Review

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Review Material 1

1.1 Discrete math

- 1. Induction
- 2. Sets
- 3. Logic

Calculus 1.2

- 1. Limits
- 2. L'Hôpital's rule
- 3. derivatives: rules

(a)
$$(fg)' = f'g + fg'$$

(b)
$$(\frac{f}{g})' = \frac{gf' - fg'}{g^2}$$
)

- 4. log rules
 - (a) $\log(ab) = \log a + \log b$
 - (b) $\log(\frac{a}{b}) = \log a \log b$
 - (c) $\log_b a = \frac{\log_c b}{\log_c a}$ (d) $n^{\log_b a} = a^{\log_b n}$

1.3 Data structures

- 1. Recursion
- 2. Linked lists
- 3. stacks
- 4. queues
- 5. BSTs

2 Binary search

```
Input: An array A[1..n]
Input: An integer n
Input: An integer to search for called target
Output: An index 1 \le i \le n such that A[i] = \text{target}
start = 1;
end = n;
while start \leq end do
   mid = \lfloor \frac{start + end}{2} \rfloor;
   if target = A[mid] then
    return mid;
   end
   else if target < A[mid] then
    end = mid-1;
   end
   else
    start = mid+1;
   end
\quad \mathbf{end} \quad
return NOT_FOUND;
```

2.1 How long does binary search take?

Let T(n) be the worst case running time for binary search on an array of size n. Then

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

is an equation that represents the running time. How do we solve this? One way is by substitution.

2.2 Substitution method

- 1. Guess a solution
- 2. Prove it's correct by induction.

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

$$T(\frac{n}{2}) = T(\frac{n}{4}) + 1$$

so
$$T(n) = T(\frac{n}{4}) + 1 + 1$$

• • •

$$T(n) = T(\frac{n}{2^k}) + k$$

We Want $2^k = n \Rightarrow k = \log_2 n$.

$$T(n) = 1 + \log_2 n.$$

2. Prove by induction.

We want to prove that $T(n) \leq c \log_2 n$ for some positive c and for all n.

Base case: $T(k) = \log_2 k \le c$ as long as c is sufficiently large.

Inductive case:

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

By the inductive hypothesis

$$\Rightarrow T(n) \le c \log_2(\frac{n}{2}) + 1$$

$$\Rightarrow T(n) \le c(\log_2 n - \log_2 2) + 1$$

$$\Rightarrow T(n) \le c \log_2 n - c + 1$$

$$\Rightarrow T(n) \le c \log_2 n - (c+1)$$

$$\Rightarrow T(n) \le c \log_2 n$$
 as long as $c+1 > 0 \Rightarrow c \ge 1$

2.3 Questions similar to binary search

3 Sorting

3.1 InsertionSort pseudocode

3.2 Analyzing insertion sort

The outer loop happens n-1 times. The inner loop, in the worst case has to run i-1 steps. So the worst case time is given by:

$$\sum_{j=1}^{n-1} j = \frac{n(n-1)}{2} = \Theta(n^2)$$

3.3 MergeSort Pseudocode

3.4 Merge

```
Input: An array A
Input: integers start1, end1, start2, end2
;// We will view A as having 2 subarrays A[start1..end1] and
 A[start2..end2]
Let result[1..end2-start1+1] be a new array;
indexL = start1;
indexR = start2;
indexRes = 1;
;// Go through both subarrays and pick the minimum element.
 Stop when one of the subarrays runs out.
while indexL \leq end1 and indexR \leq end2 do
   if A[indexL] < A[indexR] then
      result[indexRes] = A[indexL];
      indexL = indexL + 1;
   end
   else
      result[indexRes] = A[indexR];
      indexR = indexR + 1;
   end
   indexRes = indexRes + 1;
end
;// Copy the remaining subarray over
while indexL \leq end1 do
   result[indexRes] = A[indexL];
   indexL = indexL + 1;
   indexRes = indexRes + 1;
\mathbf{end}
while indexR \leq end1 do
   result[indexRes] = A[indexR];
   indexR = indexR + 1;
   indexRes = indexRes + 1;
;// Copy the result back
indexRes=1;
for i = start1 to end2 do
A[i] = result[indexRes];
end
```

3.5 Mergesort

```
Input: An array A
Input: integers start, end
if end-start \leq 0 then
| return;
end
mid = floor((start + end) / 2);
mergesort(A, start, mid);
mergesort(A, mid+1, end);
merge(A, start, mid, mid+1, end);
```

4 Algorithm complexities

4.1 Running Time and Space Complexity

<u>Definition</u>: The running time of an algorithm A on a particular input is the number of primitive operations A performs when run on the input.

