CMSC 28100

Introduction to Complexity Theory

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1

Which problems

can be solved

through computation?

Applying our theory

- Question: In the year 1988, were there 50 U.S. senators, every pair of which voted the same way more than 50% of the time?
- Step 1: Gather data

Please cite the dataset as:

Lewis, Jeffrey B., Keith Poole, Howard Rosenthal, Adam Boche, Aaron Rudkin, and Luke Sonnet (2025). *Voteview: Congressional Roll-Call Votes Database*. https://voteview.com/

Data Type:	Members' Votes v	Members' Votes	
Chamber:	Senate Only	This data includes every vote taken by every member in the selected congresses and chambers along with the probability we assign to the member taking the position they did. Members are	
Congress:	100th (1987 - 1989) 🗸		
File Format:	JSON (Web Developers) 🗸	indexed by their ICPSR ID number.	
Download Data		Click here for help using this data	

Agreement graph

- Step 2: Construct "agreement graph"
- Edge {*u*, *v*} means that senators *u* and *v*
 - agreed on most votes
- Question: Are there 50 vertices in this graph that are all adjacent to one another?



• A k-clique in a graph G = (V, E) is a set $S \subseteq V$ such that |S| = k and

every two vertices in S are connected by an edge

Example: This graph has a 4-clique
Which of the following statements is false?
A: Every vertex in a k-clique has degree at least k - 1
B: A single graph might have many k-cliques
C: If G has fewer than ^(k)₂ edges, then G does not have a k-clique
D: If every vertex has degree at least k - 1, then G has a k-clique



- Let CLIQUE = { $\langle G, k \rangle$: *G* has a *k*-clique}
- Example: Let G be the graph with the following adjacency matrix
- Does *G* have a 4-clique?



- Let CLIQUE = { $\langle G, k \rangle$: G has a k-clique}
- Example: Let G be the graph with the following adjacency matrix



- Let CLIQUE = { $\langle G, k \rangle$: G has a k-clique}
- Claim: CLIQUE is decidable
- **Proof sketch:** Given $\langle G, k \rangle$ where G = (V, E), try all possible subsets $S \subseteq V$
 - Check whether |S| = k
 - Check whether $\{u, v\} \in E$ for every $u, v \in S$ such that $u \neq v$
- If we find a *k*-clique, accept; otherwise, reject.

- Question: In the year 1988, were there 50 U.S. senators, every pair of which voted the same way more than 50% of the time?
- Step 1: Gather data 🗸
- Step 2: Construct agreement graph 🗸
- **Step 3:** Apply CLIQUE algorithm

Our algorithm is so slow that it's worthless



- Question: In the year 1988, were there 50 U.S. senators, every pair of which voted the same way more than 50% of the time?
- Checking all possible sets of senators would take longer than a lifetime!
- One begins to feel that CLIQUE might as well be undecidable!

Which problems can be solved

through computation?

Refining our model



- Our model so far: Decidable vs. undecidable
- Now we will refine our model to account for the fact that we only have a limited amount of time (and other resources)
- "Complexity theory" vs. "Computability theory"

Analogy: Gravity

 Physics 101: "Gravity is a constant downward force of 9.8 N/kg"

• Physics 102: Newton's Universal Law of

Gravitation: $F = G \cdot \frac{m_1 \cdot m_2}{r^2}$





Theory vs. practice

- Disclaimer: Our theoretical model will still not be perfectly accurate!
- Occasionally, we might categorize a problem as "tractable" even though it is not actually "solvable in practice"
- Other times, we might categorize a problem as "intractable" even though it is actually "solvable in practice"

Theory vs. practice

- Physics analogy: Newton's Universal Law of Gravitation is great, but it does not correctly predict Mercury's motion around the sun!
- "...all models are wrong, but some are useful." –George Box
- Even though our model of tractability will not be 100% accurate, it will still give us real insights into the nature of computation



Time complexity

- Let *M* be a Turing machine
- The time complexity of *M* is a function $T_M : \mathbb{N} \to \mathbb{N}$ defined as follows:

$$T_M(n) = \max_{w \in \{0,1\}^n} (\text{running time of } M \text{ on } w)$$

• We are focusing on the worst-case *n*-bit input

Scaling behavior

- We will mainly focus on the limiting behavior of $T_M(n)$ as $n \to \infty$
- How "quickly" does the time complexity $T_M(n)$ increase when we increase the input length n?

