CS310 - Advanced Data Structures and Algorithms

Runtime

September, 2020

Thanks to Prof. Nurit Haspel for many of these slides
- Sedgewick and Wayne, chapter 1.4.
- Remember recursion, basic runtime analysis.
Logarithms

- Involved in many important runtime results: Sorting, binary search etc.
- Logarithms grow slowly, much more slowly than any polynomial but faster than a constant.
- Definition: \( \log_B N = K \) if \( B^K = N \). B is the base of the log.
- Examples:
  - \( \log_2 8 = 3 \) because \( 2^3 = 8 \).
  - \( \log_{10} 100 = 2 \) because \( 10^2 = 100 \).
  - \( 2^{10} = 1024 \) (1K), so \( \log_2 1024 = 10 \).
  - \( 2^{20} = 1M \), so \( \log_2 1M = 20 \).
  - \( 2^{30} = 1G \) so \( \log_2 1G = 30 \).
Logarithms

- It requires $\log_N K$ digits to represent $K$ numbers in base $N$.
- It requires approx. $\log_2 K$ multiplications by 2 to get from 1 to $N$.
- It requires approx. $\log_2 K$ divisions by 2 to get from $N$ to 1.
- Computers work in binary, so in order to calculate how many numbers a certain amount of memory can represent we use $\log_2$
16 bits of memory can represent $2^{16}$ different numbers
$$= 2^{10} + 6 = 2^{10} \times 2^6 = 64K.$$ 

32 bits of memory can represent $2^{32}$ different numbers
$$= 2^{30} + 2 = 2^{30} \times 2^2 = 4G$$ — see previous slide. (many of 1990’s operating systems' addresses were 32 bits, so only 4 GB of addressable address space, became cramped).

64 bits (most of today’s computers' addresses).
Useful Logarithm Rules

- \( \log(nm) = \log(n) + \log(m) \)
- \( \log\left(\frac{n}{m}\right) = \log(n) - \log(m) \)
- \( \log(n^k) = k \log(n) \)
- \( \log_a(b) = \frac{\log b}{\log a} \)

If the base of \( \log \) is not specified, assume it is base 2 (although for runtime analysis it doesn’t matter)

- \( \log \): base 2
- \( \ln \): base e
When we develop an algorithm we want to know how many resources it requires.

Let $T$ and $N$ be positive numbers. $N$ is the size of the problem* and $T$ measures a resource: Runtime, CPU cycles, disk space, memory etc.

Order of growth can be important. For example – sorting algorithms can perform quadratically or as $n \times \log (n)$. Very big difference for large inputs.

We care less about constants, so $100N = O(N)$.

$100N + 200 = O(N)$.

Constant can be important when choosing between two similar run-time algorithms. Example – quicksort.

* It is not always 100% clear what the ”size of the problem” is. More on that later.
Runtime Analysis – Big-O Notation

- $T(N)$ is $O(F(N))$ if there are positive constants $c$ and $N_0$ such that $T(N) \leq c \times F(N)$ for all $N \geq N_0$.
- *i.e.*, $T(N)$ is bounded by a multiple of $F(N)$ from above for every big enough $N$.

Example – Show that $2N + 4 = O(N)$

This means – find actual $c$ and $N_0$ (there is more than one correct answer).
Runtime Analysis – Big-O Notation

- \( T(N) \) is \( O(F(N)) \) if there are positive constants \( c \) and \( N_0 \) such that \( T(N) \leq c \times F(N) \) for all \( N \geq N_0 \).

- Example – Show that \( 2N + 4 = O(N) \)

- This means – find actual \( c \) and \( N_0 \) (there is more than one correct answer).

- Idea: \( 3N \) eventually beats \( 2N \)...

  \( 2N+4 = 3N \) at \( N=4/3 \)

  So \( 2N + 4 < 3N \) for \( N > 2 \)

  i.e., \( c = 3, N_0 = 2 \)
Runtime Analysis – $\Omega$ Notation

- $T(N)$ is $\Omega(F(N))$ if there are positive constants $c$ and $N_0$ such that $T(N) \geq c \cdot F(N)$ for all $N \geq N_0$.