<u>Definition</u>: The space complexity of an algorithm A on a particular input is the amount of extra space the algorithm requires to run. Note: local variables count as $\Theta(1)$ space.

4.2 Best, Worst, Average Case

<u>Definition</u>: The best case time of an algorithm is the minimum number of primitive operations the algorithm requires over all possible inputs.

<u>Definition</u>: The worst case time of an algorithm is the maximum number of primitive operations the algorithm requires over all possible inputs.

<u>Definition</u>: The average case running time is the expectation of the running time over all possible inputs given a particular probability distribution.

4.3 $O, \Omega, \Theta, \omega, o$

<u>Definition</u>: We say that one function f(n) is O(g(n)) if there exist constants $c \in \mathbb{R}^+, n_0 \in \mathbb{N}$ such that $f(n) \leq cg(n)$ for all $n \geq n_0$.

Example: $n \in O(n^2)$ why?

<u>Definition</u>: We say that one function f(n) is $\Omega(g(n))$ if there exist constants $c \in \mathbb{R}^+, n_0 \in \mathbb{N}$ such that $f(n) \geq cg(n)$ for all $n \geq n_0$.

<u>Definition</u>: We say that one function f(n) is $\Theta(g(n))$ if there exist constants $c_1, c_2 \in \mathbb{R}^+, n_0 \in \mathbb{N}$ such that $c_1g(n) \leq f(n) \leq c_2g(n)$ for all $n \geq n_0$. limit definitions

<u>Definition</u>: We say that one function f(n) is O(g(n)) if $\lim_{n\to\infty}\frac{f(n)}{g(n)}=c$, for some $c\geq 0$

<u>Definition</u>: We say that one function f(n) is $\Omega(g(n))$ if $\lim_{n\to\infty} \frac{f(n)}{g(n)} = c$, for

some
$$c > 0$$
 or $\lim_{n \to \infty} \frac{f(n)}{g(n)} \to \infty$.

<u>Definition</u>: We say that one function f(n) is $\Theta(g(n))$ if $\lim_{n\to\infty}\frac{f(n)}{g(n)}=c$, for some c>0

Talk about o and ω .

5 Theorems

- 1. $\Theta(f(n)) = \Omega(f(n)) \cap O(f(n))$
- 2. Θ is an equivalence relation.

6 Recurrences

- 1. substitution
- 2. recursion trees + substitution
- 3. Master theorem

7 Heaps

- 1. definition
- 2. inserting
- 3. removing
- 4. building a heap
- 5. heapsort

8 Heaps pseudocode

insert(A, heapsize, value)

```
Input: A heap A Input: integers heapsize, value A[\text{heapsize}+1] = \text{value}; heapsize = heapsize+1; index = heapSize; while index \geq 0 and A[parent(index)] < A[index] do |swap(A[index], A[parent(index)]); |index = parent(index); end
```

Remove(A, heapsize)

```
Input: A heap A
Input: integer heapsize
swap(A[heapsize], A[1];
heapsize = heapsize - 1;
fixheap(A, 1, heapSize);
fixheap(A, i, heapSize)
Input: A heap A
Input: integer heapsize, i
\max = i;
if leftChild(i) \leq heapSize and A[leftChild(i)] > A[max] then
\max = \operatorname{leftChild}(i);
\mathbf{end}
if rightChild(i) \le heapSize and A[rightChild(i)] > A[max] then
\max = rightChild(i);
\mathbf{end}
if max = i then
 return;
\quad \mathbf{end} \quad
swap(A[max], A[i]);
fixheap(A, max, heapSize);
Heapsort(A, n)
Input: A heap A
Input: integer n
for i=\lfloor \frac{n}{2} \rfloor downto1 do
 fixHeap(A, i, n);
end
n = heapSize;
while heapSize > 0 do
    swap(A/1), A/heapSize);
   heapSize = heapSize-1;
   fixHeap(A, 1, heapSize);
end
```

