

Dynamic Programming

Chapter 15

What is Dynamic Programming

- Fancy talk
- A “method for efficiently solving problems that exhibit the characteristics of overlapping sub-problems and optimal substructure” (p. 203)
- **Optimal substructure**
 - A globally optimal solution can be found by combining optimal solutions to local sub-problems
 - Merge sort is globally optimal for sorting unordered lists
 - Split lists into increasingly smaller sublists
 - Merges increasingly larger sorted lists
- **Overlapping sub-problems**
 - Solving the same problem many times

Remember our friend Fibonacci Numbers?

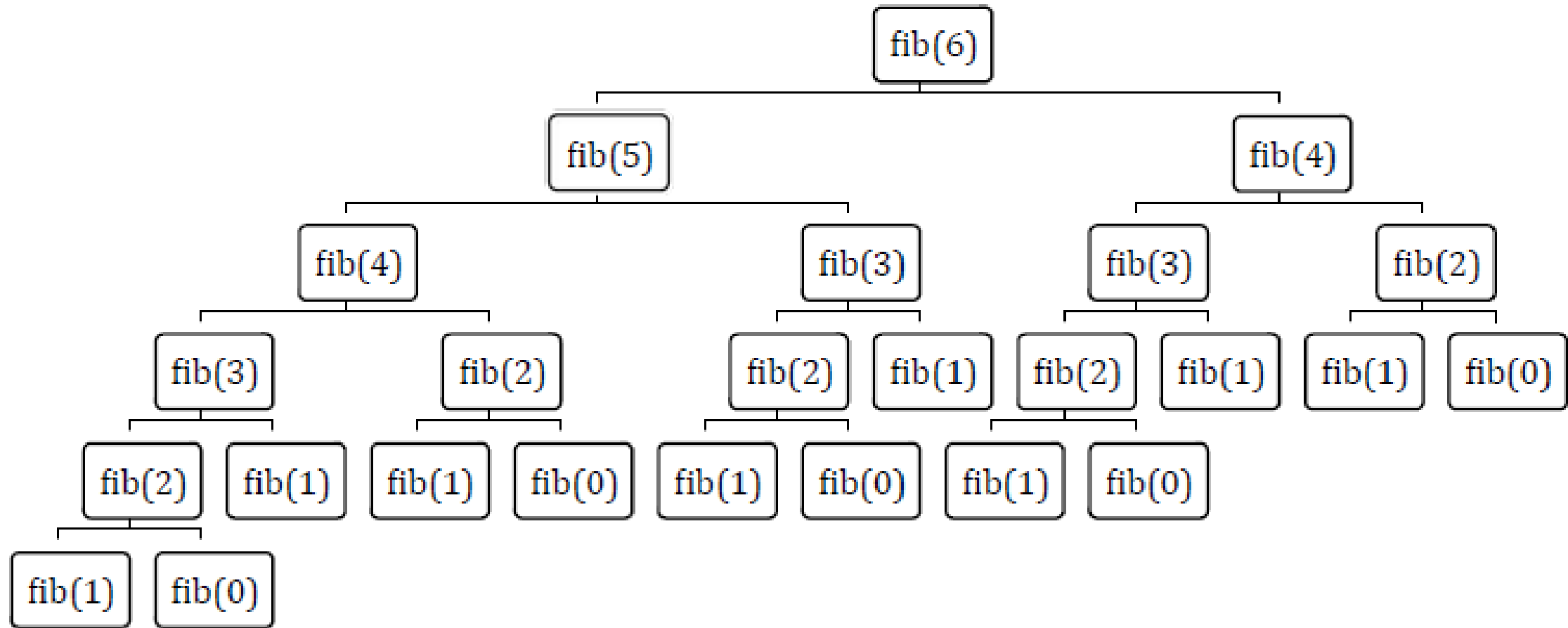
```
def fib(n):  
    """Assumes n is an int >= 0  
       Returns Fibonacci of n"""  
    if n == 0 or n == 1:  
        return 1  
    else:  
        return fib(n-1) + fib(n-2)
```