- $T(N)$ is bounded by a multiple of $F(N)$ from below for every big enough $N$.

- Example – Show that $2N + 4 = \Omega(N)$

  This means – find actual $c$ and $N_0$ (there is more than one correct answer).

  That’s easy: $c = 2$, $N_0 = 1$
• Note that although big-O is the standard notation for expressing growth of functions in C.S., S&W prefer the applied mathematician’s ~ notation.

• How are they related?

• Very simply. In the usual case that \( \Omega(F(N)) = O(F(N)) = G(N) \), the case of an “asymptotically tight bound”, we can say \( F(N) \sim G(N) \).

• For our previous example, we had \( T(N) = 2N + 4 = O(N) \), and \( T(N) = \Omega(N) \) also, so we can say \( T(N) \sim N \).
Can ~ do the whole job?

- How about an example that doesn’t qualify for ~…

- Here’s one: $T(N) = N \times \sin(N)$. Since $\sin(N) \leq 1$ for all $N$, we see that $T(N) = O(N)$. But $\sin(N)$ goes 0 and negative periodically, so no (positive) function qualifies as $\Omega(N)$.

- You can see that we had to reach pretty far to get an example. All polynomial functions have asymptotically tight bounds, as do other combinations of logs and powers.

- The function has to wiggle or jump around a lot to avoid ~ asymptotic expression.
When the runtime is estimated as a polynomial we care about the leading term only.

Thus $3n^3 + n^2 + 2n + 17 = O(n^3)$ because eventually the leading cubic term is bigger than the rest.

For a good estimate on the runtime it’s good to have both the $O$ and the $\Omega$ estimates (upper and lower bounds).

But we often settle for the big-$O$ bound, or $\sim$ expression.
<table>
<thead>
<tr>
<th>Function</th>
<th>Name</th>
</tr>
</thead>
<tbody>
<tr>
<td>$c$</td>
<td>Constant</td>
</tr>
<tr>
<td>$\log N$</td>
<td>Logarithmic</td>
</tr>
<tr>
<td>$\log^2 N$</td>
<td>Log-squared</td>
</tr>
<tr>
<td>$N$</td>
<td>Linear</td>
</tr>
<tr>
<td>$N \log N$</td>
<td>Linearithmic</td>
</tr>
<tr>
<td>$N^2$</td>
<td>Quadratic</td>
</tr>
<tr>
<td>$N^3$</td>
<td>Cubic</td>
</tr>
<tr>
<td>$2^N$</td>
<td>Exponential</td>
</tr>
</tbody>
</table>

(N log N is called “linearithmic”, page 187)
<table>
<thead>
<tr>
<th>$n$</th>
<th>$f(n)$</th>
<th>$\lg n$</th>
<th>$n$</th>
<th>$n \lg(n)$</th>
<th>$n^2$</th>
<th>$2^n$</th>
<th>$n!$</th>
</tr>
</thead>
<tbody>
<tr>
<td>10</td>
<td>$\mu s$</td>
<td>0.003</td>
<td>0.01</td>
<td>0.033</td>
<td>0.1</td>
<td>1μs</td>
<td>3.63 ms</td>
</tr>
<tr>
<td></td>
<td></td>
<td>0.004</td>
<td>0.02</td>
<td>0.086</td>
<td>0.4</td>
<td>1ms</td>
<td>77.1 y.</td>
</tr>
<tr>
<td></td>
<td></td>
<td>0.005</td>
<td>3.</td>
<td>0.147</td>
<td>0.9</td>
<td>1 sec</td>
<td>8.4 $\times 10^{15}$ y.</td>
</tr>
<tr>
<td>30</td>
<td></td>
<td>0.005</td>
<td>4.</td>
<td>0.0213</td>
<td>1.6</td>
<td>18.3 min</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>0.006</td>
<td>0.05</td>
<td>0.0282</td>
<td>2.5</td>
<td>13 d.</td>
<td></td>
</tr>
<tr>
<td>40</td>
<td></td>
<td>0.010</td>
<td>0.1</td>
<td>0.644</td>
<td>10</td>
<td>4 $\times 10^{13}$ y.</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>0.013</td>
<td>1</td>
<td>9.966</td>
<td>1ms</td>
<td></td>
<td></td>
</tr>
<tr>
<td>50</td>
<td></td>
<td>0.017</td>
<td>10</td>
<td>130</td>
<td>100ms</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>0.020</td>
<td>1ms</td>
<td>1.67</td>
<td>10 sec</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>0.023</td>
<td>0.01</td>
<td>19.93</td>
<td>16.7 min</td>
<td></td>
<td></td>
</tr>
<tr>
<td>100</td>
<td></td>
<td>0.027</td>
<td>0.1 sec</td>
<td>0.23</td>
<td>1.16 d.</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>0.030</td>
<td>1 sec</td>
<td>2.66</td>
<td>115.7 d.</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$10^n$</td>
<td></td>
<td></td>
<td></td>
<td>29.9 sec</td>
<td>31.7 y.</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

