

Algorithms Topics Review

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Fundamental Algorithms
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Beware of bugs in the below code: I
have only proved it correct, not tried
it.

Donald Knuth

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1 Asymptotics and Recurrences

1.1 Math Review

Before we talk about asymptotics and recurrences, we quickly review the logarithmic function \log .

Definition. We define the **logarithm** to be the opposite of exponentiation, i.e. we say that $\log_b(x) = y$ exactly if $b^y = x$. For example $\log_2(64) = 6$, since $64 = 2^6$.

Here's a couple useful properties of the \log that you will use in this section extensively.

(1) Product \rightarrow Summation: $\log_b(xy) = \log_b(x) + \log_b(y)$.

Proof. By definition, we know that $b^{\log_b(xy)} = xy$. However, also notice that $x = b^{\log_b(x)}$ and $y = b^{\log_b(y)} \implies xy = b^{\log_b(x)}b^{\log_b(y)} = b^{\log_b(x)+\log_b(y)} \implies b^{\log_b(xy)} = b^{\log_b(x)+\log_b(y)}$. □

(2) Quotient \rightarrow Subtraction: $\log_b\left(\frac{x}{y}\right) = \log_b(x) - \log_b(y)$.

Proof. This can be seen using the previous identity, and just taking $y \mapsto \frac{1}{y}$, and noticing that $\frac{1}{y} = \frac{1}{b^{\log_b(y)}} = b^{-\log_b(y)}$. □

(3) Power \rightarrow Scalar Multiplication: $\log_b(x^p) = p \log_b(x)$.

Proof. By definition:

$$x = b^{\log_b(x)} \implies x^p = \left(b^{\log_b(x)}\right)^p = b^{p \log_b(x)}$$

Therefore it must be true that $\log_b(x^p) = p \log_b(x)$. □

(4) Change of Base: $\log_b(x) = \frac{\log_k(x)}{\log_k(b)}$.

Proof. Starting from $x = b^{\log_b(x)}$, we can take \log_k of both sides to receive:

$$\log_k(x) = \log_k b^{\log_b(x)} = \log_b(x) \log_k(b)$$

Therefore, dividing through by $\log_k(b)$ gives us the desired identity. □

1.2 Asymptotics Analysis

In the analysis of algorithms, one of our goals is to classify growth of the

runtime and storage complexity of functions. To do so, it's in our interest to examine the limiting behavior of functions, i.e. when our input becomes large what does our function do. To this end we introduce Big O notation.

1.2.1 Big O notation

Big O notation exists to describe the limiting behavior of a function, and us Computer Scientists use it to classify algorithms in terms of their input size n . Due to this, from this point onwards all functions we define are non-negative.

We give both the informal and formal definition of a couple different useful characterizations. Let $f, g : \mathbb{R} \rightarrow \mathbb{R}$ be two functions.

- Upper bound: \mathcal{O} .

Definition. Informally, we say that $f(x) = \mathcal{O}(g(x))$ if $f(x) \leq cg(x)$, c some constant, for sufficiently large x .

Formally, $f(x) = \mathcal{O}(g(x))$ iff:

$$\limsup_{x \rightarrow \infty} \left| \frac{f(x)}{g(x)} \right| < \infty$$

For example, $n^2 = \mathcal{O}(n^2)$ and $n^2 = \mathcal{O}(n^5)$ but $n^2 \neq \mathcal{O}(n)$. To highlight the sufficiently large x portion, notice that it is true that $n^2 = \mathcal{O}(n^3 - n^2)$ ($n^3 - n^2 > n^2, \forall n > 2$.)

- Lower Bound: Ω .

Definition. Informally, we say that $f(x) = \Omega(g(x))$ if and only if $g(x) = \mathcal{O}(f(x))$, or that $f(x) \geq cg(x)$.

Formally $f(x) = \Omega(g(x)) \iff \liminf_{n \rightarrow \infty} \left| \frac{f(n)}{g(n)} \right| > 0$.

- Tight bound: θ .

Definition. We say that $f(x) = \theta(g(x))$ if $f(x) = \mathcal{O}(g(x))$ and $f(x) = \Omega(g(x))$. Another way to say this is that $\exists c \in \mathbb{R}$ such that $\frac{1}{c}g(x) \leq f(x) \leq cg(x)$, for sufficiently large enough x .

