CS251 Midterm 1 - Fall 2022

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1 Summations and Logarithm Rules

- Summations
 - Given c is a constant, $\sum_{i=m}^{n} c = c(n-m+1)$
 - $-\sum_{i=1}^{n} i = \frac{1}{2}n(n+1)$
 - $-\sum_{i=1}^{n} i^2 = \frac{1}{6}n(n+1)(2n+1)$
 - Given a function f(i), $\sum_{i=m}^{n} f(i) = \sum_{i=1}^{n} f(i) \sum_{i=1}^{m-1} f(i)$
- Log Rules
 - In CS 251, if you are just given a $\log(n)$ without a base, they probably mean $\log_2(n)$
 - $-\log(ab) = \log(a) + \log(b)$
 - $-\log(\frac{a}{b}) = \log(a) \log(b)$
 - Given 2 numbers a and $b,\,\log_a(n) = \frac{\log_b(n)}{\log_b(a)}$
 - $-\log(n^a) = a\log(n)$
 - $a^{\log_a(n)} = n$
 - $a^{b \log_a(n)} = n^b$

2 Experimental Analysis

- Limitations
 - Different machines can vary the run time
 - other processes/noise
 - May not be precise all the time

3 Recursive Functions

- Functions that call themselves in order to solve simpler problems
- Recursive functions don't call themselves infinitely; eventually stop when they reach a base case

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4 Runtime Analysis

- Represents the efficiency of an algorithm
- Three types of asymptotic runtime analysis: O(n), $\Omega(n)$, and $\Theta(n)$
- *O*(*n*)
 - The asymptotic upper bound
 - Definition: Given functions f(n) and g(n), then $f(n) \in O(g(n))$ if there exists constants c and n_0 where $0 \le f(n) \le cg(n)$ for all $n \ge n_0$
 - In other words, $f(n) \in O(g(n))$ if f(n) doesn't grow faster than g(n).
 - Growth order:
 - * $O(1) < O(\log(n)) < O(n) < O(n\log(n)) < O(n^2) < O(n^3) < O(2^n) < O(n!)$
 - Going from the definition above, multiple functions can be big- $\!O$ of another function.
 - * Ex: $n \in O(n)$, and $n \in O(n^2)$
 - Generally, if they're asking for big- $\!O$ of a function, you want to give the tightest bound of the function.
 - When giving the O(n) of a function, you take the fastest-growing term and remove the constants from it
 - * Ex: $4n^2 + 2n\log(n) + 3n + 123456 \in O(n^2)$
- $\Omega(n)$
 - Asymptotic lower bound
 - Definition: Given functions f(n) and g(n), then $f(n) \in \Omega(g(n))$ if there exists constants c and n_0 where $0 \le cg(n) \le f(n)$ for all $n \ge n_0$
 - In other words, $f(n) \in \Omega(g(n))$ if f(n) doesn't grow slower than g(n).
 - Like how multiple functions can be O(n) of a function, multiple functions can also be $\Omega(n)$ of a function
 - * Ex: $n \in \Omega(n)$, and $n \in \Omega(\log(n))$
 - Again, generally you should give the tightest bound

- Process for getting big- Ω of a function is same as getting big-O
- $\Theta(n)$
 - Asymptotic tightest bound of a function
 - $-f(n) \in \Theta(g(n))$ if f(n) doesn't grow faster or slower than g(n)
- Asymptotic Growth Properties
 - If $f(n) \in O(g(n))$ and $f(n) \in \Omega(g(n))$, then $f(n) \in \Omega(g(n))$ and vice versa
 - If $f(n) \in O(g(n))$ and $g(n) \in O(h(n))$, then $f(n) \in O(h(n))$
 - If $f(n) \in \Omega(g(n))$ and $g(n) \in \Omega(h(n))$, then $f(n) \in \Omega(h(n))$
 - If $f(n) \in \Theta(g(n))$ and $g(n) \in \Theta(h(n))$, then $f(n) \in \Theta(h(n))$
 - If $f(n) \in O(h(n))$ and $g(n) \in O(h(n))$, then $f(n) + g(n) \in O(h(n))$
 - If $f(n) \in \Theta(g(n))$, then $f(n) + g(n) \in \Theta(g(n))$
 - If $f(n) \in O(g(n))$, then $g(n) \in \Omega(f(n))$

5 Arrays and LinkedLists

6 Stacks

- Data structure to store and remove data
- Last data pushed into the stack would be the first data popped off (LIFO)
 - Think of it like a stack of plates; the last plate placed on top is the first plate taken from the stack
- Standard methods for stacks:
 - ${\tt push()}$ Add an element to the top of the stack
 - pop() Remove the element from the top of the stack
 - isEmpty() Whether or not there are elements on the stock
 - size() Number of elements on the stack
 - peek() View the element at the top of the stack without removing it
- Implementation using Arrays vs LinkedLists
 - Arrays: Lower memory overhead; unable to resize to accommodate more elements
 - LinkedLists: Pointers require more memory; can expand to increase number of elements in the stack

7 Queues

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8 Trees