Asymptotic analysis

Asymptotic analysis

• Two possible time complexities:

$$T_1(n) = 3n^2 + 14$$
$$T_2(n) = 2n^2 + 64n + \left[\sqrt{n}\right]$$

- When n is large, the leading $C \cdot n^2$ term dominates
- We will ignore the low-order terms and the leading coefficient C
- We focus on the n^2 part ("quadratic time")

Big-O notation

- $3n^2 + 14$ and $2n^2 + 64n + \left[\sqrt{n}\right]$ are both " $O(n^2)$ "
- More generally, let $T, f: \mathbb{N} \to [0, \infty)$ be any two functions
- **Definition:** We say that *T* is O(f) if there exist $C, n_* \in \mathbb{N}$ such that for every $n > n_*$, we have $T(n) \leq C \cdot f(n)$
- Notation: $T \in O(f)$ or $T \leq O(f)$ or T = O(f)

Big-O notation examples

- $3n^2 + 14$ is $O(n^2)$
- $3n^2 + 14$ is $O(n^2 + n)$
- $3n^2 + 14$ is $O(n^3)$
- $3n^2 + 14$ is not $O(n^{1.9})$

Big- Ω and big- Θ

- Let $T, f: \mathbb{N} \to [0, \infty)$ be any two functions
- We say that T is $\Omega(f)$ if there exist $c \in (0, 1)$ and $n_* \in \mathbb{N}$ such that for every $n > n_*$, we have $T(n) \ge c \cdot f(n)$
- We say that T is $\Theta(f)$ if T is O(f) and T is $\Omega(f)$

Big- Ω and big- Θ examples

- $0.1n^2 + 14$ is $\Omega(n^2)$ and $\Omega(n)$, but not $\Omega(n^3)$
- $0.1n^2 + 14$ is $\Theta(n^2)$ and $\Theta(n^2 + 2n^{1.4})$, but not $\Theta(n)$



Little-o notation

- Let $T, f: \mathbb{N} \to [0, \infty)$ be any two functions
- We say that T is o(f) if for every $c \in (0, 1)$, there exists $n_* \in \mathbb{N}$ such that for every $n > n_*$, we have $T(n) < c \cdot f(n)$
- Equivalent:

$$\lim_{n \to \infty} \frac{T(n)}{f(n)} = 0$$

Little- ω notation

- Let $T, f: \mathbb{N} \to [0, \infty)$ be any two functions
- We say that T is $\omega(f)$ if for every $C \in \mathbb{N}$, there exists $n_* \in \mathbb{N}$ such that for every $n > n_*$, we have $T(n) > C \cdot f(n)$
- Equivalent:

$$\lim_{n \to \infty} \frac{T(n)}{f(n)} = \infty$$

Summary of asymptotic notation

Notation	In words	Analogy
T is $o(f)$	T(n) grows more slowly than $f(n)$	<
T is $O(f)$	$T(n)$ is at most $C \cdot f(n)$	\leq
T is $\Theta(f)$	T(n) and $f(n)$ grow at the same rate	=
T is $\Omega(f)$	$T(n)$ is at least $c \cdot f(n)$	\geq
T is $\omega(f)$	T(n) grows more quickly than $f(n)$	>

Note: Big-*O* is not just for time complexity!

- We can use asymptotic notation (big-*O*, etc.) any time we are trying to understand some kind of "scaling behavior"
- For example, let G be a simple undirected graph with N vertices
 - G has $O(N^2)$ edges
 - If G is connected, then G has $\Omega(N)$ edges
- Admittedly, we are especially interested in time complexity...

Exponential vs. polynomial

- We are especially interested in the distinction between a polynomial time complexity, such as $T(n) = n^2$, and an exponential time complexity, such as $T(n) = 2^n$
- We write T(n) = poly(n) if there is some k such that $T(n) = O(n^k)$
- Exponentials grow much faster than polynomials!

Exponential vs. polynomial

Claim: For every constant $k \in \mathbb{N}$, we have $n^k = o(2^n)$

• **Proof:** If $n \ge k + 1$, then

$$2^{n} = \# \text{ subsets of } \{1, 2, \dots, n\} = \sum_{i=0}^{n} {n \choose i} \ge {n \choose k+1} \ge \left(\frac{n}{k+1}\right)^{k+1}$$
$$= \Omega(n^{k+1})$$
$$= \omega(n^{k}).$$