Formally we must have that:

$$\limsup_{x \rightarrow \infty} \left| \frac{f(x)}{g(x)} \right| \in \mathbb{R}_{>0}$$

To those that care, notice that having $f(x) = \mathcal{O}(g(x))$ and $\Omega(g(x)) \not\Rightarrow \lim_{x \rightarrow \infty} \left| \frac{f(x)}{g(x)} \right|$ exists. Instead \liminf and \limsup may converge to different values.

So for example, $n^2 = \theta(n^2)$ but $n^2 \neq \theta(n)$ and $\neq \theta(n^3)$.

1.2.2 Properties of Big O

There's a couple of useful properties of Big O that are good to know. Let $f_1 = \theta(g_1)$ and $f_2 = \theta(g_2)$.

- (1) Product: $f_1 f_2 = \theta(g_1 g_2)$. In addition $f\theta(g) = \theta(fg)$.
- (2) Sum: $f_1 + f_2 = \theta(g_1 + g_2)$. In particular if $f_1 = \mathcal{O}(g)$ and $f_2 = \mathcal{O}(g)$ then $f_1 + f_2 = \mathcal{O}(g)$.
- (3) Scalar multiplication: $\theta(kg) = \theta(g)$ supposing $k \neq 0$. In addition $kf_1 = \theta(g_1)$.
- (4) Elephant concept: Suppose $\max(g_1, g_2) = g_1$. Then $\theta(g_1 + g_2) = \theta(g_1)$. NOTE that this does not imply that $\theta(g_1 g_2) = \theta(g_1)$. Counterexample is $g_1(n) = g_2(n) = n$. You can think about this like θ takes summation to maximization.

1.2.3 Time Complexity Comparison

Typically for problems where we want to compare which function grows faster asymptotically, we really want to see at large x , which one dominates. Our main strategy to do this, is to reduce these functions down to functions which are more easily compared, which I call the time complexity classes. See the time complexity chart in the figures section for a good table of a common few which you should remember.

Take for examples:

- (1) 2^n versus n^2 .

Solution. It's clear that 2^n is exponential, which grows faster than n^2 which is polynomial.

□

- (2) $n^{\log(n)}$ versus n^{100} .

Solution. The left hand function is somewhere above polynomial due to the power being an increasing function of n . Therefore, it grows faster than n^{100} .

□

- (3) $n^{1/\log_2(n)}$ versus 2.

These are strange to compare, since we aren't sure what class the left hand function falls in. To try to fit it to something we understand, we remember that the logarithm takes powers to scalar multiplication, so then we notice:

$$\log_2(n^{1/\log_2(n)}) = \frac{1}{\log_2(n)} \log_2(n) = 1$$

But also $\log_2(2) = 1$. Therefore we find that these functions are actually equal in terms of asymptotic growth.

1.3 Algorithm \rightarrow Recurrence

Here we want to examine how to turn recursive code into recurrences characterizing their properties. We do this by example.

1.3.1 Fibonacci Sequence

```

1: procedure F( $n$ )
2:   if  $n \leq 2$  then
3:     Return 1
4:   else
5:     Return  $F(n-1) + F(n-2)$ 
6:   end if
7: end procedure

```

$\triangleright a_1 = 1, a_2 = 1, a_n = a_{n-1} + a_{n-2}$

Suppose we want to characterize the runtime of the above algorithm using a recurrence equation. The idea is that we count the work per level, and add it. Letting $G(n)$ characterize the runtime of $F(n)$.

```

1: procedure F( $n$ )
2:   if  $n \leq 2$  then
3:     Return 1
4:   else
5:     Return  $F(n-1) + F(n-2)$ 
6:   end if
7: end procedure

```

$\triangleright \theta(1)$
 $\triangleright \theta(1)$
 $\triangleright \theta(1)$
 $\triangleright G(n-1) + G(n-2) + \theta(1)$
 $\triangleright \theta(1)$

Notice that $\theta(1)$ summed a constant number of times is still $\theta(1)$, therefore we have:

$$G(n) = \begin{cases} \theta(1) & n \leq 2 \\ \theta(1) + G(n-1) + G(n-2) & \text{otherwise} \end{cases}$$

For characterizing things that aren't work, i.e. how many times the -1 operation happens in the above code, we can do a similar process. Let $H(n)$ characterize the number of -1 operations in $F(n)$. Then:

```

1: procedure F( $n$ )
2:   if  $n \leq 2$  then
3:     Return 1
4:   else
5:     Return  $F(n-1) + F(n-2)$ 
6:   end if
7: end procedure

