CS251**Great Ideas** in Theoretical Computer Science

Time Complexity And the Power of Algorithms



2 Main Questions in Theory of Computation

- **Computability** of a problem:
 - Is there an algorithm to solve it?

Complexity of a problem: Is there an efficient algorithm to solve it?

- time
- space (memory)
- randomness
- quantum resources

Simulations (e.g. of physical or biological systems)

- tremendous applications in science, engineering, medicine,...

Optimization problems

- arise in essentially every industry

Social good

- finding efficient ways of helping others

Artificial intelligence

Security, privacy, cryptography

- applications of computationally hard problems

Computational Complexity (Practical Computability)

list goes on



Computational Complexity (Practical Computability)

- How do we define computational complexity?
- What is the right level of abstraction to use?
- How do we analyze complexity?
- What are some interesting problems to study?
- What can we do to better understand the complexity of problems?



Kurt Friedrich Gödel (1906-1978)



One of the most important logicians in history.



John von Neumann (1903-1957)

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- quantum mechanics.
- Founded the field of game theory in mathematics.
- Created some of the first general-purpose computers.

- Mathematical formulation of

One can obviously easily construct a Turing machine, which for every formula F in first order predicate logic and every natural number n, allows one to decide if there is a proof of F of length n (length = number of symbols). Let $\psi(F,n)$ be the number of steps the machine requires for this and let $\varphi(n) = \max_{v \in V} F_{v}(F,n)$. The question is how fast $\phi(n)$ grows for an optimal machine. One can show that $\varphi(n) \ge k \cdot n$. If there really were a machine with $\varphi(n) \sim k \cdot n$ (or even $\sim k \cdot n^2$), this would have consequences of the greatest importance. Namely, it would obviously mean that in spite of the undecidability of the Entscheidungsproblem, the mental work of a mathematician concerning Yes-or-No questions could be completely replaced by a machine. After all, one would simply have to choose the natural number n so large that when the machine does not deliver a result, it makes no sense to think more about the problem. Now it seems to me, however, to be completely within the realm of possibility that $\varphi(n)$ grows that slowly.

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ENTSCHEIDUNGSPROBLEM UNDECIDABLE

provable?

mathematical statement F



True or

False

True

or

False

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mathematical provable with *n* symbols? statement Fn

 $\Psi(F,n) =$ the number of steps required for input (F,n)

a worst-case notion of $\varphi(n) = \max_{F} \Psi(F, n)$ running time

How fast does $\varphi(n)$ grow for an optimal machine? asymptotic analysis

- True
 - Or
- False

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This is the first formalization of the P vs NP problem.



Yes, the following (and many more) is uncomputable:



But these are computable:



But are they practically computable?







Part 1 of CS251:

Understand the divide between computable and uncomputable.

Part 2 of CS251:

Understand the divide between practically computable and practically uncomputable.

What is the meaning of: "The (asymptotic) running time complexity of algorithm A is $O(n^2)$."

Great Ideas in Complexity Analysis

The (worst-case) running time of an algorithm A is a function

 $T_A(n) =$ max # steps A(x) takes. inputs x of length n

- Worst-case analysis.
- Asymptotic analysis and the Big-O notation.
- Polynomial-time.



• Worst-case analysis.

Why worst-case?

• • •

We are not dogmatic about it.

Can study "average-case" (random inputs) Can try to look at "typical" instances.

BUT worst-case analysis has its advantages:

- An ironclad guarantee.
- Hard to define "typical" instances.
- Random instances are often not representative.
- Often much easier to analyze.

Great Ideas in Complexity Analysis

The running time of an algorithm A is a function

| $T_A(n) =$ | max | # steps $A(x)$ |
|------------|-------------|----------------|
| | inputs x | |
| | of length n | |

- Worst-case analysis.
- Asymptotic analysis and the Big-O notation.
- Polynomial-time.



-) takes.

• Asymptotic analysis and the Big-O notation.

$$T(n) = \frac{1}{2}n^2 + \frac{3}{2}n + 1.$$

Analogous to "too many significant digits".

"Sweet spot" of Big-O

- coarse enough to suppress details like programming language, compiler, architecture,...
- sharp enough to make comparisons between different algorithmic approaches.





Great Ideas in Complexity Analysis

The running time of an algorithm A is a function

| $T_A(n) =$ | max | # steps $A(x)$ |
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-) takes.

• **Polynomial-time.** $O(n^k)$ for some constant k. In practice: Awesome! Like really awesome! O(n)Great! $O(n \log n)$ Kind of efficient. $O(n^2)$ $O(n^3)$ Barely efficient. (???) $O(n^5)$ Would not call it efficient. $O(n^{10})$ Definitely not efficient! $O(n^{100})$ WTF?

- Polynomial-time.
 - Polynomial time In theory: Otherwise
 - Poly-time is not meant to mean "efficient in practice"
 - It means "You have done something extraordinarily better than brute force search."
 - Poly-time: mathematical insight into a problem's structure.
 - If you show, say Factoring Problem, has running time $O(n^{100})$, it will be the best result in CS history.

Efficient. Not efficient.

- Polynomial-time.
 - In theory: Polynomial time Otherwise
 - Robust to notions: elementary step, what model we use, reasonable encoding of input, implementation details.
 - Nice closure property: Plug in a poly-time alg. into another poly-time alg. —> poly-time
 - Big exponents don't really arise.
 - If it does arise, usually can be brought down.

Efficient. Not efficient.

• Polynomial-time.

