

COMP20007 Design of Algorithms

Complexity Theory

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Lecture 21

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- Complexity theory asks a different question: "What is the inherent difficulty of the **problem**?"
- It does however also uses asymptotic notation, although usually more concerned with lower bounds (Ω notation).
- Tighter ("larger") lower bounds give us guarantees on best possible algorithms.

Complexity Theory - Examples

Comparison Sorting (worst case)

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↓
if we gonna to sort array of n numbers,
we need to look at n elements

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- A trivial lower bound: $\Omega(n)$.
- A less trivial lower bound: $\Omega(\log n!) \approx \Omega(n \log n)$
 - Can be found by using a technique called Decision Trees.

$n!$ possible permutations



BINARY tree

with $n!$ leaves

height = $\log(\# \text{ leaves})$.

↑
minimum comparison.

$$h = \log(n!) = \Omega(n \log n)$$

any possible algorithm
based on comparison
sorting has to perform
at least $n \log n$

(cannot go better
than $n \log n$)
for worst case

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Matrix Multiplication *square $n \times n$*

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STRASEN'S MATRIX ALGORITHMS $O(n^{2.18})$

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This lecture: discussion about “hardness” of **problems**.

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- Optimisation problems can be framed as a sequence of decision problems:
 - Knapsack: “Is there a set of items of values at least i and weight at most j ?”

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 - “Given a graph G and a sequence of nodes $\{v_1, v_2, \dots, v_n\}$, verify if there is a path that follows that sequence.

↙ True \rightarrow n is not prime

False \rightarrow ??

Verification Problems

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- ← ▪ “Given a graph G and a sequence of nodes $\{v_1, v_2, \dots, v_n\}$, verify if there is a ~~path~~ that follows that sequence.

start from v_1
keep check whether
next node is
connected

linear

circuit

Now we can define what is P and what is NP .

P and NP

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eg. matrix multiplication

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- We can turn a verification problem into a decision problem:
 - will be able generate all candidates in parallel*
↑
 - 1) A non-deterministic “machine” generates a candidate.
 - 2) The verification algorithm verifies the solution.
 - 3) Repeat until verified.

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That's where the N in NP comes from. \Rightarrow

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any problem that can be decided in
polynomial time

can also be verified in polynomial time

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$$P \overset{?}{=} NP$$

A Million Dollar Question: Is $P = NP$?

This is one of the seven “millennium problems”: The Clay Institute’s seven most important unsolved mathematical problems.



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NP complete *Travelling salesman problem*

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- It's a daunting task to find and prove bounds for every new problem.
- **Reductions** allow us to ease this by, roughly, framing a problem as equivalent to another one we know the class.
- For instance, the Hamiltonian Circuit (HAM) problem can be reduced to the decision version of TSP.
- The **reduction function** is polynomial. Therefore, since HAM is in NP , the decision version of TSP is also in NP .

From HAM to TSP

- Suppose we have a Hamiltonian Circuit in a graph G with n nodes.

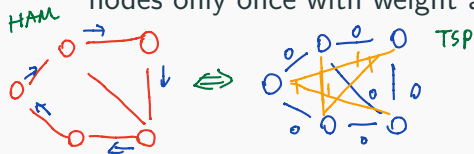
From HAM to TSP

- Suppose we have a Hamiltonian Circuit in a graph G with n nodes.
- Build a new graph G' where connected nodes in G have an edge of weight 0 and non-connected nodes have weight 1.
 - This can be done in polynomial time.

↓
iterate all nodes

From HAM to TSP

- Suppose we have a Hamiltonian Circuit in a graph G with n nodes.
- Build a new graph G' where connected nodes in G have an edge of weight 0 and non-connected nodes have weight 1.
 - This can be done in polynomial time.
- Frame Decision-TSP as “Is there a circuit that visit all nodes only once with weight at most 0?”



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 - Every problem in NP has a polynomial reduction to D or
 - A polynomial reduction from a known NP -complete problem to D exists.

NP-Completeness

A decision problem D is said to be **NP-Complete** if:

- $D \in NP$ and
 - Every problem in NP has a polynomial reduction to D **or**
 - A polynomial reduction from a known NP -complete problem to D exists.

Key property: if one finds a polynomial time algorithm to solve an NP -complete problem, then $P = NP$.

3-SAT

Proving that every problem in NP has a polynomial reduction to D is hard.

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- This feat was accomplished in the 70's by Stephen Cook and Leonid Levin for the **Boolean 3-satisfiability problem**.
- "Given a boolean formula with a maximum of three literals, is there an assignment that results in TRUE?"
 - $(x_1 \vee \bar{x}_2 \vee \bar{x}_3) \wedge (\bar{x}_1 \vee x_2) \wedge (\bar{x}_1 \vee \bar{x}_2 \vee \bar{x}_3) = \text{true}$
Handwritten: "or" above \vee , "and" above \wedge , and "true" at the end.
 - $\{x_1 = \text{true}, x_2 = \text{true}, x_3 = \text{false}\}$
Handwritten: A green arrow points from this set to the "true" result in the previous item.

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- SAT
 - Clique → find the maximum clique
 - Vertex Cover → find the set of vertices that cover all edges
 - Hamiltonian Circuit
 - Decision-TSP
 - ...
- ↓
subgraph which is complete

3-SAT

From 3-SAT, one can reduce it to many other problems, all being *NP*-complete as a consequence:

- SAT
- Clique
- Vertex Cover
- Hamiltonian Circuit
- Decision-TSP
- ...

A polynomial time algorithm for any of these would imply that $P = NP$.

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- Decision problems: P contains problems with polynomial time solutions.
- Verification problems: NP contains problems with polynomial time solutions.
- Reductions let us analyse new problems by framing them as existing ones.
- NP -completeness: solving one NP -complete problem implies in $P = NP$ due to reductions.

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- Most scientists believe $P \neq NP$.
since NP complete problem

Last Words

- Some problems are **undecidable**: COMP30026
- Some scientists tried to prove that $P \stackrel{?}{=} NP$ is undecidable.
- Most scientists believe $P \neq NP$.
- While the problem itself still eludes computer scientists, proposed solutions led to advancements in theory, even though they were wrong.