Computer Science & Engineering 423/823
Design and Analysis of Algorithms
Lecture 01 — Shall We Play A Game?

Stephen Scott

sscott@cse.unl.edu

Introduction

- In this course, I assume that you have learned several fundamental concepts on basic data structures and algorithms
- Let's confirm this
- What do I mean …

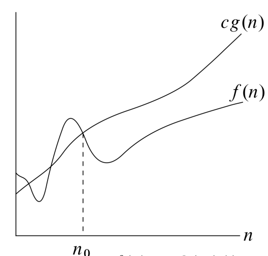
… when I say: "Asymptotic Notation"

- A convenient means to succinctly express the growth of functions
  - Big-O
  - Big-Ω
  - Big-Θ
  - Little-o
  - Little-ω
- Important distinctions between these (**not interchangeable**)

Asymptotic Notation
… when I say: "Big-O"

Asymptotic upper bound

$$O(g(n)) = \{f(n) : \exists c, n_0 > 0 \text{ s.t. } \forall n \geq n_0, 0 \leq f(n) \leq c\,g(n)\}$$



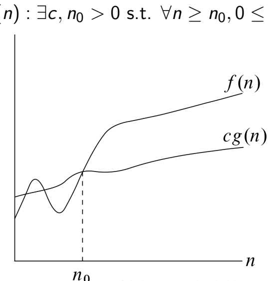
$f(n) = O(g(n))$

Can **very loosely and informally** think of this as a "$\leq$" relation between functions

Asymptotic Notation
… when I say: "Big-Ω"

Asymptotic lower bound

$$\Omega(g(n)) = \{f(n) : \exists c, n_0 > 0 \text{ s.t. } \forall n \geq n_0, 0 \leq c\,g(n) \leq f(n)\}$$



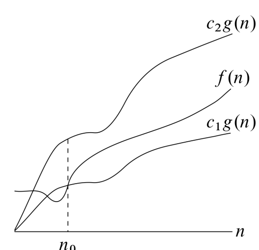
$f(n) = \Omega(g(n))$

Can **very loosely and informally** think of this as a "$\geq$" relation between functions

Asymptotic Notation
… when I say: "Big-Θ"

Asymptotic tight bound

$$\Theta(g(n)) = \{f(n) : \exists c_1, c_2, n_0 > 0 \text{ s.t. } \forall n \geq n_0, 0 \leq c_1\,g(n) \leq f(n) \leq c_2\,g(n)\}$$



$f(n) = \Theta(g(n))$

Can **very loosely and informally** think of this as a "$=$" relation between functions

Asymptotic Notation

... when I say: "Little-o"

Upper bound, not asymptotically tight

$$o(g(n)) = \{f(n) : \forall c > 0, \exists n_0 > 0 \text{ s.t. } \forall n \geq n_0, 0 \leq f(n) < c\,g(n)\}$$

Upper inequality strict, and holds for **all** $c > 0$
Can **very loosely and informally** think of this as a "$<$" relation between functions

Asymptotic Notation

... when I say: "Little-ω"

Lower bound, not asymptotically tight

$$\omega(g(n)) = \{f(n) : \forall c > 0, \exists n_0 > 0 \text{ s.t. } \forall n \geq n_0, 0 \leq c\,g(n) < f(n)\}$$

$f(n) \in \omega(g(n)) \Leftrightarrow g(n) \in o(f(n))$
Can **very loosely and informally** think of this as a "$>$" relation between functions

... when I say: "Upper and Lower Bounds"

- Most often, we analyze algorithms and problems in terms of **time complexity** (number of operations)
- Sometimes we analyze in terms of **space complexity** (amount of memory)
- Can think of **upper** and **lower** bounds of time/space for a specific **algorithm** or a general **problem**

Upper and Lower Bounds

... when I say: "Upper Bound of an Algorithm"

- The most common form of analysis
- An algorithm A has an **upper bound** of $f(n)$ for input of size n if there exists **no input** of size n such that A requires more than $f(n)$ time
- E.g., we know from prior courses that Quicksort and Bubblesort take no more time than $O(n^2)$, while Mergesort has an upper bound of $O(n \log n)$
  - (But why is Quicksort used more in practice?)
- **Aside:** An algorithm's lower bound (not typically as interesting) is like a best-case result

Upper and Lower Bounds

... when I say: "Upper Bound of a Problem"

- A problem has an **upper bound** of $f(n)$ if there exists **at least one** algorithm that has an upper bound of $f(n)$
  - I.e., there exists an algorithm with time/space complexity of at most $f(n)$ on **all** inputs of size n
- E.g., since Mergesort has worst-case time complexity of $O(n \log n)$, the problem of sorting has an upper bound of $O(n \log n)$

Upper and Lower Bounds

... when I say: "Lower Bound of a Problem"