```

$\triangleright 0$
 $\triangleright 0$
 $\triangleright 0$
 $\triangleright H(n-1) + H(n-2) + 1$
 $\triangleright 0$

Therefore:

$$H(n) = \begin{cases} 0 & n \leq 2 \\ 1 + H(n-1) + H(n-2) & \text{otherwise} \end{cases}$$

1.3.2 Merge Sort

Let $F(n)$ characterize the work of Merge Sort on an array of length n . Then:

```

1: procedure MERGESORT( $A$  : Array)
2:   Let  $n = \text{len}(A)$ .
3:   if  $n = 1$  then                                      $\triangleright \theta(1)$ 
4:     Return  $A$                                             $\triangleright \theta(1)$ 
5:   end if                                                $\triangleright \theta(1)$ 
6:    $B \leftarrow A[1 \dots \lfloor n/2 \rfloor]$                       $\triangleright \theta(1)$ 
7:    $C \leftarrow A[\lceil n/2 \rceil \dots n]$                     $\triangleright \theta(1)$ 
8:    $\text{Mergesort}(B), \text{Mergesort}(C)$                         $\triangleright F(\lfloor n/2 \rfloor) + F(\lceil n/2 \rceil)$ 
9:   Return  $\text{Merge}(B, C)$                                   $\triangleright \theta(n)$ 
10: end procedure

```

Therefore we have:

$$F(n) = \begin{cases} \theta(1) & n = 1 \\ \theta(n) + F(\lfloor n/2 \rfloor) + F(\lceil n/2 \rceil) & \text{otherwise} \end{cases}$$

Similarly we can do this for $H(n)$ characterizing storage constraints, but I'll leave that as exercise.

1.3.3 Randomized Algorithms

A classic Siegel question is to characterize various facets of the randomized algorithm:

```

1: procedure RAND( $n$ )
2:   if  $n \leq 1$  then
3:     Return 0
4:   end if
5:   Let  $x \leftarrow 1, 2$  or  $3$  with probabilities  $1/2, 1/3, 1/6$  respectively.
6:   if  $x = 1$  then
7:     Return  $2\text{Rand}(n)$ 
8:   else if  $x = 2$  then
9:     Return  $7\text{Rand}(n - 1) + 12\text{Rand}(n - 2)$ 
10:  else
11:    Return  $n\text{Rand}(n - 1)$ 
12:  end if
13: end procedure

```

Define function F, G, H which characterize runtime, exact value returned, and number of times $x \leftarrow 3$ respectively. The trick to characterizing the above, is simply to take whatever happens inside of an if statement and multiply it by the probability of the event occurring. So:

$$\begin{aligned}
F(n) &= \begin{cases} \theta(1) & n \leq 1 \\ \theta(1) + \frac{1}{2}(\theta(1) + F(n)) + \frac{1}{3}(\theta(1) + F(n-1) + F(n-2)) + \frac{1}{6}(\theta(1) + F(n-1)) & \text{otherwise} \end{cases} \\
G(n) &= \begin{cases} 0 & n \leq 1 \\ \frac{1}{2}(2H(n)) + \frac{1}{3}(7H(n-1) + 12H(n-2)) + \frac{1}{6}(nH(n-1)) & \text{otherwise} \end{cases} \\
H(n) &= \begin{cases} 0 & n \leq 1 \\ \frac{1}{2}(0 + H(n)) + \frac{1}{3}(0 + H(n-1) + H(n-2)) + \frac{1}{6}(1 + H(n-1)) & \text{otherwise} \end{cases}
\end{aligned}$$

This always appears on the exam.

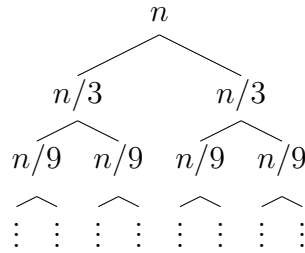
1.4 Solving Recurrences

Ok, so now that we know how to characterize certain aspects of recursive code using recurrences, one might ask, how do we solve recurrences? The idea stems behind something called the tree method. For example, consider the recurrence equation:

$$f(n) = \begin{cases} 1 & n = 1 \\ n + 2f(n/3) & \text{otherwise} \end{cases}$$

Here we call n the work function, 3 the decay rate, and 2 the branching factor.

