Part 2

1 Recap

Degree of a polynomial - The highest power in the polynomial **Monotonic** - Always going in one direction (either increasing or decreasing)

1.1 Logarithms

$$\log_a xy = \log_a x + \log_a y$$
$$\log_a \frac{x}{y} = \log_a x - \log_a y$$
$$\log_a x^s = s \cdot \log_a x$$
$$\log_a x = \frac{\log_b x}{\log_b a}$$

2 Asymptotics

Time complexity - Expressed in terms of the number of basic operations used by the algorithm when the input has a particular size

Worst-Case time complexity - Expressed in terms of the largest number of basic operations used by the algorithm when the input has a particular size

2.1 Big-O

Let f(x) and g(x) be functions from the set of integers or the set of real numbers to the set of real numbers. We say that f(x) is O(g(x)) if there are constants C and k such that

$$|f(x)| \le C \cdot |g(x)|$$

whenever $x \ge k$

The constants C and k in the definition of big-O notation are called witnesses to the relationship f(x) is O(g(x))

2.1.1 Example

Let
$$f(x) = x^2 + 2x + 1$$
. Then $f(x) = O(x^2)$

For $x \ge 1$, we have $1 \le x \le x^2$. That gives

$$f(x) = x^2 + 2x + 1 \le x^2 + 2x^2 + x^2 = 4x^2$$

for $x \ge 1$. Because the above inequality holds for every positive $x \ge 1$, using k = 1 and C = 4 as witnesses, we get

$$f(x) \le C \cdot x^2$$

for every $x \ge k$

2.1.2 Example 2

Let $f(x) = 3^x$. Then f(x) is not $O(2^x)$

Assume that there are constants k and C such that $3^x \le C \cdot 2^x$ when $x \ge k$. Then

$$\left(\frac{3}{2}\right)^x \le C$$

when $x \ge k$

But any exponential function a^x grows monotonically whenever $a \ge 1$; a contradiction

2.1.3 Sum and Product Rules

The sum rule

If
$$f_1(x)$$
 is $O(g_1(x))$ and $f_2(x)$ is $O(g_2(x))$, then $f_1(x) + f_2(x)$ is $O(\max\{|g_1(x)|, |g_2(x)|\})$

The product rule

If
$$f_1(x)$$
 is $O(g_1(x))$ and $f_2(x)$ is $O(g_2(x))$, then $f_1(x) \cdot f_2(x)$ is $O(g_1(x) \cdot g_2(x))$

2.2 Big-Omega

Let f(x) and g(x) be functions from the set of real numbers to the set of real numbers. We say that f(x) is $\Omega(g(x))$ if there are positive constants C and k such that

$$|f(x)| \ge C \cdot |g(x)|$$

whenever x > k. Note that this implies that f(x) is $\Omega(g(x))$ iff g(x) is O(f(x))

2.3 Theta

Let f(x) and g(x) be functions from the set of real numbers to the set of real numbers. We say that f(x) is $\Theta(g(x))$ if f(x) is O(g(x)) and f(x) is O(g(x))

This is the equivalent to saying that f(x) is $\Theta(g(x))$ if f(x) is O(g(x)) and g(x) is O(f(x))

2.4 Little-o

Let f(x) and g(x) be functions from the set of real numbers to the set of real numbers. We say that f(x) is o(g(x)) when

$$\lim_{x \to \infty} \frac{f(x)}{g(x)} = 0$$

The definition without the limit is

$$o(g) = \{ f : \mathbb{N} \to \mathbb{N} | \forall C > 0 \exists k > 0 : C \cdot f(n) < g(n) \forall n \ge k \}$$

This shows that f(x) is o(g(x)) implies f(x) is O(g(x))

2.4.1 Sublinear functions

A function is called sublinear if it grows slower than a linear function. With little-o notation, we can express this as

A function f(x) is called sublinear if f(x) is o(x), so if

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

2.5 Little-omega

 ω is to o what Ω is to O

$$f = \omega(g) \Leftrightarrow g = o(f)$$

or

$$\omega(g) = \{ f : \mathbb{N} \to \mathbb{N} | \forall C > 0 \exists k > 0 : f(n) > C \cdot g(n) \forall n \ge k \}$$

