

Lecture 1: Computational Models, Time Complexity & An Example

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Overview

- Computational Models
- Time Complexity & Efficiency
- Examples: 2SUM & 3SUM
- Acknowledgements

Computational Models

Main Idea: a computational model should take into account all constraints of your machine, and account for the *scarcest resource(s)*.

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- **Word RAM:**

- ① Memory modeled as array (access any position “unit time”)
- ② Each entry of the array is a *word* with pre-specified size.
- ③ Each word operation takes “unit time”
 - addition, multiplication, subtraction, division
 - read/write

Total time \leftrightarrow # elementary operations

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Finer distinction: *word RAM* and *unit cost* models.

- unit cost model \leftrightarrow one assumes that words have *unbounded* size
- word RAM \leftrightarrow words have a *pre-specified* size

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- *Assumptions*

- ① Alphabet fits into one word
- ② Input fits in memory
- ③ No huge numbers in middle of computation

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- *Example*

- ① Input: graph with n vertices
- ② vertex labeled from set $\{1, \dots, n\}$, edge with pair from $\{1, \dots, n\}^2$
2 $\log n$ bits to store vertex or edge (assume word size $O(\log n)$)
- ③ basic operations (vertex comparison, accessing vertex/edge, etc.)
constant time

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- **Bit Complexity (with word RAM):**

- ① when working with numerical algorithms, numbers may grow and no longer fit in one word - so need to account for that
- ② In this case, assume word is a bit (i.e. in $\{0, 1\}$)

cost of operation \leftrightarrow # bit-operations

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- **Bit Complexity (with word RAM):**

- ① when working with numerical algorithms, numbers may grow and no longer fit in one word - so need to account for that
- Other models exist based on different resource constraints and assumptions (CS 365, CS 466 onwards)
 - Turing Machines
 - Circuits
 - Parallel computation
 - Online, streaming
 - many more

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Asymptotics recap

Given two functions $f, g : \mathbb{N} \rightarrow \mathbb{N}$

- $f(n) = O(g(n))$ if there is a constant C s.t.

$$\lim_{n \rightarrow \infty} \frac{f(n)}{g(n)} \leq C$$

Examples:

- $\pi \cdot n^3 = O(n^3)$
- $10^{10} \cdot n^2 \log n = O(n^3)$
- $10n^3 + 100n^2 + n = O(n^3)$

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- $f(n) = \Theta(g(n))$ if $f(n) = O(g(n))$ and $f(n) = \Omega(g(n))$.
Equivalently, there is constant C such that:

$$\lim_{n \rightarrow \infty} \frac{f(n)}{g(n)} = C$$

Examples:

- $10^{10} \cdot n^3 = \Theta(n^3)$
- $10n^3 + 100n^2 + n = \Theta(n^3)$

Asymptotics recap

- $f(n) = o(g(n))$ if

$$\lim_{n \rightarrow \infty} \frac{f(n)}{g(n)} = 0$$

Examples:

- $10^{10} \cdot n^2 = o(n^3)$
- $10n^3 + 100n^2 + n = o(2^n)$
- $10n^3 + 100n^2 + n = o(n^3 \log n)$

Asymptotics recap

- $f(n) = o(g(n))$ if

$$\lim_{n \rightarrow \infty} \frac{f(n)}{g(n)} = 0$$

- $f(n) = \omega(g(n))$ if

$$\lim_{n \rightarrow \infty} \frac{f(n)}{g(n)} = \infty$$

Examples:

- $10^{-10} \cdot n^3 = \omega(n^2)$
- $10n^3 + 100n^2 + n = \omega(n)$

Practice questions

Compare the following functions:

① n^5 vs $n^5 / \log \log n$

② $2^{\sqrt{n}}$ vs $n^{\log n}$

③ $n!$ vs 2^n

④ n^n vs $2^{n \log n}$

Worst case complexity

- An algorithm “runs in time” $O(f(n))$ if there is a constant $C > 0$ s.t., on inputs of size n , it requires at most $C \cdot f(n)$ elementary operations to output a correct answer.