- A problem has a **lower bound** of $f(n)$ if, for **any** algorithm A to solve the problem, there exists **at least one** input of size n that forces A to take at least $f(n)$ time/space
- This pathological input depends on the specific algorithm A
- E.g., there is an input of size n (reverse order) that forces Bubblesort to take $\Omega(n^2)$ steps
- Also e.g., there is a different input of size n that forces Mergesort to take $\Omega(n \log n)$ steps, but none exists forcing $\omega(n \log n)$ steps
- Since **every** sorting algorithm has an input of size n forcing $\Omega(n \log n)$ steps, the sorting problem has a **time complexity lower bound** of $\Omega(n \log n)$
  - $\Rightarrow$ Mergesort is **asymptotically optimal**

Upper and Lower Bounds

... when I say: "Lower Bound of a Problem" (2)

- To argue a lower bound for a problem, can use an **adversarial** argument: An algorithm that simulates **arbitrary** algorithm A to build a pathological input
- Needs to be in some general (algorithmic) form since the nature of the pathological input depends on the specific algorithm A
- Can also **reduce** one problem to another to establish lower bounds
  - **Spoiler Alert:** This semester we will show that if we can compute convex hull in $o(n \log n)$ time, then we can also sort in time $o(n \log n)$; this cannot be true, so convex hull takes time $\Omega(n \log n)$

... when I say: "Efficiency"

- We say that an algorithm is **time-** or **space-efficient** if its worst-case time (space) complexity is $O(n^c)$ for constant c for input size n
- I.e., polynomial in the size of the input
- **Note on input size:** We measure the size of the input in terms of the **number of bits** needed to represent it
  - E.g., a graph of n nodes takes $O(n \log n)$ bits to represent the nodes and $O(n^2 \log n)$ bits to represent the edges
    - Thus, an algorithm that runs in time $O(n^c)$ is efficient
  - In contrast, a problem that includes as an input a numeric parameter k (e.g., threshold) only needs $O(\log k)$ bits to represent
    - In this case, an efficient algorithm for this problem **must** run in time $O(\log^c k)$
    - If instead polynomial in k, sometimes call this **pseudopolynomial**

... when I say: "Recurrence Relations"

- We know how to analyze non-recursive algorithms to get asymptotic bounds on run time, but what about recursive ones like Mergesort and Quicksort?
- We use a **recurrence relation** to capture the time complexity and then bound the relation asymptotically
- E.g., Mergesort splits the input array of size n into two sub-arrays, recursively sorts each, and then merges the two sorted lists into a single, sorted one
- If $T(n)$ is time for Mergesort on n elements,

$$T(n) = 2T(n/2) + O(n)$$

- Still need to get an asymptotic bound on $T(n)$

Recurrence Relations

... when I say: "Master Theorem" or "Master Method"

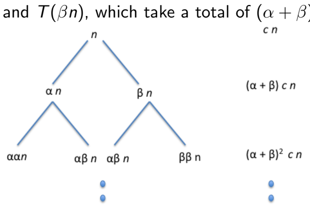
- **Theorem:** Let $a \geq 1$ and $b > 1$ be constants, let $f(n)$ be a function, and let $T(n)$ be defined as $T(n) = aT(n/b) + f(n)$. Then $T(n)$ is bounded as follows:
  1. If $f(n) = O(n^{\log_b a - \epsilon})$ for constant $\epsilon > 0$, then $T(n) = \Theta(n^{\log_b a})$
  2. If $f(n) = \Theta(n^{\log_b a})$, then $T(n) = \Theta(n^{\log_b a} \log n)$
  3. If $f(n) = \Omega(n^{\log_b a + \epsilon})$ for constant $\epsilon > 0$, and if $af(n/b) \leq cf(n)$ for constant $c < 1$ and sufficiently large n, then $T(n) = \Theta(f(n))$
- E.g., for Mergesort, can apply theorem with $a = b = 2$, use case 2, and get $T(n) = \Theta\left(n^{\log_2 2} \log n\right) = \Theta\left(n \log n\right)$

Recurrence Relations

Other Approaches

Theorem: For recurrences of the form $T(\alpha n) + T(\beta n) + O(n)$ for $\alpha + \beta < 1$, $T(n) = O(n)$

Proof: Top $T(n)$ takes $O(n)$ time ($= cn$ for some constant c). Then calls to $T(\alpha n)$ and $T(\beta n)$, which take a total of $(\alpha + \beta)cn$ time, and so on



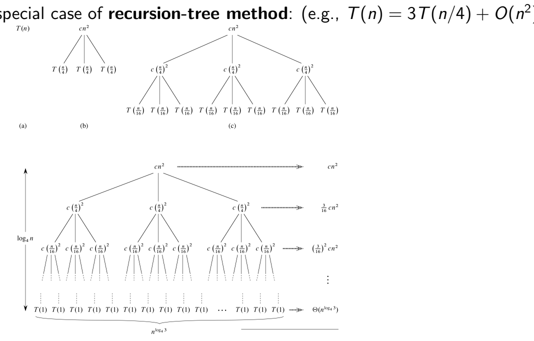
Summing these infinitely yields (since $\alpha + \beta < 1$)

$$cn(1 + (\alpha + \beta) + (\alpha + \beta)^2 + \cdots) = \frac{cn}{1 - (\alpha + \beta)} = c'n = O(n)$$