- Lowly Conceptual Complexity
- High Computational Complexity
 - $O(fib(n))$

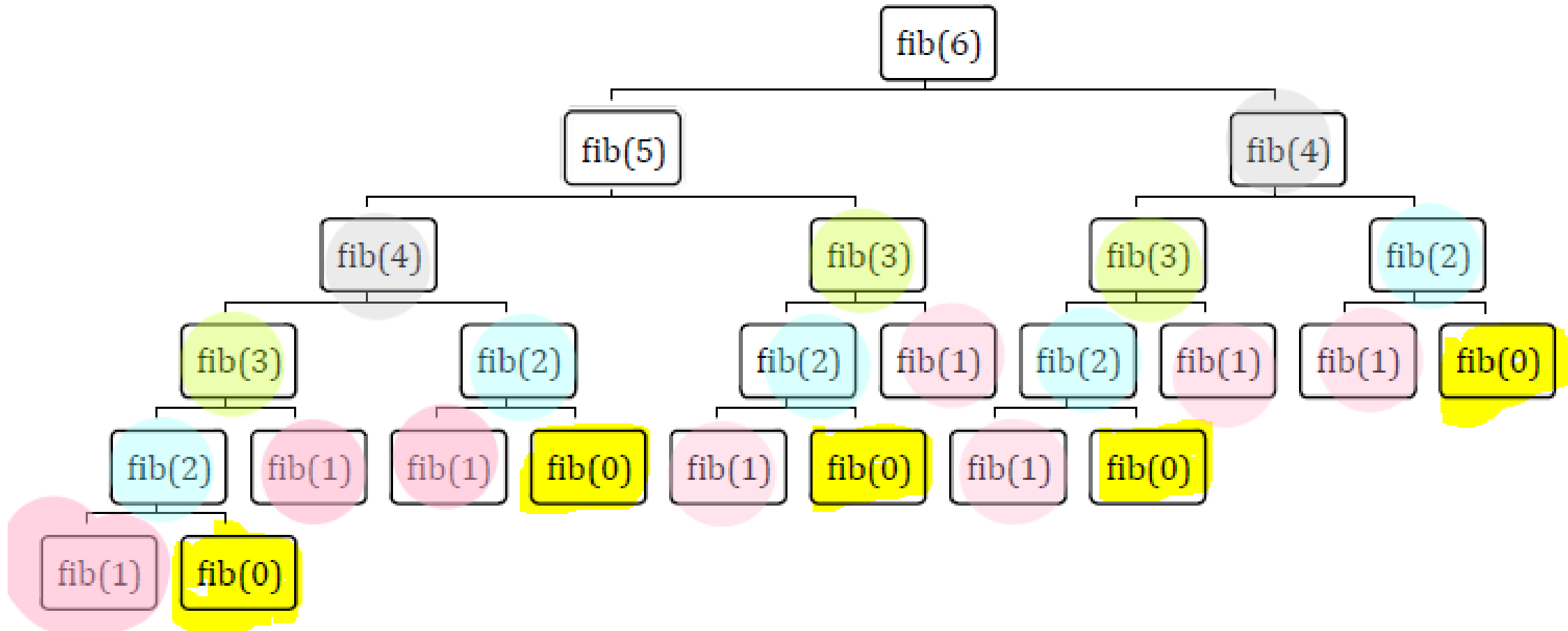
Fib(120)

- 8 Septillion
- 670 Sextillion
- 007 Quintillion
- 398 Quadrillion
- 507 Trillion
- 948 Billion
- 658 Million
- 051 Thousand
- 921

Fib(6) recursion visualized



Overlapping sub-problems



How many times?

- fib(6) X 1
 - fib(5) X 1
 - fib(4) X 2
 - fib(3) X 3
 - fib(2) X 5
 - fib(1) X 8
 - fib(0) X 5
-
- It is *almost* $\sum fib(n - i)$

Maybe we should **memorize**!

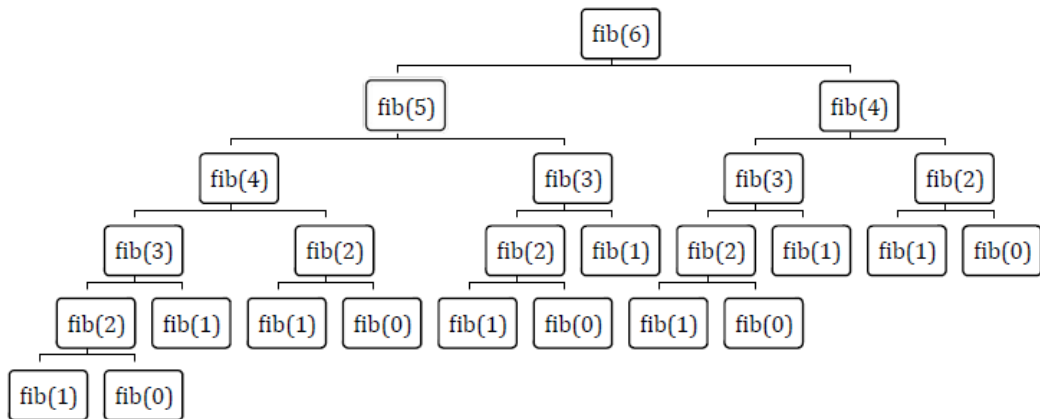
- Save the result of some key in a **memorization** table
 - Check for that key
 - If found – return the value
 - Else compute the value for the key and add to the table
-
- Close to $O(n)$ for computational complexity
 - Also $O(n)$ for memory

How about our knapsack problem?

