

# Introduction and Optimization Problems

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# Relevant Reading for Today's Lecture

- Section 12.1
- Section 5.4 (lambda functions)
- Chapter 13

# Computational Models

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- Using computation to help understand the world in which we live
- Experimental devices that help us to understand something that has happened or to predict the future



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- *Optimization models*
- Statistical models
- Simulation models

# What Is an Optimization Model?

- An objective function that is to be maximized or minimized, e.g.,
  - Minimize time spent traveling from New York to Boston
- A set of constraints (possibly empty) that must be honored, e.g.,
  - Cannot spend more than \$100
  - Must be in Boston before 5:00PM



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# Knapsack Problems

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# Knapsack Problem

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- You have limited strength, so there is a maximum weight knapsack that you can carry
- You would like to take more stuff than you can carry
- How do you choose which stuff to take and which to leave behind?
- Two variants
  - 0/1 knapsack problem
  - Continuous or fractional knapsack problem



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# My Least-favorite Knapsack Problem



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## 0/1 Knapsack Problem, Formalized

- Each item is represented by a pair,  $\langle \text{value}, \text{weight} \rangle$
- The knapsack can accommodate items with a total weight of no more than  $w$
- A vector,  $L$ , of length  $n$ , represents the set of available items. Each element of the vector is an item
- A vector,  $V$ , of length  $n$ , is used to indicate whether or not items are taken. If  $V[i] = 1$ , item  $f[i]$  is taken. If  $V[i] = 0$ , item  $f[i]$  is not taken.



# 0/1 Knapsack Problem, Formalized

Find a  $V$  that maximizes

$$\sum_{i=0}^{n-1} V[i] * I[i].value$$

subject to the constraint that

$$\sum_{i=0}^{n-1} V[i] * I[i].weight \leq w$$

# Brute Force Algorithm

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- 1 Enumerate all possible combinations of items That is to say, generate all subsets of the set of items This is called the **power set**
- 2 Remove all of the combinations whose total units exceeds the allowed weight
- 3 From the remaining combinations choose any one whose value is the largest

# Often Not Practical

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- How big is power set?
- Recall
  - A vector,  $V$ , of length  $n$ , is used to indicate whether or not items are taken. If  $V[i] = 1$ , item  $f[i]$  is taken. If  $V[i] = 0$ , item  $f[i]$  is not taken.
- How many possible different values can  $V$  have?
  - As many different binary numbers as can be represented in  $n$  bits.
- For example, if there are 100 items to choose from, the power set is of size?
  - 1,267,650,600,228,229,401,496,703,205,376

# Are We Just Being Stupid?

- Alas, no
- 0/1 knapsack problem is inherently exponential
- But don't despair

# Greedy Algorithm a Practical Alternative

- while knapsack not full  
    put “best” available item in knapsack
- But what does best mean?
  - Most valuable
  - Least expensive
  - Highest value/units

# An Example

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- You are about to sit down to a meal
- You know how much you value different foods, e g , you like donuts more than apples
- But you have a calorie budget, e g , you don't want to consume more than 750 calories
- Choosing what to eat is a knapsack problem



# A Menu

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Food	wine	beer	pizza	burger	fries	coke	apple	donut
Value	89	90	30	50	90	79	90	10
calories	123	154	258	354	365	150	95	195

- Let's look at a program that we can use to decide what to order

# Class Food

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```
class Food(object):
    def __init__(self, n, v, w):
        self.name = n
        self.value = v
        self.calories = w

    def getValue(self):
        return self.value

    def getCost(self):
        return self.calories

    def density(self):
        return self.getValue()/self.getCost()

    def __str__(self):
        return self.name + ': <' + str(self.value)\
               + ', ' + str(self.calories) + '>'
```

## Build Menu of Foods

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```
def buildMenu(names, values, calories):  
    """names, values, calories lists of same length.  
    name a list of strings  
    values and calories lists of numbers  
    returns list of Foods"""  
    menu = []  
    for i in range(len(values)):  
        menu.append(Food(names[i], values[i],  
                           calories[i]))  
    return menu
```

# Implementation of Flexible Greedy

```
def greedy(items, maxCost, keyFunction):  
    """Assumes items a list, maxCost >= 0,  
        keyFunction maps elements of items to numbers"""  
    itemsCopy = sorted(items, key = keyFunction, ←  
                        reverse = True)  
  
    result = []  
    totalValue, totalCost = 0.0, 0.0  
  
    for i in range(len(itemsCopy)): ←  
        if (totalCost+itemsCopy[i].getCost()) <= maxCost: ←  
            result.append(itemsCopy[i])  
            totalCost += itemsCopy[i].getCost()  
            totalValue += itemsCopy[i].getValue()  
  
    return (result, totalValue)
```

# Algorithmic Efficiency

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```
def greedy(items, maxCost, keyFunction):  
→ itemsCopy = sorted(items, key = keyFunction,  
                      reverse = True)  
    result = []  
    totalValue, totalCost = 0.0, 0.0  
  
    for i in range(len(itemsCopy)): ←  
        if (totalCost+itemsCopy[i].getCost()) <= maxCost:  
            result.append(itemsCopy[i])  
            totalCost += itemsCopy[i].getCost()  
            totalValue += itemsCopy[i].getValue()  
  
    return (result, totalValue)
```

## Question 3

## Using greedy

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```
def testGreedy(items, constraint, keyFunction):
    taken, val = greedy(items, constraint, keyFunction)
    print('Total value of items taken =', val)
    for item in taken:
        print('    ', item)
```