9 Quicksort

9.1 Partition

The partition algorithm selects an element as the pivot, and the moves everything smaller or equal to the left and everything greater than or equal to the right. The invariant is that every number in $A[start..b] \leq pivot$ and every number in $A[b+1..i-1] \geq pivot$. Everything in A[i..end] is unknown.

```
Partition(A, start, end)

Input: an array A

Input: integers start and end

Output: The pivot index

b = \text{start};

for i = \text{start} + 1 to end do

if A[i] < pivot then

b = b + 1;
\text{swap}(A, i, b);
end

end

swap(A, start, b);
return b;
```

9.2 Quicksort

The idea is to run partition on the array and then recursively sort both subarrays.

```
Quicksort(A, start, end)

Input: an array A

Input: integers start and end if end \leq start then | return; end

p = partition(A, start, end); Quicksort(A, start, p-1); Quicksort(A, p+1, end);
```

9.3 Analysis

The worse case for quicksort is when the array is already sorted or reverse sorted. The pivot will always not give us a good split and we will wind up with a running time of $1+2+3+\cdot+n=\Theta(n^2)$. However, if we pick a random pivot, then the running time will be $\Theta(n \log n)$ with high probability.

10 Selection

10.1 Finding the max or the min

The straightforward algorithm for finding the min or the max is the following:

```
Min(A, n)

Input: an array A

Input: an integer n, the length of A

Output: The minimum of A

min = A[1];

for i=2 to n do

if A[i] < min then

| min = A[i];
| end

end

return min;

This takes n-1 comparisons in the worst case. Max is similar.
```

10.2 Simultaneous max and min

If we want to find the max and min at the same time, we could do it in n-1+n-1=2n-2 comparisons. Or we can find them simultaneously with the following recursive algorithm.

Min-And-Max(A, start, end)

```
Input: an array A
    Input: integers start and end
    Output: An ordered pair (min, max)
    if end - start \leq 1 then
         if A[start] < A[end] then
          return (A[start], A[end]);
         end
         else
          return (A[end], A[start]);
         end
    end
    mid = \lfloor \frac{start + end}{2} \rfloor;
    (\min Left, \max Left) = \min -And -Max(A, start, \min);
    (\min Right, \max Right) = \min -And -Max(A, \min +1, end);
    \min = \min \text{Left};
    \max = \max \text{Left};
    if minRight < min then
     \min = \min Right;
    \mathbf{end}
    if maxRight > max then
     \max = \max Right;
    end
    return (min, max);
10.2.1
          Analysis
How long does this take?
    It obeys the occurrence: T(n) = 2T(n/2) + 1, T(2) = 2.
    T(n) = 2T(\frac{n}{2}) + 1
    \Rightarrow = 4T(\frac{n}{4}) + 2 + 1\Rightarrow = 8T(\frac{n}{8}) + 4 + 2 + 1
    \Rightarrow = 2^k T(\frac{n}{2^k}) + 1 + 2 + \dots + 2^{k-1}
Let \frac{n}{2^k} = 2 \Rightarrow 2^k = \frac{n}{2}, and 1 + 2 + \dots + 2^{k-1} = 2^k - 1 = \frac{n}{2} - 1.
\Rightarrow = 2\frac{n}{2} + \frac{n}{2} - 1.
```

10.3 Finding the Kth smallest

This has solution $T(n) = \frac{3n}{2} - 1$.

We can find the kth smallest number in an array as follows: Take the array A and turn it into a min heap. Then pop the heap k times. This takes $\Theta(n + k \log n)$. If k is small, this is a good algorithm, but if $k = \Theta(n)$, this is no longer all that good.

A better algorithm is based on partition. Call partition using the pivot. Once that happens, if k < pivotindex then you look in the left subarray. Otherwise, you look in the right subarray. This takes $\Theta(n)$ time with high probability.

11 Graphs

11.1 Definitions

<u>Definition</u>: A Graph is a pair G = (V, E) where V is a set of vertices and E is a set of edges. If G is a directed graph, then each $e \in E$ is an ordered pair (u, v) representing that u and v are related. If G is undirected, then each $e \in E$ is an unordered pair, $\{u, v\}$. (Abuse of notation: most books and papers use (u, v) even for undirected graphs, but this is technically not true.)

