Dynamic Programming

UF Programming Team

What is dynamic programming?

Let's look at an example

What is $2^5 + 5! + 100$?

 $\rightarrow 252$

Now imagine I write a '+ 1' to the end of the previous expression

What is $2^5 + 5! + 100 + 1$?

 $\rightarrow 253$

How were you able to calculate that expression so quickly?

What is dynamic programming? (cont.)

You didn't need to recalculate the entire expression because you *memorized* the value of the partial expression to use for a later time

That's exactly what *dynamic programming* is!

To put it simply, dynamic programming is remembering stuff to save some time later

What is dynamic programming? (cont.)

A more "mathematical" definition

Dynamic programming is a method for solving complex problems by breaking it down into a collection of simpler subproblems

Dynamic programming problems exhibit two properties:

- 1) Overlapping subproblems
- 2) Optimal substructure

What does all of this mean? Let's look at some examples

Fibonacci Sequence

As you might have seen before, the Fibonacci sequence is one in which a term in the sequence is determined by the sum of the two terms before it

$$\rightarrow$$
 1, 1, 2, 3, 5, 8, 13, 21, 34, ...

We can write it as
$$f_n = f_{n-1} + f_{n-2}$$
 where $f_0 = 1$ and $f_1 = 1$

Let's say we wanted to write a recursive function for this sequence to determine the **n**th Fibonacci number

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

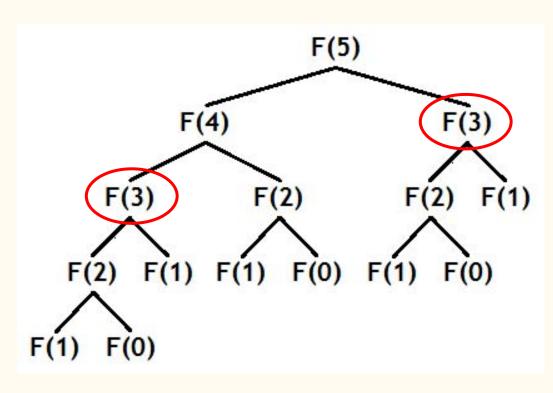
```
What will be the function calls if we wanted to determine fib(5)?
\rightarrow fib(5)
\rightarrow fib(4) + fib(3)
\rightarrow fib(3) + fib(2) + fib(3)
\rightarrow fib(2) + fib(1) + fib(2) + fib(3)
\rightarrow fib(1) + fib(0) + 1 + fib(2) + fib(3)
\rightarrow 1 + 1 + 1 + \frac{fib(2)}{} + \frac{fib(3)}{}
```

Is it necessary to compute fib(2) and fib(3)?

This tree represents the function calls for the function fib(5)

Notice that when we calculate fib (4), we also calculate the value of fib(3)

When we call fib(5), it calls fib(3), but if we already have the value of that function call from before, there's no need to recompute it!



Since fib(5) asks us to call the function fib(3) multiple times, we have found an overlapping subproblem - a subproblem that is reused numerous times, but gives the same result each time it's solved

Rather than solving these overlapping subproblems every time, we can do the following:

- → solve the subproblem once and save it's value
- → when you need to solve the subproblem *again*, rather than going through all the computation to do the solving, return the *memorized* value

```
int[] dp = new int[ SIZE ]; // all values initialized to 0
public int fib( int n ) {
    if ( n == 1 || n == 0)
        return 1;
    if ( dp[ n ] != 0 )
        return dp[ n ];
    return dp[n] = fib(n-1) + fib(n-2);
```

Knapsack Problem

Condensed Problem Statement

You have a knapsack that can hold up to a certain weight W, and you have N items that you can pack for a trip; however, all of these items might not fit in your knapsack

Each item has a weight w_i and a value v_i

Your goal is to pack some items into your bag such that the total weight of all the items doesn't exceed your knapsack's weight limit W, and the sum of all the values of the items in your knapsack is maximized

Knapsack Problem (cont.)

What are some approaches we can take to solve this problem?

- \rightarrow Calculate all subsets of items and see which subset has the highest value, yet stays under the knapsack's weight limit
- \rightarrow Create some ratio for each item v_i/w_i and take the items with the highest ratio until you run out of items
- → Dynamic programming!

