-instance x, it's okay that C(x, y) returns "no" given some certificate y
- As long as *there is one certificate* y making C(x, y) return "yes", it is fine
- But if x is a "no"-instance, then C(x, y) should return "no" for all certificates

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(Example) A verification algorithm C(x, y) for SAT:

- Notice that here x is a boolean formula with boolean variables x_1, \ldots, x_n
- Given *y* as a bit string, decode *y* into a T/F assignment to *x*₁,...,*x*_n
 - The simplest thing to do is to take the first *n* bits in *y* and take them as the T/F assignment to x_1, \ldots, x_n
 - If y has less than n bits, return "no"
- Then use the T/F assignment of *x*₁,...,*x*_n from the certificate *y* to verify whether the boolean formula evaluate to true; If true, return "yes"; otherwise, return "no"

(Example) A verification algorithm C(x, y) for HAM-CYCLE:

- Given *y* as a bit string, decode *y* into a sequence of *n* vertices where *n* is the number of vertices in the input graph *G* := *x*
 - If y cannot be decoded into n vertices, return "no"
 - Ignore the remaining bits
- Then verify whether the *n* vertices form a valid Hamiltonian cycle

The Complexity Class **NP**

The complexity class **NP** is a set of decision problems such that a problem $Q \in NP$ if and only if there is a verification algorithm C(x, y) for Q running in polynomial time in term of the size of the Q's instance x

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Example: SAT, HAM-CYCLE $\in NP$

- There is one complexity class **NPC** which is yet to be defined
- Roughly saying, NPC is the set of "hardest" problems in NP
- But to do that, we need a way to compare the "difficulty" of problems
- For that, we introduce the notion of "*reducibility*", which is probably the single most important notion in the topic

Polynomial reduction

A decision problem Q_1 is said to **polynomially reduces** to (or simply **reduces** to) another decision problem Q_2 if there is a polynomial time $(O(|x_1|^k))$ algorithm \mathcal{F} taking an instance x_1 for Q_1 and computing an instance x_2 for Q_2 such that:

• x_1 is a "yes"-instance for Q_1 iff x_2 is a "yes"-instance for Q_2

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■ *x*₁ is a "yes"-instance for *Q*₁ iff *x*₂ is a "yes"-instance for *Q*₂

(Implications) If Q_1 polynomially reduces to Q_2 :

- *Q*¹ is "no harder" than *Q*² in the sense that
- Any polynomial-time algorithm \mathcal{A} for Q_2 can be used to solve Q_1 in polynomial-time, by doing:
 - Given an instance x_1 of Q_1 , use \mathcal{F} to compute an instance x_2 of Q_2
 - ▶ Then use *A* to decide whether *x*² is a "yes"-instance for *Q*²
 - ▶ Return "yes" if *A* returns "yes", and return "no" if *A* returns "no",
- So if Q_2 can be solved in polynomial time, then Q_1 also can

So whether a problem Q_1 reduces to another problem Q_2 completely relies on whether you can find a "reduction algorithm" \mathcal{F}

Example:

- *Q*₁: Given a string *x*₁, does *x*₁ contain the letter "a"?
- Q₂: Given a string x₂, does x₂ contain the letter "b"?

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- Q_1 : Given a string x_1 , does x_1 contain the letter "a"?
- *Q*₂: Given a string *x*₂, does *x*₂ contain the letter "b"?
- *Q*₁ reduces to *Q*₂ with the reduction algorithm: given an instance *x*₁ of *Q*₂, replace each occurrence of "a" in *x*₁ with "b" and each occurrence of "b" in *x*₁ with "a" and produce an instance *x*₂ of *Q*₂

The Complexity Class **NPC**

- A problem $Q \in NP$ is called *NP-Complete* if *all* problems in *NP* reduce to *Q*
- The complexity class *NPC* ⊆ *NP* is the set of all NP-Complete problems

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proof:

- Let Q be a problem in P
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Proposition

 $P \subseteq NP$

proof:

- Let Q be a problem in P
- Then there is an algorithm *A* solving *Q* in polynomial time
- To show that $Q \in NP$, we only need to design a polynomial-time verifier C(x, y) for Q
- To do this, in *C*, we only need to invoke *A* on *x*, and return the answer of *A* (certificate *y* is completely ignored)

Is P = NP?