2.6 General Rules

```
If f_1(x) is o(g(x)) and f_2(x) is o(g(x)), then f_1(x) + f_2(x) is o(g(x)).

If f_1(x) is O(g(x)) and f_2(x) is o(g(x)), then f_1(x) + f_2(x) is O(g(x)).

If f_1(x) is \Theta(g(x)) and f_2(x) is o(g(x)), then f_1(x) + f_2(x) is \Theta(g(x)).

Equivalent to \leq
O(g) = \{f : \mathbb{N} \to \mathbb{N} | \exists C, k > 0 : \mathbf{f}(\mathbf{n}) \leq \mathbf{C} \cdot \mathbf{g}(\mathbf{n}) \forall n \geq k\}

Equivalent to \geq
O(g) = \{f : \mathbb{N} \to \mathbb{N} | \exists C, k > 0 : \mathbf{f}(\mathbf{n}) \geq \mathbf{C} \cdot \mathbf{g}(\mathbf{n}) \forall n \geq k\}

Equivalent to \leq
O(g) = \{f : \mathbb{N} \to \mathbb{N} | \exists C_1, C_2, k > 0 : \mathbf{C}_1 \cdot \mathbf{g}(\mathbf{n}) \leq \mathbf{f}(\mathbf{n}) \leq \mathbf{C}_2 \cdot \mathbf{g}(\mathbf{n}) \forall n \geq k\}

Equivalent to \leq
O(g) = \{f : \mathbb{N} \to \mathbb{N} | \forall C > 0 \exists k > 0 : \mathbf{C} \cdot \mathbf{f}(\mathbf{n}) < \mathbf{g}(\mathbf{n}) \forall n \geq k\}

Equivalent to \leq
O(g) = \{f : \mathbb{N} \to \mathbb{N} | \forall C > 0 \exists k > 0 : \mathbf{f}(\mathbf{n}) > \mathbf{C} \cdot \mathbf{g}(\mathbf{n}) \forall n \geq k\}

Equivalent to \leq
```

3 Sorting

3.1 Insertion Sort

Listing 1: InsertionSort $(a_1 ..., a_n \in \mathbb{R}, n \ge 2)$

```
1
   for j=2 to n do
2
        x = a_i
3
        i=j-1
4
        while i>0 and a_i>x do
5
             a_{i+1} = a_i
6
             i=i-1
7
        end while
8
        a_{i+1} = x
   end for
```

We know:

- When j has a certain value, it inserts the j-th element into already sorted sequence a_1, \ldots, a_{j-1}
- Can be proved by using invariant "after jth iteration first j+1 elements are in order"
- Running time between n-1 and $\frac{n(n-1)}{2}$ worst case $O(n^2)$

3.2 Selection sort

Listing 2: SelectionSort $(a_1, ..., a_n \in \mathbb{R}, n \ge 2)$

```
for i=1 to n-1 do
1
2
         elem = a_i
3
        pos = i
4
         for j=i+1 to n do
5
             if a_i<elem then
6
                  elem=a_i
7
                   pos=j
             end if
8
9
         end for
10
         swap a_i and a_{pos}
11
    end for
```

How does it work?

Invariant: after ith iteration positions 1,...,i contain the overall i many smallest elements in order Not necessarily the first i elements (as it was in InsertionSort)

In the ith iteration of outer loop, we search the ith smallest element in remainder (positions $i_1, ..., n$) of input and swap it into position i

- elem keeps track of current idea of value ith smalllest element
- pos keeps track of the current idea of position of ith smallest element

Time complexity:

$$\sum_{i=1}^{n-1} \sum_{j=i+1}^{n} 1 = \sum_{i=1}^{n-1} (n-i)$$

$$= \left(\sum_{i=1}^{n-1} n\right) - \left(\sum_{i=1}^{n-1} i\right)$$

$$= (n-1) \cdot n - \frac{n(n-1)}{2}$$

$$= \frac{n(n-1)}{2}$$

$$= O(n^2)$$

3.3 Bubble sort

Listing 3: BubbleSort-1 $(a_1, ..., a_n \in \mathbb{R}, n \ge 2)$

```
1 for i=1 to n-2 do

2 for j=1 to n-1 do

3 if a_j > a_{j+1} then

4 swap a_j and a_{j+1}

5 end if

6 end for
```

This can be improved by keeping track of whether or not an element was swapped

Listing 4: BubbleSort-1 $(a_1, ..., a_n \in \mathbb{R}, n \ge 2)$

```
for i=1 to n-1 do
1
2
        swaps=0
3
        for j=1 to n-1 do
4
             if a_i > a_{i+1} then
5
                  swap a_i and a_{i+1}
6
                  swaps=swaps+1
7
             end if
8
        end for
9
        if swaps ==0 then
10
             break
        end if
11
12
   end for
```