What we do to solve this is *unroll* the recursive term over and over again. We represent each unrolling as a new level of the tree, so it may look like:



The top level looks like $n + 2f(n/3)$, but then we unroll $f(n/3)$ to $n/3 + 2(n/9)$, which is our second level. To then figure out what our summation totals to, we sum across the level, and then downward. In the above example, the first level totals to n , the second to $(2/3)n$, the third to $(4/9)n$, etc. In fact, we will find that in general the j th level will sum to $\frac{2^j}{3^j}n$; this is guaranteed by the unrolling. But what about the leaf level?

In general, we have to examine the leaf level separately, because the recurrence defines something different for it. Here, our recurrence says that each leaf has cost 1. Looking at our tree, we see that at each level the number of vertices doubles (powers of branching factor), therefore at the leaf level k we must have 2^k leaves. Each costs 1, therefore the contribution from the leaf level is 2^k .

Therefore our final total actually looks something like $n + \frac{2}{3}n + \frac{2^2}{3^2}n + \cdots + \frac{2^{k-1}}{3^{k-1}}n + 2^k$, for some stopping point k . Let's find k .

k is determined by the point we can *unroll* no longer, i.e. the decay rate has been applied sufficiently enough times such that we get down to our base case, 1. In other words, we want to solve for k where:

$$\frac{n}{3^k} = 1 \implies n = 3^k \implies k = \log_3(n)$$

Since we choose n a power of 3, we find that k is an integer like we wanted it to be. Then, we can write our final answer as:

$$f(n) = n \left(1 + \frac{2}{3} + \frac{2^2}{3} + \cdots + \left(\frac{2}{3} \right)^{\log_3(n)-1} \right) + 2^{\log_3(n)}$$

We make one note here about the leaf level. Notice that we can say:

$$2^{\log_3(n)} = \frac{n}{n} 2^{\log_3(n)} = n \frac{2^{\log_3(n)}}{3^{\log_3(n)}} = n \left(\frac{2}{3} \right)^{\log_3(n)}$$

This looks exactly like our pattern! What's happening? What we've discovered is that our leaf level *obeys* our recurrence, and I claim that this is in general true if the work at the level matches the work function. For example, the work function $w(n)$ is n here. The base case is at $n = 1$, therefore looking at $w(1)$ we see it's 1. *This matches our base case*, i.e. that at $n = 1, f(n) = 1$. Whenever this happens, it's unnecessary to compute the leaf level separately, and we can pull it into our summation. Rough reasoning is that it's modeled perfectly by the recurrence. If we had it that when $n = 1, f(n) = 5$, we could not do this. Therefore we can write:

$$f(n) = n \left(1 + \frac{2}{3} + \frac{2^2}{3} + \cdots + \left(\frac{2}{3} \right)^{\log_3(n)} \right)$$

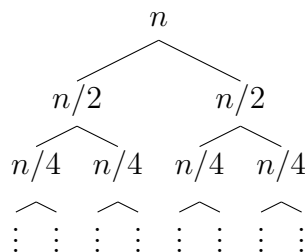
Let's solve a couple different types of common recurrences you might see.

1.4.1 Basic Recurrences

(1) Solve the recurrence:

$$A(n) = \begin{cases} 1 & n = 1 \\ n + 2A(n/2) & \text{otherwise} \end{cases}$$

Solution. For this we have work function $f(n) = n$, decay rate 2 and branching factor 2. The tree we draw looks like:



Summing across, we come across the surprising fact that each level sums to n . This is roughly because the decay rate and the branching factor cancel each other out. In general, we find this to be true when $f(\delta(n)) = \beta$ where β is the branching factor and δ is the decay rate as a function of n (can you see why?). Ok, so now considering the tree, we can ask how many terms are there? Recall this is solving for $\frac{n}{2^k} = 1 \implies k = \log_2(n)$. This tells us that there must be $\log_2(n) + 1$ levels (k tells us k th level, but count starting from 0). Finally we notice that $f(1) = A(1)$, which implies that we don't have to do the leaf level separately. Therefore our solution is:

$$A(n) = n + n + \cdots + n = n(\text{Number of levels}) = n(\log_2(n) + 1)$$

□

(2) Solve the recurrence:

$$B(n) = \begin{cases} 5, & n = 1 \\ n + 2B(n/2), & \text{otherwise} \end{cases}$$

