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Recursion and Dynamic Programming

While there are a large number of recursive problems, many follow similar patterns. A good hint that a problem is recursive is that it can be built off of subproblems.

When you hear a problem beginning with the following statements, it's often (though not always) a good candidate for recursion: "Design an algorithm to compute the nth ...", "Write code to list the first n...", "Implement a method to compute all...", and so on.

> Tip: In my experience coaching candidates, people typically have about 50% accuracy in their "this sounds like a recursive problem" instinct. Use that instinct, since that 50% is valuable. But don't be afraid to look at the problem in a different way, even if you initially thought it seemed recursive. There's also a 50% chance that you were wrong.

Practice makes perfect! The more problems you do, the easier it will be to recognize recursive problems.

How to Approach

Recursive solutions, by definition, are built off of solutions to subproblems. Many times, this will mean simply to compute `f(n)` by adding something, removing something, or otherwise changing the solution for `f(n-1)`. In other cases, you might solve the problem for the first half of the data set, then the second half, and then merge those results.

There are many ways you might divide a problem into subproblems. Three of the most common approaches to develop an algorithm are bottom-up, top-down, and half-and-half.

Bottom-Up Approach

The bottom-up approach is often the most intuitive. We start with knowing how to solve the problem for a simple case, like a list with only one element. Then we figure out how to solve the problem for two elements, then for three elements, and so on. The key here is to think about how you can *build* the solution for one case off of the previous case (or multiple previous cases).

Top-Down Approach

The top-down approach can be more complex since it's less concrete. But sometimes, it's the best way to think about the problem.

In these problems, we think about how we can divide the problem for case N into subproblems.

Be careful of overlap between the cases.

Half-and-Half Approach

In addition to top-down and bottom-up approaches, it's often effective to divide the data set in half.

For example, binary search works with a "half-and-half" approach. When we look for an element in a sorted array, we first figure out which half of the array contains the value. Then we recurse and search for it in that half.

Merge sort is also a "half-and-half" approach. We sort each half of the array and then merge together the sorted halves.

▸ Recursive vs. Iterative Solutions

Recursive algorithms can be very space inefficient. Each recursive call adds a new layer to the stack, which means that if your algorithm recurses to a depth of n, it uses at least O(n) memory.

For this reason, it's often better to implement a recursive algorithm iteratively. *All* recursive algorithms can be implemented iteratively, although sometimes the code to do so is much more complex. Before diving into recursive code, ask yourself how hard it would be to implement it iteratively, and discuss the tradeoffs with your interviewer.

▸ Dynamic Programming & Memoization

Although people make a big deal about how scary dynamic programming problems are, there's really no need to be afraid of them. In fact, once you get the hang of them, these can actually be very easy problems.

Dynamic programming is mostly just a matter of taking a recursive algorithm and finding the overlapping subproblems (that is, the repeated calls). You then cache those results for future recursive calls.

Alternatively, you can study the pattern of the recursive calls and implement something iterative. You still "cache" previous work.

> A note on terminology: Some people call top-down dynamic programming "memoization" and only use "dynamic programming" to refer to bottom-up work. We do not make such a distinction here. We call both dynamic programming.

One of the simplest examples of dynamic programming is computing the nth Fibonacci number. A good way to approach such a problem is often to implement it as a normal recursive solution, and then add the caching part.

Fibonacci Numbers

Let's walk through an approach to compute the nth Fibonacci number.

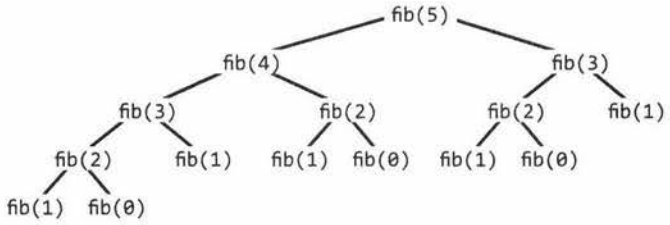
Recursive

We will start with a recursive implementation. Sounds simple, right?

```
1  int fibonacci(int i) {
2    if (i == 0) return 0;
3    if (i == 1) return 1;
4    return fibonacci(i - 1) + fibonacci(i - 2);
5  }
```

What is the runtime of this function? Think for a second before you answer.