Polynomial time In theory: Otherwise

- **Summary**: Poly-time vs not poly-time is a qualitative difference, not a quantitative one.

Efficient. Not efficient.

poll.cs251.com

What is the running time in terms of the input length?

def isPrime(N):
if (N < 2):
 return False
for factor in range(2, N):
 if (N % factor == 0):
 return False
 return True</pre>

Poll Answer

Algorithms on numbers involve **<u>BIG</u>** numbers.

This is still small! Imagine having thousands of digits.

Poll Answer

B = 5693030020523999993479642904621911725098567020556258102766251487234031094429

 $B \approx 5.7 \times 10^{75}$ (5.7 quattorvigintillion) len(B) = 251



An algorithm repeating B times is practically uncomputable.

len(B) = # bits to write B $len(B) \approx \log_2 B$

Poll Answer

iterations: $\approx N$

 $N = 2^{\log_2 N} = 2^{\operatorname{len}(N)} = 2^n$

exponential in input length



CS251 computational model for complexity analysis



CS251 computational model for complexity analysis

The Random-Access Machine (RAM) model

Good combination of reality & simplicity.

+,-,/,*,<,>,etc. e.g. 15*251

memory access e.g. A[94]

Small number: Bounded by a polynomial in **input length**. Large number: Not small.



Arithmetic operations/comparisons take 1 step **only if** the numbers are small.

takes 1 step for "small numbers"

takes 1 step

Example: Are the numbers small or large?

Small number: Bounded by a polynomial in **input length**. Large number: Not small.

def foo(int B): return B + B 

What is the complexity of addition, multiplication, etc. when the numbers are large?

Integer Addition



What is the running-time of this algorithm?



Integer Addition

36185027886661311069865932815214971104 + 65743021169260358536775932020762686101 101928049055921669606641864835977657205

steps to produce C is O(n)

A BC

36185027886661311069865932815214971104 A B5932020762686101 Х 214650336722050463946651358202698404452609868137425504 C



steps: $O(\operatorname{len}(A) \cdot \operatorname{len}(B)) = O(n^2)$



Probably this is the best, what else can you really do?

A good algorithm designer always thinks: **HOW CAN WE DO BETTER?!?**

What algorithm does Python use?



Integer Multiplication n = length of one of the numbersa b $= a \cdot 10^{n/2} + b$ A = 5678 $= c \cdot 10^{n/2} + d$ $B = [1 \ 2 \ 3 \ 4]$ C

 $A \cdot B = (a \cdot 10^{n/2} + b) \cdot (c \cdot 10^{n/2} + d)$ $= ac \cdot 10^{n} + (ad + bc) \cdot 10^{n/2} + bd$ **Use recursion!**



$A \cdot B = (a \cdot 10^{n/2} + b) \cdot (c \cdot 10^{n/2} + d)$ = $ac \cdot 10^n + (ad + bc) \cdot 10^{n/2} + bd$

- Recursively compute *ac*, *ad*, *bc*, and *bd*.
- Do the multiplications by 10^n and $10^{n/2}$. $\rightarrow O(n)$
- Do the additions.

 $T(n) \le 4 \cdot T(n/2) + O(n)$

$$b^2 + b^2$$

 $(c \cdot 10^{n/2} + d)$ $(bc) \cdot 10^{n/2} + bd$ $(c \cdot 10^{n/2} + bd)$ $(bc) \cdot 10^{n/2} + bd$ $(bc) \cdot 10^{n/2} + bd$



distinct nodes at level j:work done per node at level j:# levels:

Total: $\sum_{j=0}^{\log_2 n} cn2^j = O(n^2)$

4^j $cn2^{j}$ for level j $c(n/2^j)$ $\log_2 n$

 $A \cdot B = (a \cdot 10^{n/2} + b) \cdot (c \cdot 10^{n/2} + d)$ = $ac \cdot 10^n + (ad + bc) \cdot 10^{n/2} + bd$

Hmm, we don't really care about *ad* and *bc*. We just care about their sum. Maybe we can get away with 3 recursive calls?



 $A \cdot B = (a \cdot 10^{n/2} + b) \cdot (c \cdot 10^{n/2} + d)$ $= ac \cdot 10^{n} + (ad + bc) \cdot 10^{n/2} + bd$

(a + b)(c + d) = ac + ad + bc + bd

- Recursively compute: ac, bd, (a + b)(c + d)

- Then: (ad + bc) = (a + b)(c + d) - ac - bd

$T(n) \le 3 \cdot T(n/2) + O(n)$ Is this better??



distinct nodes at level *j*: work done per node at level j: # levels:

Total: $\sum_{j=0}^{\log_2 n} cn(3^j/2^j) = O(n^{\log_2 3})$

 3^j $c(n/2^j)$ $\leftarrow \frac{cn(3^j/2^j)}{\text{for level } j}$ $\log_2 n$





Probably this is the best, what else can you really do?

A good algorithm designer always thinks: HOW CAN WE DO BETTER?!?

Cut the integer into 3 parts of length n/3 each. Replace 9 multiplications with only 5. $T(n) \le 5 \cdot T(n/3) + O(n)$

$$T(n) = O(n^{\log_3 5})$$

Can do $T(n) = O(n^{1+\epsilon})$ for any $\epsilon > 0$.

Fastest known: *n*log *n* Harvey, Hoeven

ey, Hoeven (2019)

Lessons



It is not easy to understand the power of algorithms.



Always try to do better!

What is next?

- Graphs and more examples of efficient algorithms
- Polynomial time vs Exponential time