Solution. The difference between this one at the last one is the leaf level. Here we have that $B(1) \neq f(1)$, which implies we need to compute the leaf level separately. There are $2^{\log_2(n)} = n$ leaves, and each has work 5, which implies that the leaf level cost is $5n$. Therefore we can write our answer as:

$$B(n) = n\log_2(n) + 5n$$

□

1.4.2 Changing the Leaf Level

What if we have a recurrence like:

$$C(n) = \begin{cases} 8, & n = 8 \\ n + 3C(n/2), & \text{otherwise} \end{cases}$$

In this case what's strange is that we've changed when we enter the leaf level. The tree method, however, handles this perfectly. Before we asked when $\frac{n}{b^k} = 1$ where b was the decay rate. Here the base case is when $n = 8$, so we instead ask $\frac{n}{2^k} = 8 = 2^3 \implies k = \log_2(n) - 3$. Then the problem is solved in the same exact manner as in the basic recurrences.

1.4.3 Multiple Decay Rates

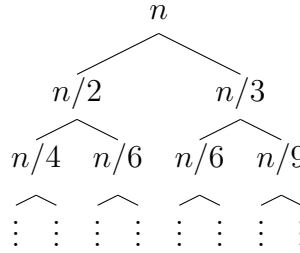
What happens if we have a recurrence like:

$$D(n) = \begin{cases} 1, & n = 1 \\ n + D(n/2) + D(n/3), & \text{otherwise} \end{cases}$$

What we lose is the guarantee that all leaves live on the same level. In fact, the end of the *unrolling* will come sooner for the harsher decay rate, and later for the kinder decay rate. In $D(n)$, we see that $\frac{n}{2^k} \rightarrow_k 1$ slower than $\frac{n}{3^k} \rightarrow_k 1$. To resolve this problem, what we do is approximate; we say that our leaf level k lives somewhere between the leaf level defined by 2 and 3.

If we follow the decay rate 2 all of the way down, we know that our leaf level is $k_2 = \log_2(n)$. If we follow 3, similarly we will receive $k_3 = \log_3(n)$. We say that our "leaf level" lives between these two, or $\log_3(n) \leq k \leq \log_2(n)$.

Then to solve our problem we have the tree:



We find that our summation looks like:

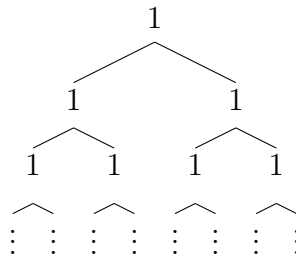
$$D(n) \approx n \left[1 + \frac{5}{6} + \frac{5^2}{6^2} + \cdots + \left(\frac{5}{6} \right)^k \right], \quad \log_3(n) \leq k \leq \log_2(n)$$

1.4.4 Strange Decay Rates

What happens if we have a recurrence like:

$$E(n) = \begin{cases} 1, & n = 1 \\ 1 + 2E(\delta(n)), & \text{otherwise} \end{cases}$$

Lots of people get stuck on this, but I claim that our tree method handles this perfectly. The tree itself looks like:



The real question is, where is the leaf level? Before we asked for decay rate $\delta(n) = \frac{n}{b}$, how many times do we have to apply it to get down to the base case. This formulated as $\frac{n}{b^k} = 1 \implies k = \log_b(n)$. Our question in general is for what k does $\delta^k(n) = 1$, where k isn't a power but repeated function compositions. For example if $\delta(n) = n - 1$, then we would be asking $n - k(-1) = 1 \implies k = n - 1$.

2 Dynamic Programming

Dynamic programming is a technique from optimization field, specially it's a method to solve problem if the problem exhibits **optimal substructure** and **overlapping subproblems**.

Definition. A problem is said to have **optimal substructure** if it can be constructed from optimal solutions of its subproblems.

For an example, suppose T a tree and consider the problem where $\forall v \in T$, you want to compute a field \min such that $\min[v] = \min\{w.val : w \in ST(v)\}$ where $ST(v)$ denotes the subtree rooted by v . This problem exhibits optimal substructure, as for arbitrary vertex v , you have $\min[w]$ computed for all $w \in Children[v]$, then you can construct $\min[v]$ as the minimum of your childrens answers and your own.

Definition. A problem is said to have **overlapping subproblems** if the problem can be broken down into subproblems which are reused several times.