## Using greedy

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```
def testGreedy(maxUnits):  
    print('Use greedy by value to allocate', maxUnits,  
          'calories')  
    testGreedy(foods, maxUnits, Food.getValue)  
    print('\nUse greedy by cost to allocate', maxUnits,  
          'calories')  
    testGreedy(foods, maxUnits,  
                lambda x: 1/Food.getCost(x))  
    print('\nUse greedy by density to allocate', maxUnits,  
          'calories')  
    testGreedy(foods, maxUnits, Food.density)  
  
testGreedy(800)
```

?

# lambda

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- lambda used to create anonymous functions
  - `lambda <id1, id2, . . . idn>: <expression>`
  - Returns a function of n arguments
- Can be very handy, as here
- Possible to write amazing complicated lambda expressions
- **Don't** - use `def` instead

## Using greedy

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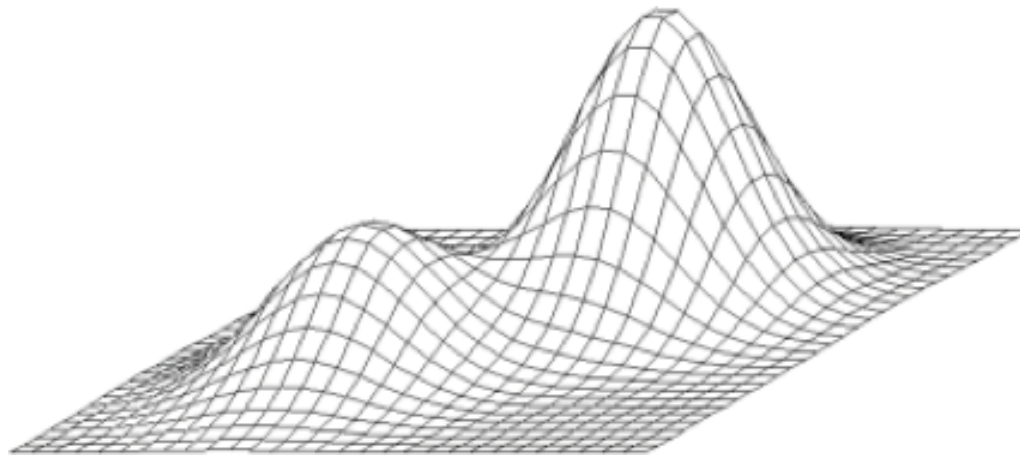
```
def testGreedy(foods, maxUnits):
    print('Use greedy by value to allocate', maxUnits,
          'calories')
    testGreedy(foods, maxUnits, Food.getValue)
    print('\nUse greedy by cost to allocate', maxUnits,
          'calories')
    testGreedy(foods, maxUnits,
                lambda x: 1/Food.getCost(x))
    print('\nUse greedy by density to allocate', maxUnits,
          'calories')
    testGreedy(foods, maxUnits, Food.density)