- **Greedy** algorithm $O(n \log(n))$
 - Didn't guarantee an optimal solution
- **Exhaustive enumeration** (brute force) $O(2^n)$
 - Found the optimal solution
 - but who has that kind of time
- Can we find
 - Optimal substructure?
 - Overlapping sub problems

Rooted Binary Tree

- There is exactly one node with no parents. This is the **root**
- All other nodes have exactly one parent
- Each node has no more than two children
- A child node with no children is called a **leaf**



Decision Tree

- Each node represents a decision
 - In our case True or False
 - The left child represents the True choice
 - The right child represents the False choice
- Generate left-first, depth-first
 - For each node if decision is True we generation the left node
 - Repeat until false
 - Return to the parent
 - Generate the right node
 - Eventually all possible solutions are generated

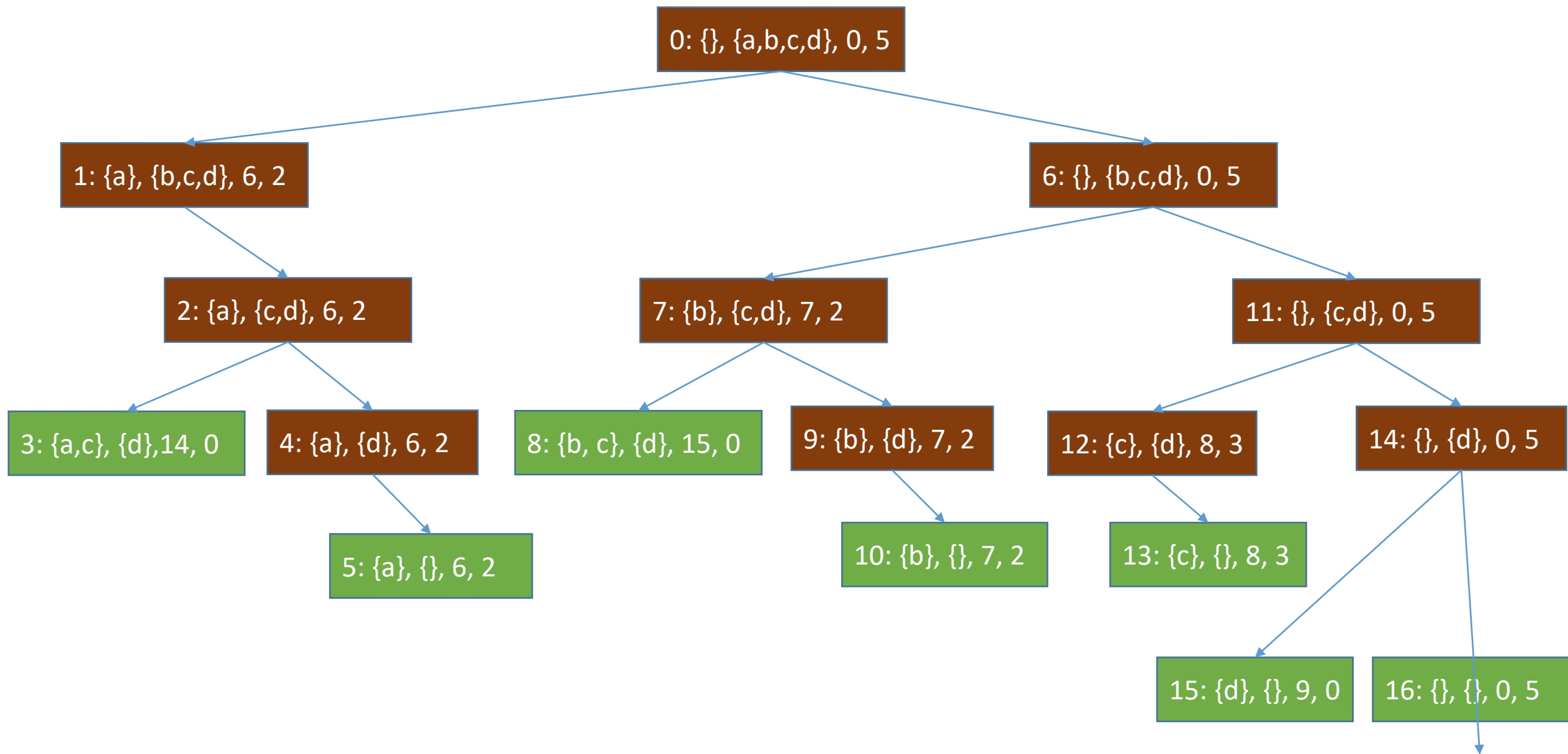
Building a decision tree for the knapsack problem