CS310 - Advanced Data Structures and Algorithms
Rule for sums (e.g. - two consecutive blocks of code): If \( T_1(N) = O(F(N)) \) and \( T_2(N) = O(G(N)) \) then \( T_1 + T_2 = O(\max(F(N), G(N))) \). The biggest contribution dominates the sum. Same for \( \sim \) here and below.

Rule for products (e.g. - an inner loop run by an outer loop): If \( T_1(N) = O(F(N)) \) and \( T_2(N) = O(G(N)) \) then \( T_1 \cdot T_2 = O(F(N) \cdot G(N)) \).

Example:
\[
(n^2 + 2n + 17) \cdot (2n^2 + n + 17) = O(n^2 \cdot n^2) = O(n^4).
\]
(Remember to ignore all but the leading term).

If we sum over a large number of terms, we multiply the number of terms by the estimated size of one term.

Example: Sum of \( i \) from 1 to \( N \). Average size of an element:
\[
\frac{N}{2}.
\]
There are \( N \) terms so the sum is \( O(N^2) \). Exact form:
\[
\frac{N \cdot (N-1)}{2}.
\]
The runtime of a loop is the runtime of the statements in the loop * number of iterations.

Example: bubble sort

```c
/* sort array of ints in A[0] to A[n-1] */
int bubblesort(int A[], int n)
{
    int i, j, temp;
    for(i =0; i < n-1; i++) /* n passes of loop */
    /* n-i passes of loop */
    for(j =n-1; j >i; j--)
            temp = A[j-1];
            A[j] = temp;
        }
}
```
Loops

- Work from inside out:
  - Calculate the body of inner loop (constant – an if statement and three assignments).
  - Estimate the number of passes of the inner loop: $n-i$ passes.
  - Estimate the number of passes of the outer loop: $n$ passes.
    - Each pass counts $n, n-1, n-2, \ldots, 1$.
  - Overall $1 + 2 + 3 + \ldots + n$ passes of constant operations:
    $$\frac{n \times (n-1)}{2} = O(n^2).$$

- This is not the fastest sorting algorithm but it's simple and works in-place. Good for small size input.

- We'll talk a bit about sorting later on (but only briefly. It was CS210 material).
Recursive Functions

- Recursive functions perform some operations and then call themselves with a different (usually smaller) input.

- Example: factorial.

```c
int factorial (int n)
{
    if(n<=1) return 1;
    return n*factorial(n-1);
}
```
Let us define $T(n)$ as a function that measures the runtime. $T(n)$ can be polynomial, logarithmic, exponential etc. $T(n)$ may not be given explicitly in closed form, especially in recursive functions (which lend themselves easily to this kind of analysis). We have to find a way to derive the closed form from the recurrence formula.
Recursive Analysis

- Let us denote the run-time on input \( n \) as some function \( T(n) \) and analyze \( T(n) \).

- \( O(1) \) operations before recursive call – if statement and a multiplication.

- The recursive part calls the same function with \( n - 1 \) as input, so this part runs \( T(n - 1) \)

- So: \( T(n) = c + T(n - 1) \).

- Similarly: \( T(n - 1) = c + T(n - 2) \) \( \Rightarrow \) \( T(n) = 2c + T(n - 2) \).

- After \( n \) such equations we reach \( T(1) = k \) (just the if-statement).

- \( T(n) = (n - 1) \times c + k = O(n) \).