names = ['wine', 'beer', 'pizza', 'burger', 'fries',
         'cola', 'apple', 'donut', 'cake']
values = [89,90,95,100,90,79,50,10]
calories = [123,154,258,354,365,150,95,195]
foods = buildMenu(names, values, calories)
testGreedy(foods, 750)
```

[Run code](#)

# Why Different Answers?

- Sequence of locally "optimal" choices don't always yield a globally optimal solution



- Is greedy by density always a winner?
  - Try `testGreedy(foods, 1000)`

# The Pros and Cons of Greedy

- Easy to implement
- Computationally efficient
  
- But does not always yield the best solution
  - Don't even know how good the approximation is
- In the next lecture we'll look at finding truly optimal solutions

# Brute Force Algorithm

- 1. Enumerate all possible combinations of items.
- 2. Remove all of the combinations whose total units exceeds the allowed weight.
- 3. From the remaining combinations choose any one whose value is the largest.



# Search Tree Implementation

- The tree is built top down starting with the root
- The first element is selected from the still to be considered items
  - If there is room for that item in the knapsack, a node is constructed that reflects the consequence of choosing to take that item. By convention, we draw that as the left child
  - We also explore the consequences of not taking that item. This is the right child
- The process is then applied **recursively** to non-leaf children
- Finally, choose a node with the highest value that meets constraints

# A Search Tree Enumerates Possibilities

Left-first, depth-first  
enumeration

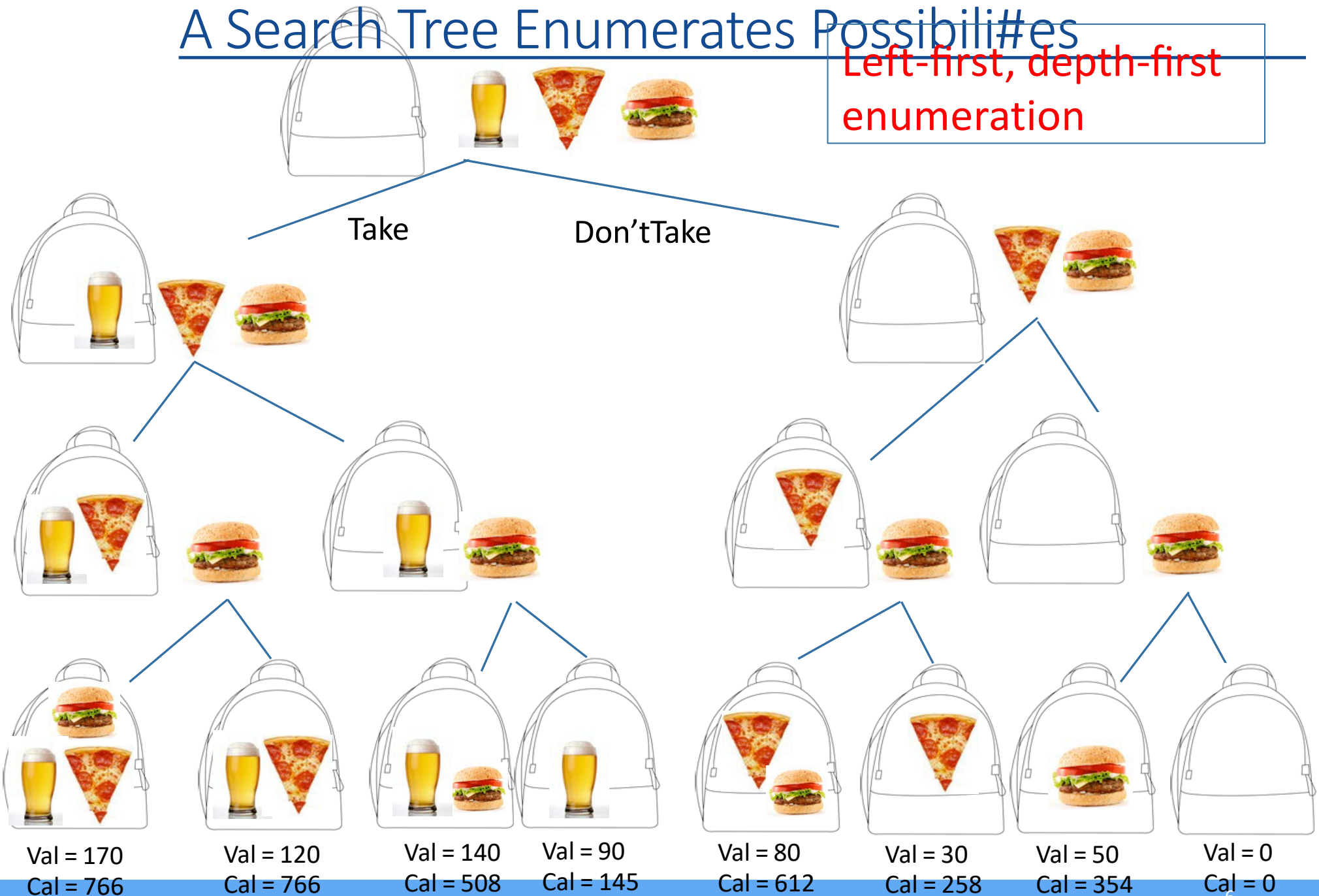




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# Computational Complexity

- Time based on number of nodes generated
- Number of levels is number of items to choose from
- Number of nodes at level  $i$  is  $2^i$
- So, if there are  $n$  items the number of nodes is
  - $\sum_{i=0}^n 2^i$
  - I.e.,  $O(2^{n+1})$
- An obvious optimization: don't explore parts of tree that violate constraint (e.g., too many calories)
  - Doesn't change complexity
- Does this mean that brute force is never useful?
  - Let's give it a try

# Header for Decision Tree Implementation

```
def maxVal(toConsider, avail):  
    """Assumes toConsider a list of items,  
        avail a weight  
    Returns a tuple of the total value of a  
        solution to 0/1 knapsack problem and  
        the items of that solution"""
```

`toConsider`. Those items that nodes higher up in the tree (corresponding to earlier calls in the recursive call stack) have not yet considered

`avail`. The amount of space still available



## Body of maxVal (without comments)

```
if toConsider == [] or avail == 0:
    result = (0, ())
elif toConsider[0].getUnits() > avail:
    result = maxVal(toConsider[1:], avail)
else:
    nextItem = toConsider[0]
    withVal, withToTake = maxVal(toConsider[1:],
                                avail - nextItem.getUnits())
    withVal += nextItem.getValue()
    withoutVal, withoutToTake = maxVal(toConsider[1:], avail)
    if withVal > withoutVal:
        result = (withVal, withToTake + (nextItem,))
    else:
        result = (withoutVal, withoutToTake)
return result
```

Does not actually build search tree

Local variable `result` records best solution found so far



# Try on Example from Lecture 1

- With calorie budget of 750 calories, chose an optimal set of foods from the menu

Food	wine	beer	pizza	burger	fries	coke	apple	donut
Value	89	90	30	50	90	79	90	10
calories	123	154	258	354	365	150	95	195

# Search Tree Worked Great

- Gave us a better answer
- Finished quickly
- But  $2^8$  is not a large number
  - We should look at what happens when we have a more extensive menu to choose from

# Code to Try Larger Examples