If you said $O(n)$ or $O(n^2)$ (as many people do), think again. Study the code path that the code takes. Drawing the code paths as a tree (that is, the recursion tree) is useful on this and many recursive problems.



Observe that the leaves on the tree are all `fib(1)` and `fib(0)`. Those signify the base cases.

The total number of nodes in the tree will represent the runtime, since each call only does $O(1)$ work outside of its recursive calls. Therefore, the number of calls is the runtime.

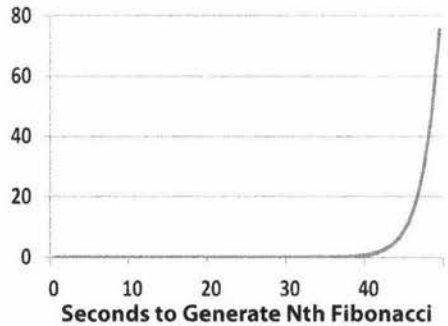
> Tip: Remember this for future problems. Drawing the recursive calls as a tree is a great way to figure out the runtime of a recursive algorithm.

How many nodes are in the tree? Until we get down to the base cases (leaves), each node has two children. Each node branches out twice.

The root node has two children. Each of those children has two children (so four children total in the "grandchildren" level). Each of those grandchildren has two children, and so on. If we do this n times, we'll have roughly $O(2^n)$ nodes. This gives us a runtime of roughly $O(2^n)$.

> Actually, it's slightly better than $O(2^n)$. If you look at the subtree, you might notice that (excluding the leaf nodes and those immediately above it) the right subtree of any node is always smaller than the left subtree. If they were the same size, we'd have an $O(2^n)$ runtime. But since the right and left subtrees are not the same size, the true runtime is closer to $O(1.6^n)$. Saying $O(2^n)$ is still technically correct though as it describes an upper bound on the runtime (see "Big O, Big Theta, and Big Omega" on page 39). Either way, we still have an exponential runtime.

Indeed, if we implemented this on a computer, we'd see the number of seconds increase exponentially.



We should look for a way to optimize this.

Top-Down Dynamic Programming (or Memoization)

Study the recursion tree. Where do you see identical nodes?

There are lots of identical nodes. For example, `fib(3)` appears twice and fib(2) appears three times. Why should we recompute these from scratch each time?

In fact, when we call `fib(n)`, we shouldn't have to do much more than `O(n)` calls, since there's only `O(n)` possible values we can throw at `fib`. Each time we compute `fib(i)`, we should just cache this result and use it later.

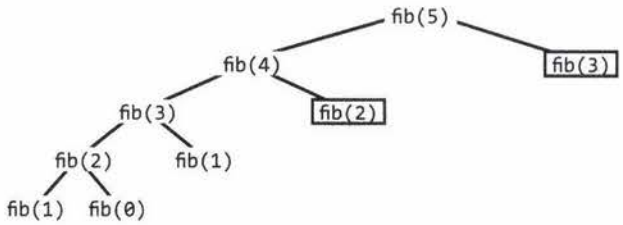
This is exactly what memoization is.