Recurrence Relations

Still Other Approaches

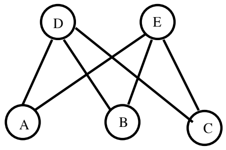
Previous theorem special case of **recursion-tree method**: (e.g., $T(n) = 3T(n/4) + O(n^2)$)



Another approach is **substitution method** (guess and prove via induction)

Graphs
... when I say: "(Undirected) Graph"

A **(simple, or undirected)** graph $G = (V, E)$ consists of V, a nonempty set of vertices and E a set of **unordered** pairs of distinct vertices called **edges**

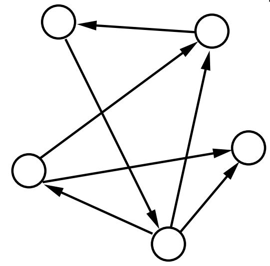


V={A,B,C,D,E}

E={ (A,D),(A,E),(B,D), (B,E),(C,D),(C,E)}

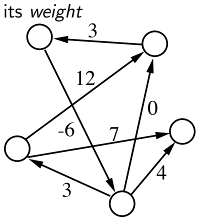
Graphs
... when I say: "Directed Graph"

A **directed** graph (digraph) $G = (V, E)$ consists of V, a nonempty set of vertices and E a set of *ordered* pairs of distinct vertices called *edges*



Graphs
... when I say: "Weighted Graph"

A **weighted** graph is an undirected or directed graph with the additional property that each edge e has associated with it a real number $w(e)$ called its *weight*

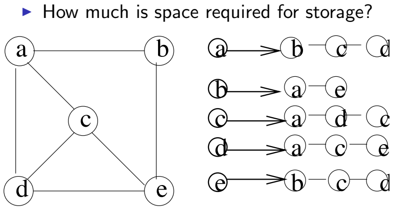


Graphs
... when I say: "Representations of Graphs"

- Two common ways of representing a graph: **Adjacency list** and **adjacency matrix**
- Let $G = (V, E)$ be a graph with n vertices and m edges

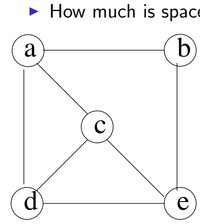
Graphs
... when I say: "Adjacency List"

- For each vertex $v \in V$, store a list of vertices adjacent to v
- For weighted graphs, add information to each node
- How much is space required for storage?



Graphs
... when I say: "Adjacency Matrix"

- Use an $n \times n$ matrix M, where $M(i, j) = 1$ if (i, j) is an edge, 0 otherwise
- If G weighted, store weights in the matrix, using ∞ for non-edges
- How much is space required for storage?



	a	b	c	d	e
a	0	1	1	1	0
b	1	0	0	0	1
c	1	0	0	1	1
d	1	0	1	0	1
e	0	1	1	1	0

Algorithmic Techniques

... when I say: "Dynamic Programming"

- **Dynamic programming** is a technique for solving **optimization problems**, where we need to choose a "best" solution, as evaluated by an **objective function**
- **Key element:** Decompose a problem into **subproblems**, optimally solve them recursively, and then combine the solutions into a final (optimal) solution
- **Important component:** There are typically an exponential number of subproblems to solve, but many of them overlap
  - ⇒ Can re-use the solutions rather than re-solving them
- Number of distinct subproblems is polynomial
- Works for problems that have the **optimal substructure property**, in that an optimal solution is made up of optimal solutions to subproblems
  - Can find optimal solution if we consider all possible subproblems
- Example: All-pairs shortest paths

Algorithmic Techniques

... when I say: "Greedy Algorithms"

- Another optimization technique
- Similar to dynamic programming in that we examine subproblems, exploiting optimial substructure property
- **Key difference:** In dynamic programming we considered all possible subproblems
- In contrast, a greedy algorithm at each step commits to just one subproblem, which results in its **greedy choice** (locally optimal choice)
- Examples: Minimum spanning tree, single-source shortest paths

Algorithmic Techniques

... when I say: "Divide and Conquer"

- An algorithmic approach (not limited to optimization) that splits a problem into sub-problems, solves each sub-problem recursively, and then combines the solutions into a final solution
- E.g., Mergesort splits input array of size n into two arrays of sizes $\lceil n/2 \rceil$ and $\lfloor n/2 \rfloor$, sorts them, and merges the two sorted lists into a single sorted list in $O(n)$ time
  - Recursion bottoms out for $n = 1$
- Such algorithms often analyzed via recurrence relations

Conclusion

- This was a deliberately brief overview of concepts you should already know
- I expect you to understand it well during lectures, homeworks, and exams
- **It is all covered in depth in the textbook!**