For an example, consider the Fibonacci number sequence $a_n = a_{n-1} + a_{n-2}$, $a_2 = a_1 = 1$. Consider the value a_5 . Notice that we can express it as a graph (see figure 2) with many incoming edges (in particular a DAG). Whereas problems with optimal substructure but not overlapping subproblems look like the problem $\min[v]$ problem, and can be modeled by trees.

The idea behind the dynamic programming problems we deal with is that if we remember problems as we do it, we can eliminate the "overlapping" problems and reduce our computational cost as much as possible.

We've discussed three problems that we call "representative" of a lot of dynamic programming techniques: GCD, Woodcut, and Matrix Chain. We find that many dynamic programming problems reduce down to similar techniques needed to solve these. In this section we discuss how to tackle these problems fully, but before that we introduce **memoization**.

2.1 Memoization through Fibonacci

As discussed above, the Fibonacci sequence $F_n = F_{n-1} + F_{n-2}$, $F_2 = F_1 = 1$, is a prime example of a dynamic programming problem, since it has both optimal substructure and

overlapping subproblems. Using the recurrence relationship defined above we can write recursive code to solve this problem:

```

1: procedure F( $n$ )                                ▷  $a_1 = 1, a_2 = 1, a_n = a_{n-1} + a_{n-2}$ 
2:   if  $n \leq 2$  then
3:     Return 1
4:   else
5:     Return  $F(n - 1) + F(n - 2)$ 
6:   end if
7: end procedure

```

However, if we were to run just this we would find ourselves choked by the runtime cost almost immediately. This is a consequence of the overlapping subproblems portion of Fibonacci, i.e. we're repeatedly computing the same pieces of data. How do we resolve this? We implement **memoization**.

Definition. Memoization is an optimization technique where we store and cache the results of expensive function calls. The idea is that if we want to compute said function again, we look in our cache first. (Memoization \leftarrow making a memo.)

Let's take a look at this implemented in the Fibonacci sequence.

```

1: Let Memo[1..n] be a integer valued array initialized to -1.
2: procedure F( $n$ )                                ▷ Recursive or top down
3:   if  $n \leq 2$  then
4:     Return 1.
5:   else if Memo[ $n$ ]  $\neq -1$  then                    ▷ If we have computed  $n$ , use that result
6:     Return Memo[ $n$ ].
7:   else                                           ▷ Otherwise, compute it, store it, and return it.
8:     Memo[ $n$ ] =  $F(n - 1) + F(n - 2)$ .
9:     Return Memo[ $n$ ].
10:  end if
11: end procedure

```

We can also implement this iteratively using a lookup table:

```

1: procedure F( $n$ )                                ▷ Iterative or bottom up
2:   Let Memo[1..n] be a integer valued array.
3:   Let Memo[1], Memo[2] = 1.
4:   for  $i = 3 \rightarrow n$  do
5:     Memo[ $i$ ] = Memo[ $i - 1$ ] + Memo[ $i - 2$ ]
6:   end for
7: end procedure

```

Without the memoization table, our runtime was exponential, but what about now? It's clear by the iterative version that our usage of memoization brings us to $\theta(n)$ work, which is basically a night and day difference. In general we can examine the new runtime of our dynamic programming problem by looking at the memoization table, and trying to figure out how long it would take to fill it.

2.2 Greatest Common Subsequence

The problem is as follows: Suppose you are given two sequence A and B . Your objective is to find a subsequence $S \subseteq A, B$ such that the length of S is maximized. This is a classic problem for applications in revision control, the diff utility on your computer, and many more NLP like reasons.