With just a small modification, we can tweak this function to run in `O(n)` time. We simply cache the results of `fibonacci(i)` between calls.

```
1  int fibonacci(int n) {
2    return fibonacci(n, new int[n + 1]);
3  }
4
5  int fibonacci(int i, int[] memo) {
6    if (i == 0 || i == 1) return i;
7
8    if (memo[i] == 0) {
9      memo[i] = fibonacci(i - 1, memo) + fibonacci(i - 2, memo);
10   }
11   return memo[i];
12 }
```

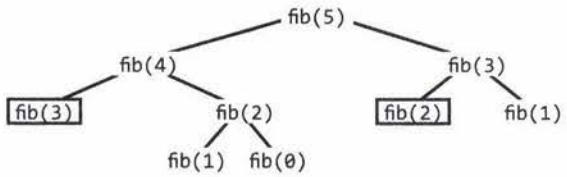
While the first recursive function may take over a minute to generate the 50th Fibonacci number on a typical computer, the dynamic programming method can generate the 10,000th Fibonacci number in just fractions of a millisecond. (Of course, with this exact code, the `int` would have overflowed very early on.)

Now, if we draw the recursion tree, it looks something like this (the black boxes represent cached calls that returned immediately):



How many nodes are in this tree now? We might notice that the tree now just shoots straight down, to a depth of roughly n. Each node of those nodes has one other child, resulting in roughly 2n children in the tree. This gives us a runtime of `O(n)`.

Often it can be useful to picture the recursion tree as something like this:



This is *not* actually how the recursion occurred. However, by expanding the further up nodes rather than the

lower nodes, you have a tree that grows wide before it grows deep. (It's like doing this breadth-first rather than depth-first.) Sometimes this makes it easier to compute the number of nodes in the tree. All you're really doing is changing which nodes you expand and which ones return cached values. Try this if you're stuck on computing the runtime of a dynamic programming problem.

Bottom-Up Dynamic Programming

We can also take this approach and implement it with bottom-up dynamic programming. Think about doing the same things as the recursive memoized approach, but in reverse.

First, we compute `fib(1)` and `fib(0)`, which are already known from the base cases. Then we use those to compute `fib(2)`. Then we use the prior answers to compute `fib(3)`, then `fib(4)`, and so on.

```
1  int fibonacci(int n) {
2    if (n == 0) return 0;
3    else if (n == 1) return 1;
4
5    int[] memo = new int[n];
6    memo[0] = 0;
7    memo[1] = 1;
8    for (int i = 2; i < n; i++) {
9      memo[i] = memo[i - 1] + memo[i - 2];
10   }
11   return memo[n - 1] + memo[n - 2];
12 }
```

If you really think about how this works, you only use `memo[i]` for `memo[i+1]` and `memo[i+2]`. You don't need it after that. Therefore, we can get rid of the memo table and just store a few variables.

```
1  int fibonacci(int n) {
2    if (n == 0) return 0;
3    int a = 0;
4    int b = 1;
5    for (int i = 2; i < n; i++) {
6      int c = a + b;
7      a = b;
8      b = c;
9    }
10   return a + b;
11 }
```

This is basically storing the results from the last two Fibonacci values into a and b. At each iteration, we compute the next value (`c = a + b`) and then move (`b, c = a + b`) into (`a, b`).

This explanation might seem like overkill for such a simple problem, but truly understanding this process will make more difficult problems much easier. Going through the problems in this chapter, many of which use dynamic programming, will help solidify your understanding.

Additional Reading: Proof by Induction (pg 631).

Interview Questions

8.1 **Triple Step:** A child is running up a staircase with n steps and can hop either 1 step, 2 steps, or 3 steps at a time. Implement a method to count how many possible ways the child can run up the stairs.

Hints: #152, #178, #217, #237, #262, #359

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8.2 **Robot in a Grid:** Imagine a robot sitting on the upper left corner of grid with `r` rows and `c` columns. The robot can only move in two directions, right and down, but certain cells are "off limits" such that the robot cannot step on them. Design an algorithm to find a path for the robot from the top left to the bottom right.

Hints: #331, #360, #388

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8.3 **Magic Index:** A magic index in an array `A[0...n-1]` is defined to be an index such that `A[i] = i`. Given a sorted array of distinct integers, write a method to find a magic index, if one exists, in array A.