Before we go over how to solve this problem using dynamic programming, let's see why the other solutions don't work

Subsets Solution

Let's calculate all subsets of the N items that we have

How many subsets are there?

$$\rightarrow 2^N$$

So we need to go through all 2^N subsets....but if N is big^* , this is going to take a while

*big in this case can be as small as 20, since $2^{20} \sim 1,000,000$

Ratio Solution

Imagine we have a knapsack with W = 6, and are given the following set of items

$$\mathbf{w} = \{2, 2, 2, 5\}$$

$$\mathbf{v} = \{7, 7, 7, 20\}$$

Let's find the v / w ratio of each item

$$\rightarrow v / w = \{3.5, 3.5, 3.5, 4\}$$

Now that we have the ratios, let's take items with the highest ratio until we no longer have any space left

We will take the item with w = 5, v = 20 first and put it into our knapsack

We now have 6 - 5 = 1 weight left in our knapsack

Since we only have *1* weight left, we cannot fit any of the other items in our knapsack (since each of their weights are *2*), so we end up with a value of 20!

But....if we would've taken the other three items and left the last item behind, we would have a value of 21 instead (7 + 7 + 7 = 21)

 $w = \{2, 2, 2, 5\}$ $v = \{7, 7, 7, 20\}$ $v / w = \{3.5, 3.5, 3.5, 4\}$

We determined that the greedy approach for knapsack does not work, so now we will try to use dynamic programming to solve this problem; let's try and create a *recursive function* that can get us the answer!

Let's start by iterating over each item we have, starting from item $\boldsymbol{0}$ and going to item N-1

We will also be keeping track of how much weight we have left in the knapsack as we go through the items

Note: when we're on an item, we only have two options: *take* or *ignore*

 $\rightarrow 0/1$ Knapsack name derivation

```
public int solve( int index, int remainingWeight ) {
    // Determines the max value you can get when starting at
    // the item at index with remainingWeight left to use
}
```

Imagine that the function has an implementation that gives us the answer we want; what would be the values of index and remainingWeight on our initial call so that we get the answer for the *entire* problem?

```
\rightarrow solve( 0, W )
```

Let's try and figure out some *base cases* for this function (*e.g.*, in the function fib(), the base cases were n == 0 and n == 1)

What happens if remainingWeight == 0?

 \rightarrow the max value we get by starting at any index with **no weight left** will be 0!

What happens if index == N?

 \rightarrow the max value we get by starting at an index *outside of our item range* will be 0!

Great, we have some base cases to work with now!

Let's look at every other case where index != N and remainingWeight > 0

What happens if weight[index] > remainingWeight?

Well, if the weight of the item we are looking at is *greater* than the amount of weight we have left, there's no way we can take this item, so we *ignore* it!

But what do we return? 0? Integer.MAX_VALUE? A different function call?

→ solve(index + 1, remainingWeight)

→ the max value we get by starting at an index *where we can't take the item* will be determined by the max value we get by starting at the *next* item with the *same* remaining weight to use

Last case: what happens if weight[index] <= remainingWeight?

Remember, we only have two options: take or ignore

We know what ignoring an item looks like:

→ solve(index + 1, remainingWeight)

But what does *taking* an item look like?

Well, we know that remainingWeight will be different

 \rightarrow we took the item, so we need to subtract out its weight from the remaining weight

We also know that since we *took* the item, we can add value[index] to our result

Our resulting function call for *taking* an item would be

- → value[index] + solve(index + 1, remainingWeight weight[index])
- \rightarrow the max value we get by starting at an index *where we take the item* can be determined by the sum of
 - \rightarrow the value of the item, and
 - \rightarrow the max value we get by starting at the **next** item with the new remaining weight

Wait, we just saw two separate function calls for the case where we have enough weight to take an item

```
→ solve( index + 1, remainingWeight )

→ value[ index ] + solve( index + 1, remainingWeight - weight[ index ] )

So which one do we use? Which one are we returning? Which one will get us the max value?
```

We now know our solution handles every case for Knapsack, giving us the optimal solution when we call solve (0, W), and it shows the problem has an *optimal* substructure - that is, an optimal solution can be constructed from the optimal solutions of its subproblems

If we solve any subproblem, solve (i, j), we are guaranteed to get the optimal answer, and we can use these optimal subproblems to solve *other* subproblems

We know that the problem has optimal substructure, but does it have any *overlapping subproblems*?

Let's look at an example

$$v = \{100, 70, 50, 10\}$$

$$\mathbf{w} = \{10, 4, 6, 12\}$$

$$W = 12$$

Imagine that we take the first item and then ignore the next two

```
\rightarrow we will be at solve( index = 3, remainingWeight = 2)
```

Imagine that we ignore the first item and then take the next two

```
\rightarrow we will be at solve( index = 3, remainingWeight = 2)
```

We have now determined we have *overlapping subproblems*, so we can save the value of a specific <code>index/remainingWeight</code> pair so we don't have to recompute the solution to that subproblem each time!

We can now code a solution to the Knapsack Problem!

Break up into groups of 2-3 and work on the following problem

spoj.com/problems/KNAPSACK

Other problems to work on

- → spoj.com/problems/COINS
- → spoj.com/problems/PARTY
- → spoj.com/problems/ROCK