```
import random ←
```

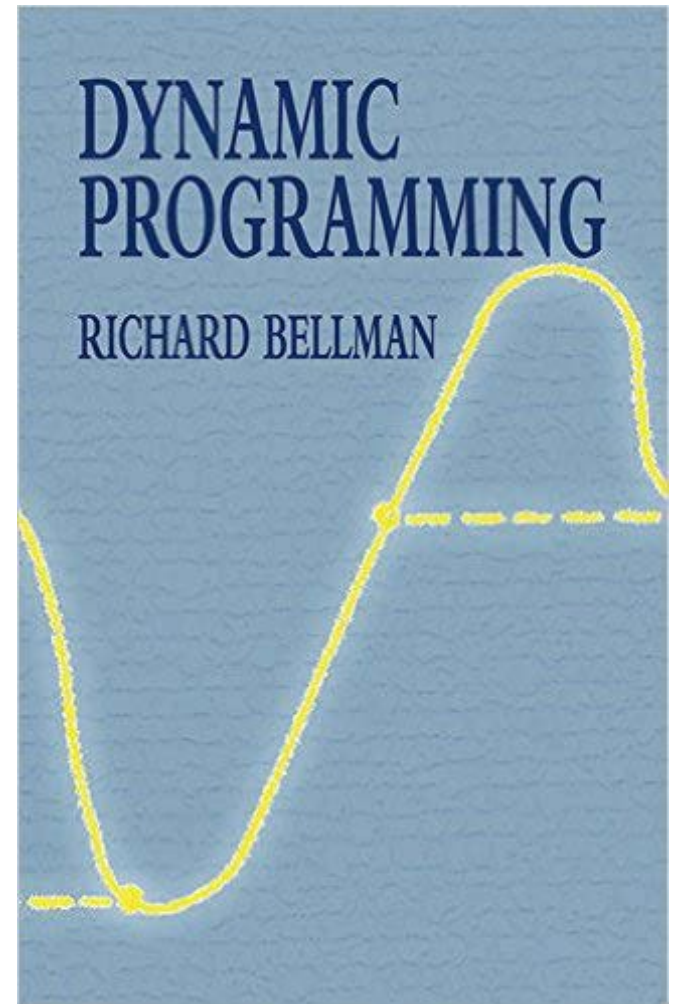
```
def buildLargeMenu(numItems, maxVal, maxCost):  
    items = []  
    for i in range(numItems):  
        items.append(Food(str(i),  
                           random.randint(1, maxVal),  
                           random.randint(1, maxCost)))  
    return items
```

```
for numItems in (5,10,15,20,25,30,35,40,45,50,55,60):  
    items = buildLargeMenu(numItems, 90, 250)  
    testMaxVal(items, 750, False)
```



# Is It Hopeless?

- In theory, yes
- In practice, no!
- Dynamic programming to the rescue



# Dynamic Programming?

Sometimes a name is just a name

“The 1950s were not good years for mathematical research... I felt I had to do something to shield Wilson and the Air Force from the fact that I was really doing mathematics... What title, what name, could I choose? ... It's impossible to use the word dynamic in a pejorative sense. Try thinking of some combination that will possibly give it a pejorative meaning. It's impossible. Thus, I thought dynamic programming was a good name. It was something not even a Congressman could object to. So I used it as an umbrella for my activities.

-- Richard Bellman

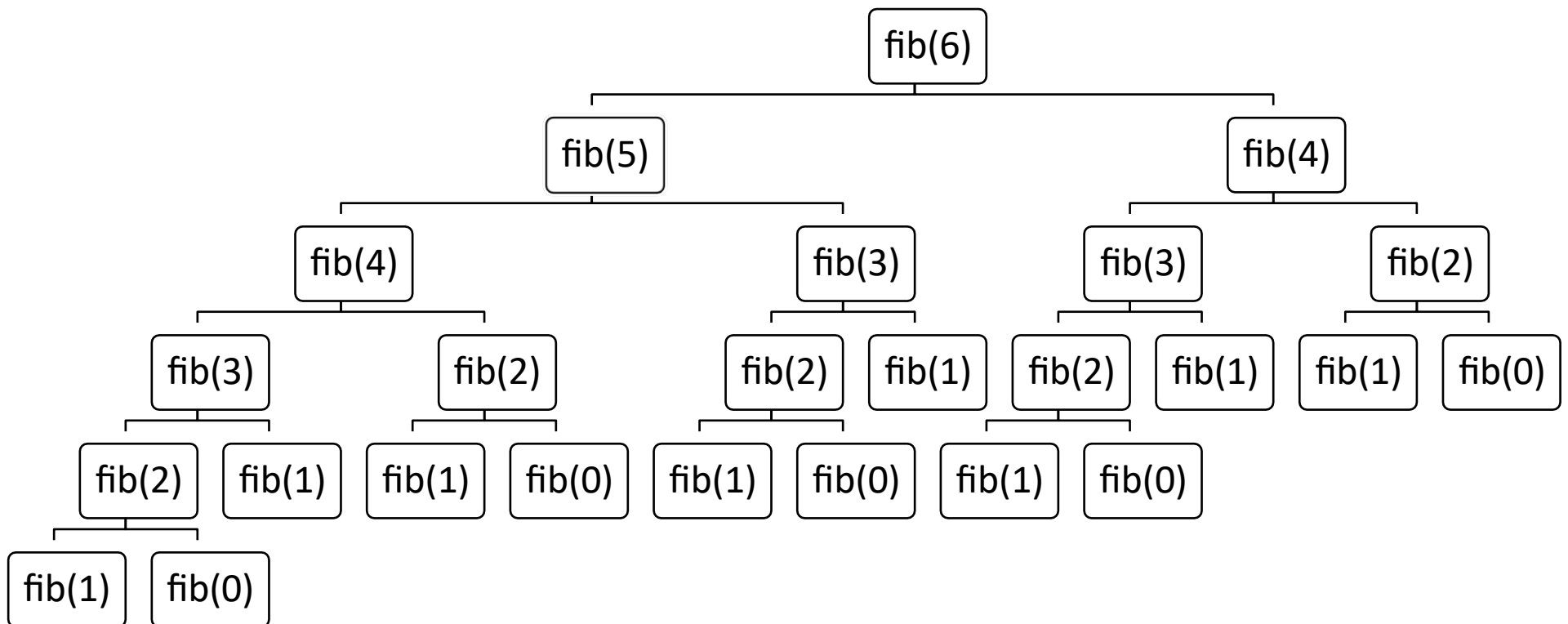
# Recursive Implementation of Fibonnaci