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- “Mathematically:” given algorithm A and input x , let $T_A(x)$ be running time of algorithm A on input x .

Worst-case running time is:

$$T_A(n) = \max_{size(x)=n} T_A(x)$$

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 - ignore leading constant
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- Asymptotic notation allows us to focus on main growth of complexity
 - ignore leading constant
 - ignore lower order terms
- For instance:
 - binary search runs in time $O(\log n)$
 - sorting (using say merge-sort) runs in time $O(n \log n)$

Efficient algorithms

- with concept of asymptotic analysis, when will an algorithm be “efficient”?

An algorithm is “efficient” when there is a constant $\gamma > 0$ such that the algorithm runs in time $O(n^\gamma)$

Polynomial time.

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Polynomial time.

- Of course, the smaller the constant γ , the more efficient our algorithm will be.
- Why care so much about polynomial time?
 - Composition (i.e. can use subroutines)
 - For many problems, “trivial” algorithms run in exponential time (i.e. $2^{n^{O(1)}}$)

“Practical” algorithms

- “Practice” depends on the setting that one is working on, thus it is loosely defined
 - some settings this means nearly linear time $(O(n \log^c n))$
 - sometimes even *sub-linear* time! (CS 466)
 - other times fast for *most* inputs
 - other times for small enough inputs (leading constant matters)
 - etc.

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For instance, an algorithm running in time $100n^3$ is much better (in practice) than one which runs in time $2^{1000} \cdot n$.

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3-SUM problem

- **Input:** Set of integers $\{a_1, \dots, a_n\}$, integer c
- **Output:** $\begin{cases} \text{YES, if } \exists i, j, k \in [n] \text{ such that } a_i + a_j + a_k = c \\ \text{NO, otherwise} \end{cases}$

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- Naive algorithm: for each triple i, j, k , check whether $a_i + a_j + a_k = c$

Running time: $O(n^3)$

(4 ops to check each triple)

Can we do better?

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Can we do better?

- Less naive:
 - 1 Sort the set of numbers, so can assume we have $a_1 \leq a_2 \leq \dots \leq a_n$
 - 2 For each pair i, j , let $b_{i,j} = c - a_i - a_j$
 - 3 Binary search to check if there is k such that $a_k = b_{i,j}$

Running time: $O(n^2 \log n + n \log n) = O(n^2 \log n)$

Can we do better?

Last attempt

- Sort the set of numbers, so can assume we have $a_1 \leq a_2 \leq \dots \leq a_n$
- For each $k \in [n]$, let $b_k := c - a_k$
- Decide if there are $i, j \in [n]$ such that $a_i + a_j = b_k$

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if we can solve the 2-SUM problem, then can solve 3-SUM by
“calling” 2-SUM for each $k \in [n]$

Reduction!

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- Running time = $O(n \times (\text{running time for 2-SUM}) + n \log n)$

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Can we do 2-SUM with running time better than $O(n \log n)$?

2-SUM

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2-SUM

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- Idea: see board

2-SUM

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- Algorithm:
 - 1 Write $\beta_i := b - a_i$ for each $i \in [n]$, and let $j, t \in [n]$ be counters, initially set to $j = 1$ and $t = n$.
 - 2 While $t > 0$:
 - if $\beta_j > a_t$, then $j \leftarrow j + 1$
 - if $\beta_j = a_t$, then return YES
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 - 3 Return NO

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- Running time: n executions of the loop, each loop iteration takes at most 2 operations.

Thus: $O(n)$

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- So the running time of our last 3-SUM algorithm is

$$O(n^2 + n \log n) = O(n^2)$$

Conclusion

- Computational models (basis for modeling computation)
- Running time dependent on the model
- Efficient algorithms (beating exhaustive search)
- Reductions
- flavour of course

Acknowledgement

- Based on Lap Chi's first lecture

<https://cs.uwaterloo.ca/~lapchi/cs341/notes/L01.pdf>

References I



Cormen, Thomas and Leiserson, Charles and Rivest, Ronald and Stein, Clifford.
(2009)

Introduction to Algorithms, third edition.

MIT Press