- What is the decision?
 - Given space available, can I take the next thing?
- What do I need to know?
 - Items I have already taken
 - What's left
 - How much room do I have left *
 - How much is it all worth *
- When are we done?
 - When I have no items left or knapsack is full

Stuff

- Consider a capacity of 5 (somethings?)

| Name | Value | Weight |
|------|-------|--------|
| a | 6 | 3 |
| b | 7 | 3 |
| c | 8 | 2 |
| d | 9 | 5 |



Codey, Code, Code

- Since we are building our tree depth-first that implies **recursion**

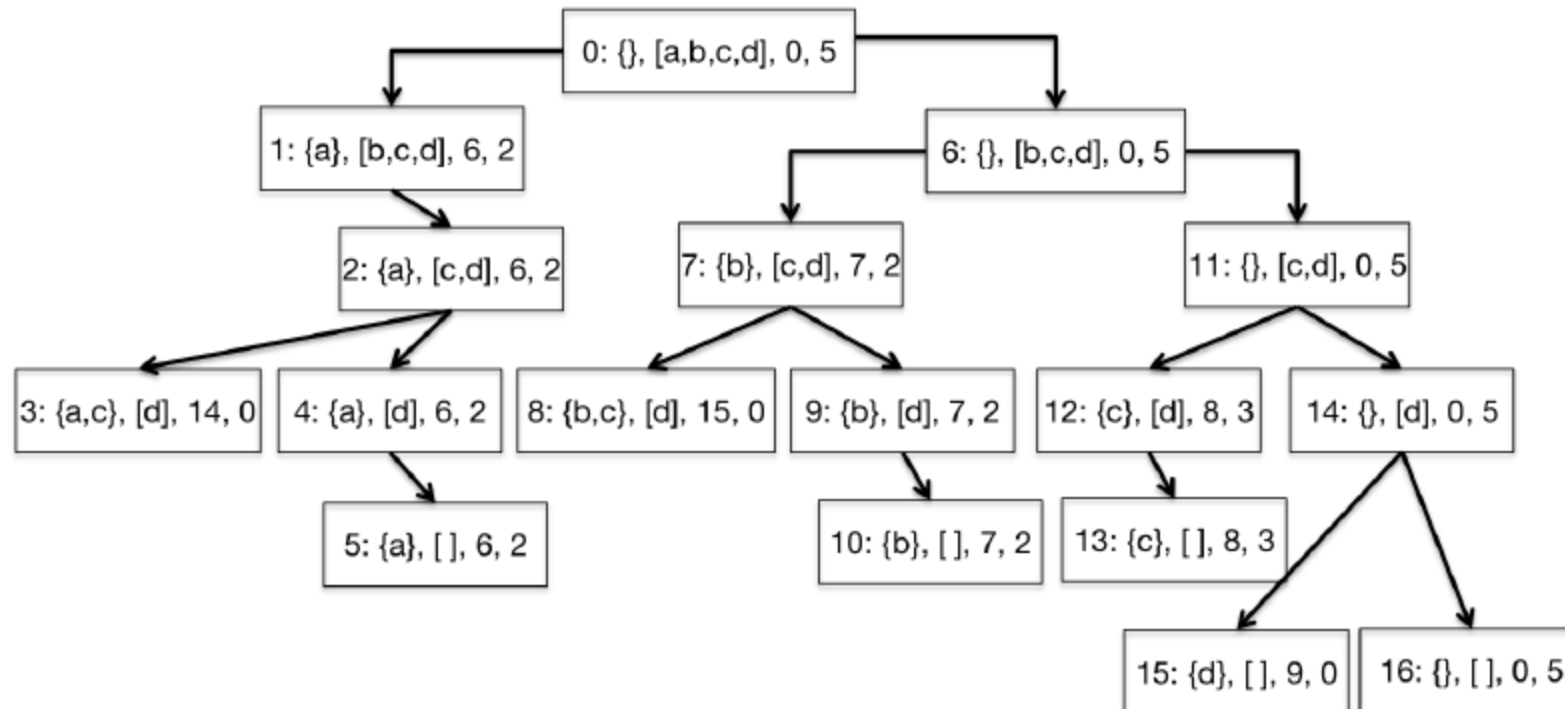


How deep (tall) is your tree?