```
def fib(n):  
    if n == 0 or n == 1:  
        return 1  
    else:  
        return fib(n - 1) + fib(n - 2)
```

```
fib(120) =  
8,670,007,398,507,948,658,051,921
```



# Call Tree for Recursive Fibonacci(6) = 13



# Clearly a Bad Idea to Repeat Work

- Trade a time for space
- Create a table to record what we've done
  - Before computing  $\text{fib}(x)$ , check if value of  $\text{fib}(x)$  already stored in the table
  - If so, look it up
  - If not, compute it and then add it to table
  - Called **memoization**



# Using a Memo to Compute Fibonacci

```
def fastFib(n, memo = {}):  
    """Assumes n is an int >= 0, memo used only by  
        recursive calls  
        Returns Fibonacci of n"""  
    if n == 0 or n == 1:  
        return 1  
    try:  
        return memo[n]  
    except KeyError:  
        result = fastFib(n-1, memo) +\  
                 fastFib(n-2, memo)  
        memo[n] = result  
        return result
```

# When Does It Work?

- **Optimal substructure**: a globally optimal solution can be found by combining optimal solutions to local subproblems
  - For  $x > 1$ ,  $\text{fib}(x) = \text{fib}(x - 1) + \text{fib}(x - 2)$
- **Overlapping subproblems**: finding an optimal solution involves solving the same problem multiple times
  - Compute  $\text{fib}(x)$  or many times

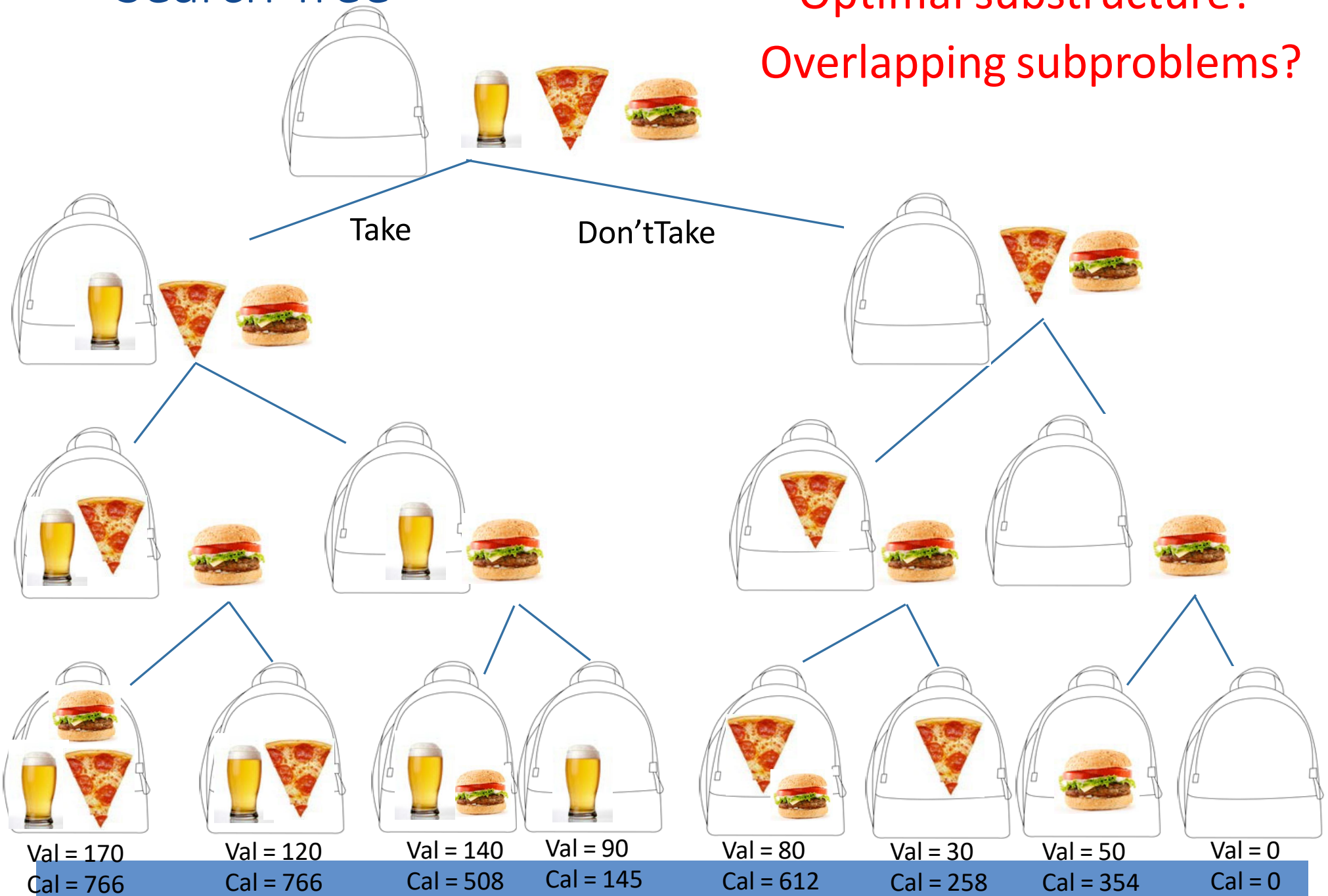
# What About 0/1 Knapsack Problem?

- Do these conditions hold?

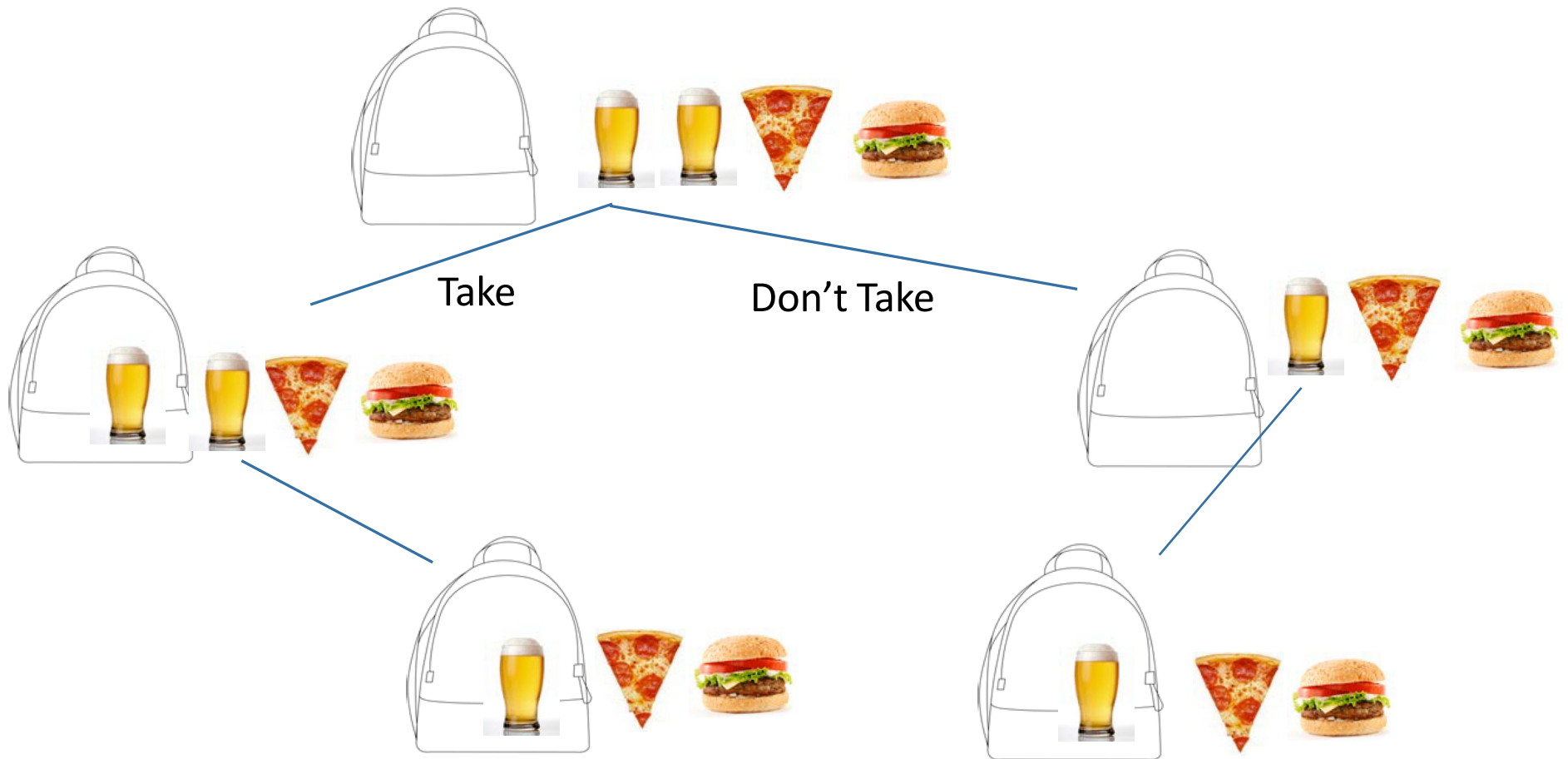


# Search Tree

Optimal substructure?  
Overlapping subproblems?



# A Different Menu

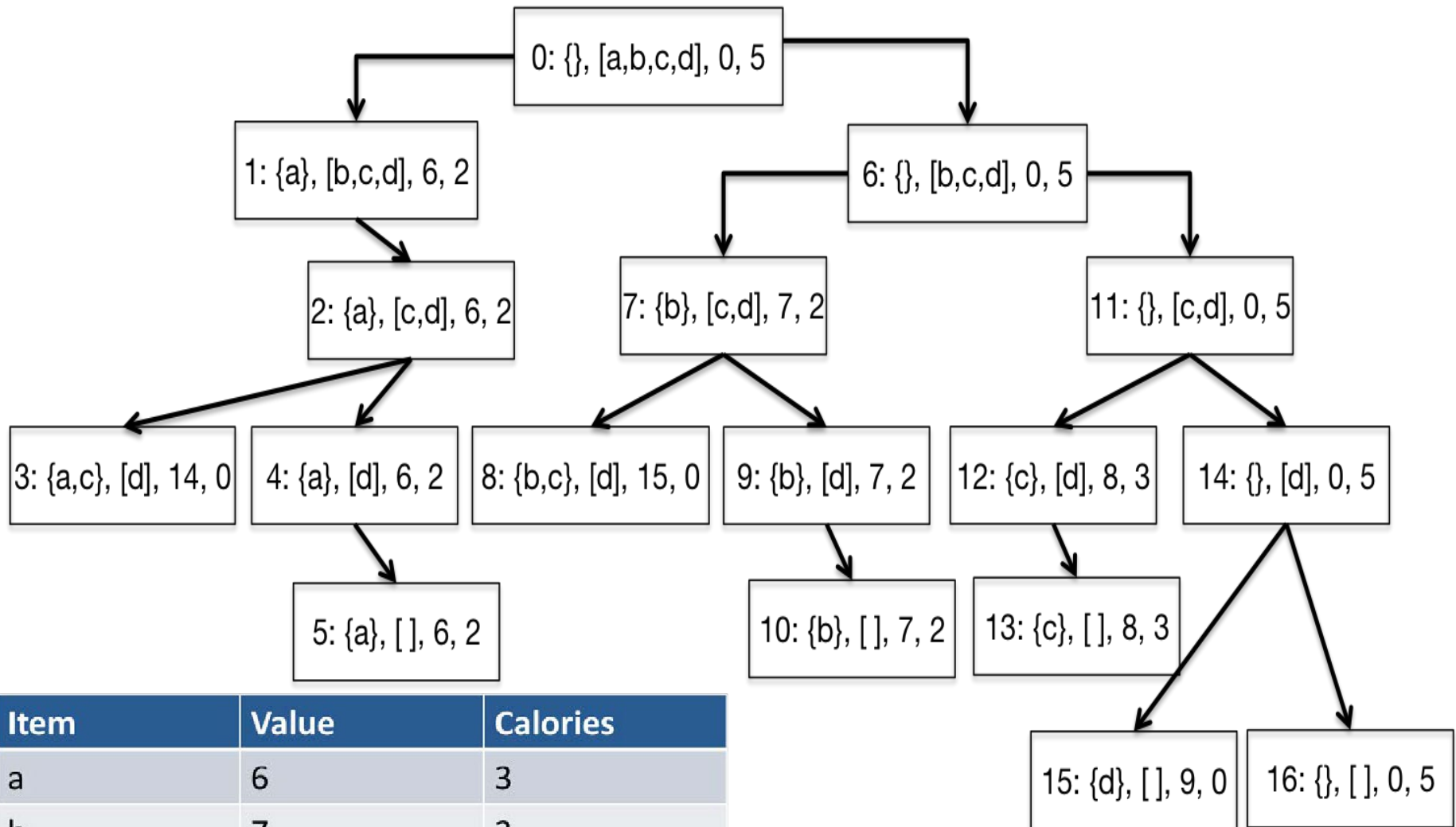


# Need Not Have Copies of Items

Item	Value	Calories
a	6	3
b	7	3
c	8	2
d	9	5

# Search Tree

- Each node = <taken, leS, value, remaining calories>



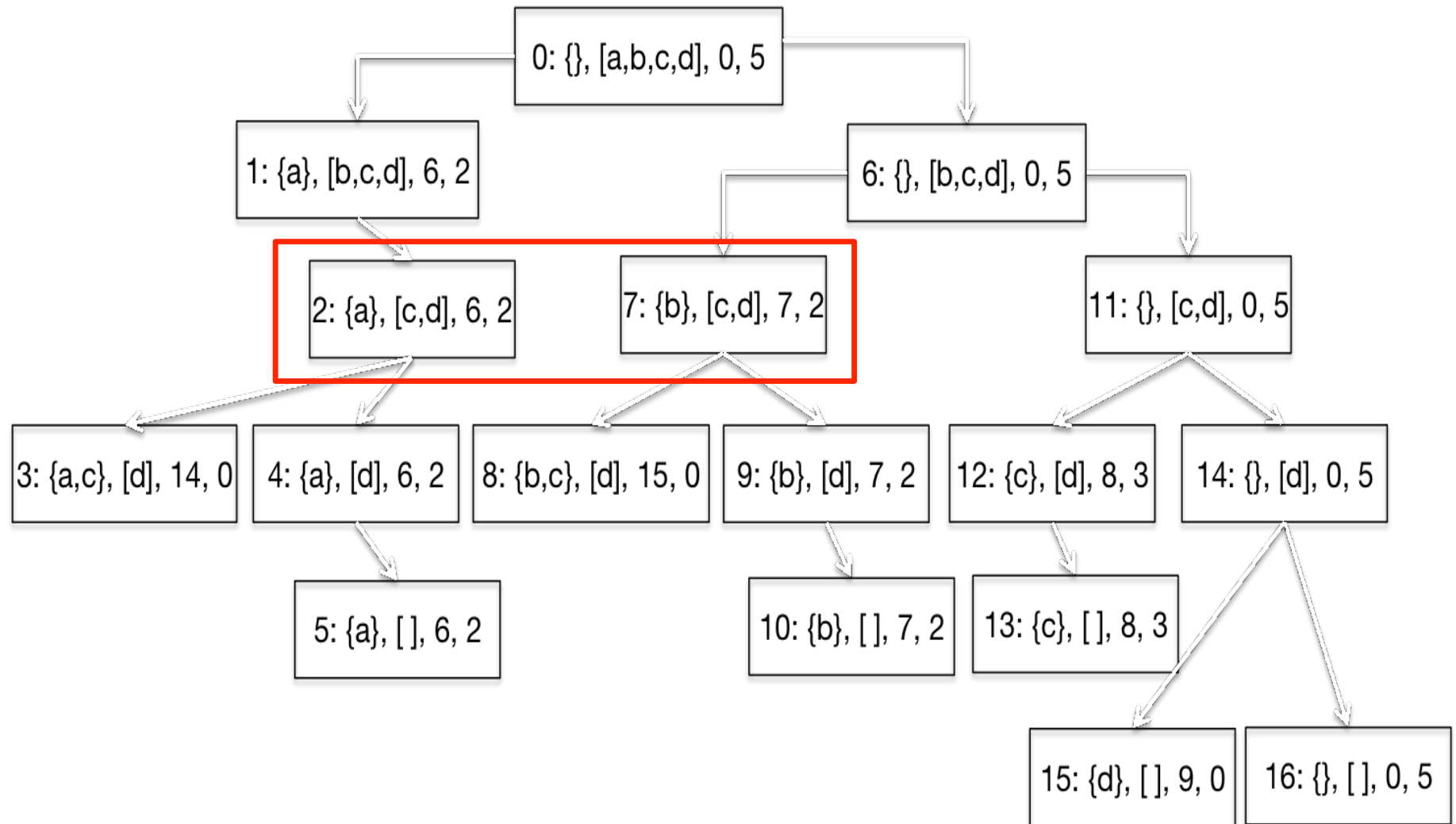
Item	Value	Calories
a	6	3
b	7	3
c	8	2
d	9	5

# What Problem is Solved at Each Node?

- Given remaining weight, maximize value by choosing among remaining items
- Set of previously chosen items, or even value of that set, doesn't matter!