- The biggest question in CS: Is **P** = **NP**?
- This question was raised in the 1970's, and there is not an answer till this day
- The common belief is that **P** ! = **NP**
- The key lies in those NP-Complete problems, because if you can find an algorithm for a single NP-Complete problem, then all problems in NP, including all the other NP-Complete problems, can be solved in polynomial time (so P = NP)
- However, there are tons of NP-Complete problems out there, and *no one* has ever found a polynomial-time algorithm *for any of them* till this day

Is *P* = *NP***?**

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proof:

- Let *Q* be an NP-Complete problem and let *A* be a polynomial-time algorithm for *Q*
- Let Q′ be an arbitrary problem in **NP**
- Since Q' reduces to Q, we have a polynomial-time reduction algorithm \mathcal{F} from Q' to Q
- Then we can have a polynomial-time algorithm for Q': given an instance x' of Q', compute an instance x of Q using the algorithm \mathcal{F} , then you just return whatever \mathcal{A} returns on x

- *P*: Decision problems for which there is a polynomial-time algorithm
- **NP**: Decision problems for which there is a polynomial-time verifier

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Proposition *NP* ⊂ *EXP*

- P: Decision problems for which there is a polynomial-time algorithm
- **NP**: Decision problems for which there is a polynomial-time verifier
- **EXP**: Decision problems for which there is an **exponential-time** algorithm

Proposition

 $NP \subseteq EXP$

proof:

- Let Q be a problem in **NP** with a verifier C(x, y)
- Given an instance *x* of *Q*, we enumerate all possible certificates for *x* and see whether there is one certificate *y* making *C*(*x*, *y*) return "yes"
- If there is such a certificate, we return "yes" for *x*, otherwise, we return "no"
- Notice that we only need to enumerate certificates of up to a size m = poly(|x|), because any certificate beyond size m will not be helpful to us (see the "decoding" process for certificates)
- Total time would be $2^{poly(|x|)}f(|x|)$, where f(|x|) is the time complexity of C(x, y)

The million-dollar question



(Figure from [K&T] slides)

Some remarks

- The term "NP" does not stand for "non-polynomial time" (we don't know whether these problems can or cannot be solved in polynomial time)
- It stands for "non-deterministic polynomial-time solvable" (the verification algorithm we write is indeed a "non-deterministic algorithm")
- As mentioned, if you have shown that a problem is NP-complete, then you should do something else rather trying to find a polynomial-time algorithm for it
- But people on this planet *haven't proved* that an NP-Complete problem does not have a polynomial-time algorithm
- Only that people believe so because there are tons of NP-Complete problems and no one has ever found a polynomial-time algorithm for *any* of them

How to show that a problem is NP-Complete?

How to show that a problem *Q* is NP-Complete?

- 1. Show that $Q \in NP$ by providing a polynomial-time verifier
- 2. Show that Q is "*NP-hard*", i.e., all problems in *NP* reduce to Q

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- 2. Show that Q is "*NP-hard*", i.e., all problems in *NP* reduce to Q
- To do that, you need a "first" NP-hard problem *Q**
- Then you only need to show that *Q*^{*} reduces to *Q*
 - Due to the *transitivity* of reducibilities (Q_1 reduces to Q_2 , Q_2 reduces to $Q_3 \Rightarrow Q_1$ reduces to Q_3)

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- 1. Show that $Q \in \mathbf{NP}$ by providing a polynomial-time verifier
- 2. Show that Q is "*NP-hard*", i.e., all problems in *NP* reduce to Q
- To do that, you need a "first" NP-hard problem *Q**
- Then you only need to show that *Q*^{*} reduces to *Q*
 - Due to the *transitivity* of reducibilities (Q_1 reduces to Q_2 , Q_2 reduces to $Q_3 \Rightarrow Q_1$ reduces to Q_3)
- So the general strategy for showing a problem Q to be NP-hard is to first find a problem Q* known to be NP-hard, and then reduce Q* to Q