Proof of correctness

A sequence $(a_1, ..., a_n)$ is sorted if for every adjacent pair a_i, a_{i+1} we have $a_i \le a_{i+1}$ Bubble sort achieves just that

Time complexity

$$\sum_{i=1}^{n-1} \sum_{j=1}^{n-1} 1 = \sum_{i=1}^{n-1} (n-1)$$
$$= (n-1)^2 = O(n^2)$$

3.4 Mergesort

Listing 5: list MergeSort (list m)

```
1 if length(m) ≤ 1 then
2    return m
3 end if
4 int middle = length(m) / 2
5 list left, right, leftsorted, rightsorted
6 left = m[1..middle]
7 right = m[middle+1..length(m)]
8 leftsorted = MergeSort(left)
9 rightsorted = MergeSort(right)
10 return Merge(leftsorted, rightsorted)
```

There is then the merge function:

Listing 6: list MergeSort (list left, list right)

```
list result
   while length(left)>0 or length(right)>0 do
2
3
       if length(left)>0 and length(right)>0 then
4
           if first(left) ≤ first(right) then
5
                append first(left) to result
                left = rest(left)
6
7
           else
8
            #Keeping extra copies of the data in the result array
9
                append first(right) to result
10
                right = rest(right)
11
           end if
12
       else if length(left)>0 then
13
           append left to result
14
           left = empty list
15
                # Length(right) > 0
16
           append right to result
17
           right = empty list
18
       end if
   end while
19
   return result
```

3.5 Quicksort

Listing 7: QuickSort(int A[1..n], int left, int right)

```
if (left<right) then
    #rearrange/partition in place
    #return value "pivot" is index of pivot element in A[] after partitioning
    pivot=Partition(A,left,right)
    #Now:
    #Everything in A[left...pivot-1] is smaller than pivot
    #Everything in A[pivot+1..right] is bigger than pivot</pre>
```

```
8    QuickSort (A,left,pivot-1)
9    QuickSort(A,pivot_1,right)
10 end if
```

An example of the partition function is

Listing 8: int Partition(A[1...n], int left, int right)

```
int x =A[right]
  int i=left-1
3
  for j=left to right-1 do
4
       if A[j]<x then</pre>
5
           i=i+1
6
           swap A[i] and A[j]
7
       end if
8
  end for
9
  swap A[i+1] and A[right]
  return i+1
```

4 Recurrences

4.1 Induction

Basically:

- "guess" correct solution (good job all sorting algorithms are n log n)
- verify base case(s) and step

Consider the recurrence for merge sort:

$$T(n) \le \begin{cases} d & \text{if } n \le c, \text{ for constants } c, d > 0 \\ 2 \cdot T(n/2) + a \cdot n & \text{otherwise} \end{cases}$$

To get the base case, do as follows:

$$d \le \alpha n \log_2 n \le \alpha c \log_2 c \quad \Leftrightarrow \quad \alpha \ge \frac{d}{c \log_2 c}$$

As for the inductive step, plug the guess in

$$\begin{split} T(n) &\leq 2T(n/2) + an \\ T(n) &\leq 2\alpha \frac{n}{2} \log_2 \frac{n}{2} + an \\ T(n) &\leq 2\alpha \frac{n}{2} \left(\log_2(n) - \log_2(2) \right) + an \\ T(n) &\leq 2\alpha \frac{n}{2} \left(\log_2(n) - 1 \right) + an \\ T(n) &\leq \alpha n \left(\log_2(n) - 1 \right) + an \\ T(n) &\leq \alpha n \log_2(n) - \alpha n + an \\ T(n) &\leq \alpha n \log_2 n \quad \text{if } \alpha n \geq an \Leftrightarrow \alpha \geq a \end{split}$$

The requirement that $\alpha \ge a$ suggests there isn't much room for (asymptotic) improvement, as both are constants

4.2 Iterative substitution

Expand the recurrence

$$T(n) \le 2T(n/2) + an$$

 $\le 2(2T(n/4) + an/2) + an = 4T(n/4) + an + an$
 $= 4T(n/4) + 2an \le 4(2T(n/8) + an/4) + 2an$
 $= 8T(n/8) + an + 2an = 8T(n/8) + 3an$
 $\le 8(2T(n/16) + an/8) + 3an = 16T(n/16) + an + 3an$
 $= 16T(n/16) + 4an$

4.3 Master Theorem

This can be used to solve recurrences of the form:

$$T(n) = aT(n/b) + f(n)$$

for $a \ge 1$ and $b \ge 1$

There are 3 cases, but rob says he'll give you them