<u>Definition</u>: A path is a sequence of vertices $(v_0, v_1, v_2, \dots, v_k)$. The length of a path is the number of edges in the path.

<u>Definition</u>: A cycle is a path that starts and ends at the same vertex. A simple cycle is a cycle that doesn't repeat vertices. <u>Definition</u>: A graph is connected if every vertex is reachable from every other vertex. Connected components of a graph are parts of the graph in which every vertex is reachable from every other vertex.

<u>**Definition**</u>: The outdegree of a vertex v is the number of edges that leave v. The indegree of a vertex v is the number of edges that enter v. In an undirected graph, we just talk about degree.

<u>Definition</u>: a forest is an acyclic, undirected graph. A tree is an acyclic, undirected, connected graph. A directed, acyclic graph is called a "dag."

11.2 BFS

```
Input: the adjacency lists of a graph G = (V, E)

Let visited be a new array;

for v \in V do

| visited[v] = false;

end

for v \in V do

| if not visited[v] then

| BFS-Visit(G, v);

| end

end
```

```
Input: the adjacency lists of a graph G = (V, E)
   Input: The source vertex v
   Input: The visited array
   Let Q = \emptyset;
   ;// Q is the empty queue
   Q.enqueue(v);
   visited[v] = true;
   visit(v);
   while Q \neq \emptyset do
       w = Q.dequeue();
       for u \in Adj[w] do
           if not visited[u] then
              Q.enqueue(u);
              visited[u] = true;
              visit(u);
           \quad \text{end} \quad
       end
   \quad \mathbf{end} \quad
   Time Complexity: \Theta(V+E).
11.3
        DFS
   Input: the adjacency lists of a graph G = (V, E)
   Let visited be a new array;
   for v \in V do
    visited[v] = false;
   end
   for v \in V do
       if not visited/v/ then
        DFS-Visit(G, v);
       end
   \quad \mathbf{end} \quad
   Input: the adjacency lists of a graph G = (V, E)
   Input: The source vertex v
   Input: The visited array
   visited[v] = true;
   visit(v);
   for u \in Adj[v] do
       if not visited/u/ then
        DFS-Visit(G, u, visited);
       end
```

end

11.4 Dijkstra-Prim

```
Input: the adjacency lists of a graph G = (V, E, w)
Input: s, the source vertex
Let F = V;
;// F is the fringe
Let parent[|V|] be a new array;
Let H be a min heap;
Let T = \emptyset;
;// T is the MST
Let dist[|V|] be a new array;
;// dist[i] is the smallest edge to add vertex i into the
 tree
for v \in V do
   H.insert((v, \infty));
   parent[v] = null;
   dist[v] = \infty;
\mathbf{end}
H.decreaseKey(s, 0);
for v \in Adj[s] do
   H.decreaseKey(v, w(s, v));
   parent[v] = s;
   dist[v] = w(u,v);
end
while F \neq \emptyset do
   u = H.removeMin();
   T = T \cup \{parent[u], u, w(u, parent(u))\};
   for v \in Adj[u] and v \in T do
       if w(u,v) < dist[v] then
          H.decreaseKey(v, w(u,v));
          dist[v] = w(u,v);
       end
   end
   F = F \setminus \{u\};
end
```

N.B.: You need to remember where in the heap each v is so that you can implement decreaseKey() in $\Theta(\log V)$ time.

11.5 Kruskal

```
Input: the adjacency lists of a graph G = (V, E, w)
   Input: s, the source vertex
   T = \emptyset;
   Let Edges[|E|] be a new array;
   Copy all edges into the array;
   sort(Edges);
   for e \in Edges do
       if adding e doesn't create a cycle then
        \mid \ T = T \cup \{e\};
       end
   \mathbf{end}
   How do you decide if adding e creates a cycle? Use a Union-Find D.S. =
Disjoint sets D.S.
   Make-Set(n):
Create an array parent[n]. set parent[i] = null for all 1 \le i \le n
   Union(x, y): attach the smaller of the two trees to the larger.
make the root of the larger tree the representative.
   Find(x): return the representative of x, but when you do it, bring up all of
the pointers to the root.
```

12 Dynamic Programming

12.1 Binomial Coefficients