- Iterative function performs the same.
A Problematic Example

The well known Fibonacci series, where each number is the sum of the previous two numbers: 0 1 1 2 3 5 8 13 ...

\[ f(n) = f(n-1) + f(n-2), \text{ where } f(0) = 0, f(1) = 1 \]

This is a recursive definition.

The following recursive program calculates the \( n^{th} \) term in the Fibonacci series (assume \( n \) is non-negative and the first term is the zero-th):

```c
int fib(int n)
{
    if(n == 0) return 0;
    if(n == 1) return 1;
    return fib(n-2) + fib(n-1);
}
```

What is the problem here?
Ill-Behaved Recursion – Illustration

\[ T(n) = T(n-1) + T(n-2) + T(n-3) + T(n-4) \]
Ill-Behaved Recursion

- The problem is the double recursion which runs on the same input so we do a lot of redundant work.
- The call tree looks like a big binary tree.
- Two or more recursive calls are not necessarily bad, as long as we split the work too!
- Example: Merge sort – sort recursively two halves of an array and merge.
- Call recursively twice, but on different input! The work is split between recursive calls in a smart way.
- The exact runtime is $O(1.618^n)$. The full analysis is beyond the scope for now.
- But it is exponential! (remember the illustration above).
- How do we fix the fibonacci program?
Binary Search

Definition: Search for an element in a sorted array.
- Return array index where element is found or a negative value if not found.
- Implemented in Java as part of the Collections API.
- Start in the middle of the array.
- If the element is smaller than that, search in the smaller half. Otherwise - search in the larger half.
Binary Search Example

Key       List
8         1 2 3 4 5 6 7 8 9
8>4       1 2 3 4 5 6 7 8 9
8>6       1 2 3 4 5 6 7 8 9
8=8       1 2 3 4 5 6 7 8 9
static <T> int binarySearch(T[] a, Tkey, Comparator<? super T> c)
static int binarySearch(Object[] a, Object key)

The version without the Comparator uses “natural order” of the array elements, i.e., calls compareTo of the element type to compare elements.

Thus the elements need to be Comparable – the element type implements Comparable<ElementType> in the generics setup. Or the old Comparable works here too.
// Hidden recursive routine.
private static <AnyType extends Comparable<? super AnyType>> int binarySearch( AnyType[] a, AnyType x, int low, int high )
{
    if( low > high )
        return NOT_FOUND;

    int mid = ( low + high ) / 2;

    if( a[ mid ].compareTo( x ) < 0 )
        return binarySearch( a, x, mid + 1, high );
    else if( a[ mid ].compareTo( x ) > 0 )
        return binarySearch( a, x, low, mid - 1 );
    else
        return mid;
}
Binary Search

What is that `<supert>` clause?

The `Comparable <supert>` specifies that `T ISA Comparable < Y >`, where `Y` is `T` or any superclass of it.

This allows the use of a `compareTo` implemented at the top of an inheritance hierarchy (i.e., in the base class) to compare elements of an array of subclass elements.

For example, we commonly use a unique id for equals, `hashCode` and `compareTo` across a hierarchy, and only want to implement it once in the base class.
You should be able to guess this one out by now (I hope):

\[ T(N) = T(N/2) + O(1) \]

\[ T(N) = O(\log N) \]
Mergesort Recurrence Formula

\[ T(n) = \begin{cases} 
C & \text{if } n \text{ is 1} \\
2 \times T\left(\frac{n}{2}\right) + cn & \text{otherwise}
\end{cases} \]

Notice that \( c \) and \( C \) are not the same constant!
Identities like this come up frequently in algorithmic analysis. It’s important to have ways of solving them. We’ll see a couple.