FOLLOW UP

What if the values are not distinct?

Hints: #170, #204, #240, #286, #340

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8.4 **Power Set:** Write a method to return all subsets of a set.

Hints: #273, #290, #338, #354, #373

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8.5 **Recursive Multiply:** Write a recursive function to multiply two positive integers without using the * operator. You can use addition, subtraction, and bit shifting, but you should minimize the number of those operations.

Hints: #166, #203, #227, #234, #246, #280

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8.6 **Towers of Hanoi:** In the classic problem of the Towers of Hanoi, you have 3 towers and `N` disks of different sizes which can slide onto any tower. The puzzle starts with disks sorted in ascending order of size from top to bottom (i.e., each disk sits on top of an even larger one). You have the following constraints:

(1) Only one disk can be moved at a time.

(2) A disk is slid off the top of one tower onto another tower.

(3) A disk cannot be placed on top of a smaller disk.

Write a program to move the disks from the first tower to the last using stacks.

Hints: #144, #224, #250, #272, #318

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8.7 **Permutations without Dups:** Write a method to compute all permutations of a string of unique characters.

Hints: #150, #185, #200, #267, #278, #309, #335, #356

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8.8 **Permutations with Dups:** Write a method to compute all permutations of a string whose characters are not necessarily unique. The list of permutations should not have duplicates.

Hints: #161, #190, #222, #255

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8.9 **Parens:** Implement an algorithm to print all valid (e.g., properly opened and closed) combinations of n pairs of parentheses.

EXAMPLE

Input: 3

Output: `((()))`, `(()())`, `(())()`, `()(())`, `()()()`

Hints: #138, #174, #187, #209, #243, #265, #295

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8.10 **Paint Fill:** Implement the "paint fill" function that one might see on many image editing programs. That is, given a screen (represented by a two-dimensional array of colors), a point, and a new color, fill in the surrounding area until the color changes from the original color.

Hints: #364, #382

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8.11 **Coins:** Given an infinite number of quarters (25 cents), dimes (10 cents), nickels (5 cents), and pennies (1 cent), write code to calculate the number of ways of representing n cents.

Hints: #300, #324, #343, #380, #394

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8.12 **Eight Queens:** Write an algorithm to print all ways of arranging eight queens on an 8x8 chess board so that none of them share the same row, column, or diagonal. In this case, "diagonal" means all diagonals, not just the two that bisect the board.

Hints: #308, #350, #371

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8.13 **Stack of Boxes:** You have a stack of n boxes, with widths w_i, heights h_i, and depths d_i. The boxes cannot be rotated and can only be stacked on top of one another if each box in the stack is strictly larger than the box above it in width, height, and depth. Implement a method to compute the height of the tallest possible stack. The height of a stack is the sum of the heights of each box.

Hints: #155, #194, #214, #260, #322, #368, #378

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8.14 **Boolean Evaluation:** Given a boolean expression consisting of the symbols `0` (false), `1` (true), & (AND), | (OR), and ^ (XOR), and a desired boolean result value `result`, implement a function to count the number of ways of parenthesizing the expression such that it evaluates to `result`.

EXAMPLE

```
countEval("1^0|0|1", false) -> 2
countEval("0&0&0&1^1|0", true) -> 10
```

Hints: #148, #168, #197, #305, #327

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Additional Questions: Linked Lists (#2.2, #2.5, #2.6), Stacks and Queues (#3.3), Trees and Graphs (#4.2, #4.3, #4.4, #4.5, #4.8, #4.10, #4.11, #4.12), Math and Logic Puzzles (#6.6), Sorting and Searching (#10.5, #10.9, #10.10), C++ (#12.8), Moderate Problems (#16.11), Hard Problems (#17.4, #17.6, #17.8, #17.12, #17.13, #17.15, #17.16, #17.24, #17.25).

Hints start on page 662.