- The tree can possibly have $n + 1$ levels (generation)
- Each generation can possibly have 2^{i-1} nodes
- Total possible nodes $\sum 2^i$
- Or $2^n - 1$ possible nodes

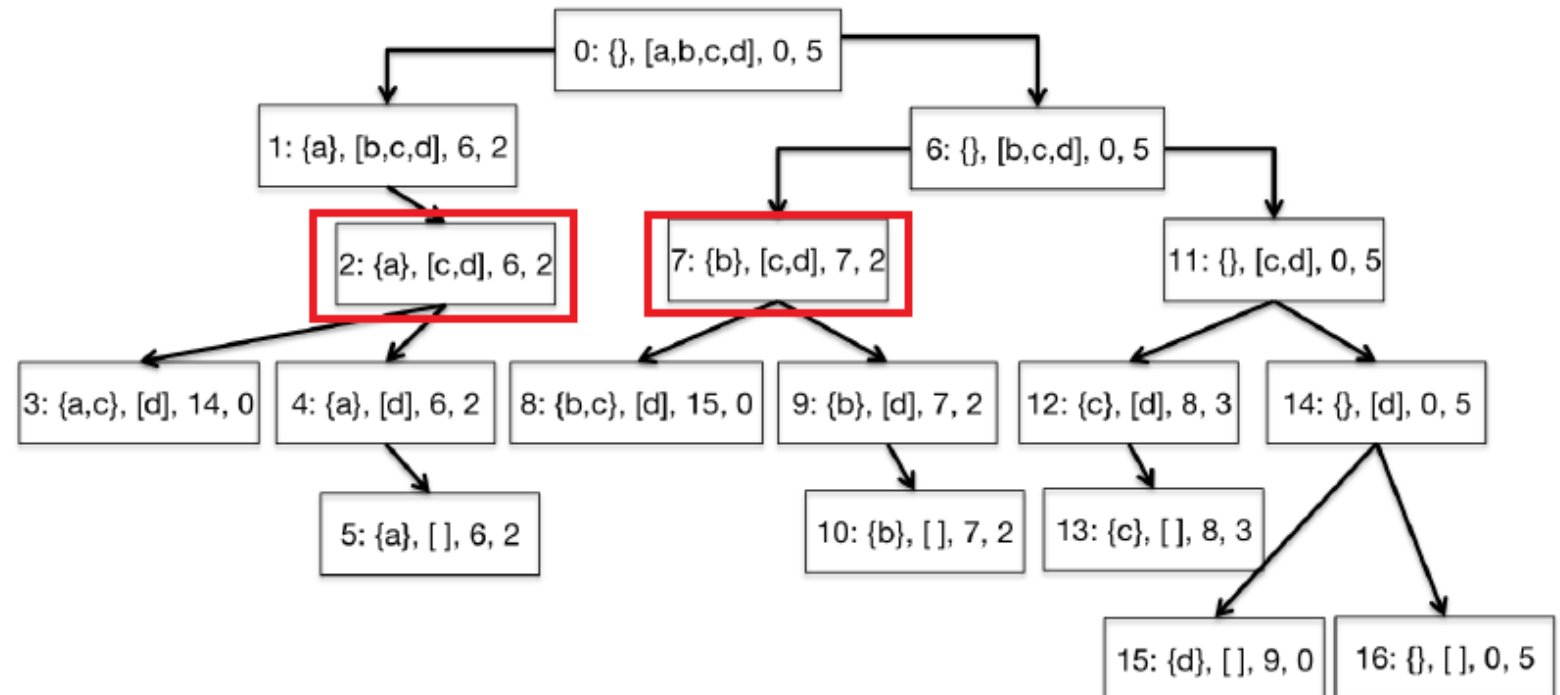
Can we optimize this silly thing?

- The **rooted binary tree** is the **optimal substructure**
- What about an **overlapping subproblem**?



Hint, hint

- If we think back to our implementation what were the key elements?
 - Items to Consider
 - Since we always work from the beginning of the list this can be a count
 - Available Weight



Dynamic Programming vs Divide-and-Conquer

- Both based on breaking a problem down into subproblems
- Divide-and-Conquer
 - Decompose into increasingly small subproblems
 - Not dependent, primarily, on problem structure
- Dynamic Programming
 - Subproblem is only slightly smaller than the original
 - Number of subproblems to solve should be significantly fewer than total number of subproblems