# Overlapping Subproblems



# Modify maxVal to Use a Memo

- Add memo as a third argument
  - `def fastMaxVal(toConsider, avail, memo = {}):`
- Key of memo is a tuple
  - (items left to be considered, available weight)
  - Items left to be considered represented by `len(toConsider)`
- First thing body of function does is check whether the optimal choice of items given the available weight is already in the memo
- Last thing body of function does is update the memo

# Performance

len(items)	2**len(items)	Number of calls
2	4	7
4	16	25
8	256	427
16	65,536	5,191
32	4,294,967,296	22,701
64	18,446,744,073,709,551,616	42,569
128	Big	83,319
256	Really Big	176,614
512	Ridiculously big	351,230
1024	Absolutely huge	703,802

# How Can This Be?

- Problem is exponential
- Have we overturned the laws of the universe?
- Is dynamic programming a miracle?
- No, but computational complexity can be subtle
- Running time of `fastMaxVal` is governed by number of distinct pairs, `<toConsider, avail>`
  - Number of possible values of `toConsider` bounded by `len(items)`
  - Possible values of `avail` a bit harder to characterize
    - Bounded by number of distinct sums of weights
    - Covered in more detail in assigned reading

# Summary of Lectures 1

- Many problems of practical importance can be formulated as **optimization problems**
- **Greedy algorithms** often provide adequate (though not necessarily optimal) solutions
- Finding an optimal solution is usually **exponentially hard**
- But **dynamic programming** often yields good performance for a subclass of optimization problems— those with optimal substructure and overlapping subproblems
  - Solution always correct
  - Fast under the right circumstances

# The “Roll-over” Optimization Problem

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$$\text{Score} = ((60 - (a+b+c+d+e)) * F + a * \text{ps1} + b * \text{ps2} + c * \text{ps3} + d * \text{ps4} + e * \text{ps5})$$

Objective:

Given values for F, ps1, ps2, ps3, ps4, ps5

Find values for a, b, c, d, e that maximize score

Constraints:

a, b, c, d, e are each 10 or 0

$a + b + c + d + e \geq 20$