One basic way is to form a recursion tree. Mergesort is a good example:

1. If the array has at most one item – return.
2. Split it in half, call merge sort recursively on each half.
3. Merge the two sorted halves.
public static <AnyType extends Comparable<? super AnyType>>
    void mergeSort(AnyType [] a) {
    AnyType [] tmpArray = (AnyType []) new
            Comparable[a.length];
    mergeSort(a, tmpArray, 0, a.length - 1);
}

// Internal method that makes recursive calls.
private static <AnyType extends Comparable<? super AnyType>>
    void mergeSort(AnyType[ ] a, AnyType[ ] tmpArray,
                int left, int right) {
    if( left < right ) {
        int center = ( left +right ) / 2; mergeSort( a, tmpArray, left, center );
        mergeSort( a, tmpArray, center +1, right );
        merge( a, tmpArray, left, center +1, right );
    }
}
private static <AnyType extends Comparable<? super AnyType>>
    void merge(AnyType[] a, AnyType[] tmpArray,
                int leftPos, int rightPos, int rightEnd) {
        int leftEnd = rightPos - 1;
        int tmpPos = leftPos;
        int numElements = rightEnd - leftPos + 1;
        // Main loop
        while (leftPos <= leftEnd && rightPos <= rightEnd) {
            if (a[leftPos].compareTo(a[rightPos]) <= 0) {
                tmpArray[tmpPos++] = a[leftPos++];
            } else {
                tmpArray[tmpPos++] = a[rightPos++];
            }
            while (leftPos <= leftEnd) {
                tmpArray[tmpPos++] = a[leftPos++];
            }
            while (rightPos <= rightEnd) {
                tmpArray[tmpPos++] = a[rightPos++];
            }
        }
        // Copy tmpArray back
        for (int i = 0; i < numElements; i++, rightEnd--) {
            a[rightEnd] = tmpArray[rightEnd];
        }
    }
Linear-time Merging of Sorted Arrays

1 13 24 26
1 13 24 26
1 13 24 26
1 13 24 26

2 15 27 38
2 15 27 38
2 15 27 38
2 15 27 38

1 2 13 15
1 2 13 15
1 2 13 15
1 2 13 15
1 2 13 15 24 26 27 38

...
$T(N) = 2 \cdot T(N/2) + O(N)$

$= 2 \cdot (2 \cdot T(N/4) + O(N/2)) + O(N)$

$= 4 \cdot T(N/4) + O(N) + O(N)$

$= 4 \cdot (2 \cdot T(N/8) + O(N/4)) + O(N) + O(N)$

$= 8 \cdot T(N/8) + O(N) + O(N) + O(N)$

$= \ldots = 2 \log N \cdot T(1) + O(N) + O(N) + \ldots + O(N)$

$= N \cdot O(1) + O(N) + O(N) + \ldots + O(N)$

The terms are expanded $\log N$ times, each produces an $O(N)$. $\log N$ terms of $O(N)$ is $O(N\log N)$.
If \( N = 2^p \), then there are \( p \) rows with \( cn \) on the right, and one last row with \( dn \) on the right.

Since \( p = \log n \), this means that the total cost is \( cN \log N + dN \). In other words, this is what we call an \( O(N \log N) \) algorithm.
Another Way to Look at Runtime

- What does “linear runtime” really mean?
- A linear function (program, algorithm) requires resources that scale \textit{linearly} with the input size.
- Say a linear algorithm runs for 5 seconds on an input of size 10. How much time will it (approximately) run on an input of size 20?
What does "linear runtime" really mean?

A linear function (program, algorithm) requires resources that scale linearly with the input size.

Say a linear algorithm runs for 5 seconds on an input of size 10. How much time will it (approximately) run on an input of size 20?

\[ f(n) = O(n) \Rightarrow f(n) = cn \text{ for some } c. \text{ This means } f(2n) \approx c \cdot 2n. \]

Doubling the input size roughly doubles the runtime.

The exact runtime depends on the constant, the machine specs etc.

If a quadratic algorithm \( f(n) = O(n^2) \) runs for 5 seconds on an input of size 10. How much time will it (approximately) run on an input of size 20?
Best case: the minimum time for any instance of size \( n \)
- Worst case: the maximum time for any instance of size \( n \)
  - Unless otherwise specified, \( O(f(n)) \) means the worst case runtime

Average case: the average time for all instances of size \( n \)

Successful sequential search
- Average case: \( O(n) \)
- Worst case: \( O(n) \)

Unsuccessful sequential search: \( O(n) \)

Successful binary search
- Average case: \( O(\log n) \)
- Worst case: \( O(\log n) \)

Unsuccessful binary search: \( O(\log n) \)