$$GCS(i, j) = \begin{cases} 0, & ij = 0 \\ 1 + GCS(i - 1, j - 1), & A[i] = A[j] \\ \max(GCS(i - 1, j), GCS(i, j - 1)), & \text{otherwise} \end{cases}$$

```
1: Let  $A[1..n]$  and  $B[1..m]$  be two character arrays.
2: procedure GCS( $i, j$ )
3:   if  $ij = 0$  then
4:     Return 0.
5:   else if  $A[i] = B[j]$  then
6:     Return  $1 + GCS(i - 1, j - 1)$ .
7:   else
8:     Return  $\max(GCS(i - 1, j), GCS(i, j - 1))$ .
9:   end if
10: end procedure
```

```
1: Let  $A[1..n]$  and  $B[1..m]$  be two character arrays.
2: Let  $Memo[1..n, 1..m]$  be a 2d array initialized to  $-1$ .
3: procedure GCS( $i, j$ )
4:   if  $ij = 0$  then
5:     Return 0.
6:   else if  $Memo[i, j] \neq -1$  then
7:     Return  $Memo[i, j]$ .
8:   else if  $A[i] = B[j]$  then
9:      $Memo[i, j] = 1 + GCS(i - 1, j - 1)$ .
10:  else
11:     $Memo[i, j] = \max(GCS(i - 1, j), GCS(i, j - 1))$ .
12:  end if
13:  Return  $Memo[i, j]$ .
14: end procedure
```

```

1: Let  $A[1..n]$  and  $B[1..m]$  be two character arrays.
2: Let  $Memo[1..n, 1..m]$  be a 2d array initialized to  $-1$ .
3: Let  $Decisions[1..n, 1..m]$  be a 2d array.
4: procedure GCS( $i, j$ )
5:   if  $ij = 0$  then
6:     Return 0.
7:   else if  $Memo[i, j] \neq -1$  then
8:     Return  $Memo[i, j]$ .
9:   else if  $A[i] = B[j]$  then
10:     $Memo[i, j] = 1 + GCS(i - 1, j - 1)$ .
11:     $Decisions[i, j] = (i - 1, j - 1)$ .
12:  else
13:     $v_1, v_2 = GCS(i - 1, j), GCS(i, j - 1)$ .
14:    if  $v_1 > v_2$  then
15:       $Memo[i, j] = v_1$ .
16:       $Decisions[i, j] = (i - 1, j)$ .
17:    else
18:       $Memo[i, j] = v_2$ .
19:       $Decisions[i, j] = (i, j - 1)$ .
20:    end if
21:  end if
22:  Return  $Memo[i, j]$ .
23: end procedure

```

3 Figures

3.1 Common Time Complexities

Notation	Name	Example
$O(1)$	constant	Determining if a binary number is even or odd; Calculating $(-1)^n$; Using a constant-size lookup table
$O(\log \log n)$	double logarithmic	Number of comparisons spent finding an item using interpolation search in a sorted array of uniformly distributed values
$O(\log n)$	logarithmic	Finding an item in a sorted array with a binary search or a balanced search tree as well as all operations in a Binomial heap
$O((\log n)^c)$ $c > 1$	polylogarithmic	Matrix chain ordering can be solved in polylogarithmic time on a parallel random-access machine .
$O(n^c)$ $0 < c < 1$	fractional power	Searching in a k-d tree
$O(n)$	linear	Finding an item in an unsorted list or in an unsorted array; adding two n -bit integers by ripple carry
$O(n \log^* n)$	n log-star n	Performing triangulation of a simple polygon using Seidel's algorithm , or the union-find algorithm . Note that $\log^*(n) = \begin{cases} 0, & \text{if } n \leq 1 \\ 1 + \log^*(\log n), & \text{if } n > 1 \end{cases}$
$O(n \log n) = O(\log n!)$	linearithmic, loglinear, or quasilinear	Performing a fast Fourier transform ; Fastest possible comparison sort ; heapsort and merge sort
$O(n^2)$	quadratic	Multiplying two n -digit numbers by a simple algorithm; simple sorting algorithms, such as bubble sort , selection sort and insertion sort ; (worst case) bound on some usually faster sorting algorithms such as quicksort , Shellsort , and tree sort
$O(n^c)$	polynomial or algebraic	Tree-adjoining grammar parsing; maximum matching for bipartite graphs ; finding the determinant with LU decomposition
$L_n[\alpha, c] = e^{(c+o(1))(\ln n)^\alpha (\ln \ln n)^{1-\alpha}}$ $0 < \alpha < 1$	L-notation or sub-exponential	Factoring a number using the quadratic sieve or number field sieve
$O(c^n)$ $c > 1$	exponential	Finding the (exact) solution to the travelling salesman problem using dynamic programming ; determining if two logical statements are equivalent using brute-force search
$O(n!)$	factorial	Solving the travelling salesman problem via brute-force search; generating all unrestricted permutations of a poset ; finding the determinant with Laplace expansion ; enumerating all partitions of a set

Figure 1: Don't worry about polyarithmitic and L notation. (src. Wikipedia)

3.2 Fibonacci Overlapping Subproblems

Figure 2: Fibonacci has overlapping subproblems

