# CS483 Analysis of Algorithms Lecture 07 – Dynamic Programming 01 \*

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<sup>\*</sup>this lecture note is based on *Algorithms* by S. Dasgupta, C.H. Papadimitriou, and U.V. Vazirani and *Introduction to the Design and Analysis of Algorithms* by Anany Levitin.

## **Dynamic Programming**

Dynamic Programming
A Toy Example: Fibonacci
number (again)
Shortest path in DAGs
Longest increasing
subsequences
Binomial Coefficient
Binomial Coefficient
Knapsack Problem
Knapsack Problem
Knapsack Problem and
Memory Functions
Summary

☐ A term coined by Richard Bellman in the 1940s



(Image from ieee.org. Richard Bellman, 1920 - 1984)

- ☐ Some problems solved by dynamic programming
  - Longest increasing subsequences
  - Fibonacci number
  - Knapsack problem
  - All-pairs shortest path problem (Floyd's algorithm)
  - Optimal binary search tree problem
  - Multiplying a sequence of matrices
  - String matching (or DNA sequence matching), where we search for the string closest to the pattern
  - Convex decomposition of polygons
  - ...

## A Toy Example: Fibonacci number (again)

Shortest path in DAG Longest increasing subsequences

**Binomial Coefficient** 

**Binomial Coefficient** 

Knapsack Problem

Knapsack Problem

Knapsack Problem and Memory Functions

a a substitution

Summary

$$\Box$$
  $f(n) = f(n-1) + f(n-2), f(0) = 1, f(1) = 1$ 

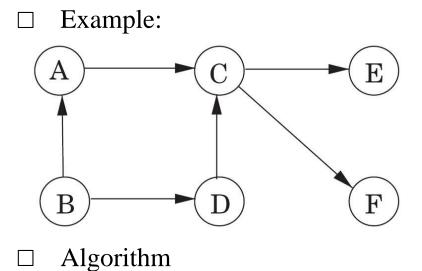
☐ Recursive brute force approach:

☐ DP approach:

- $\square$  What's the difference?
- □ What's the difference between divide-n-conquer and dynamic programming?

## **Shortest path in DAGs**

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**Algorithm 0.1:** DAG-SHORTEST-PATH(G, s)

# Longest increasing subsequences

| Dynamic Programming A Toy Example: Fibonacci number (again) Shortest path in DAGs     Longest increasing     subsequences Binomial Coefficient Binomial Coefficient Knapsack Problem Knapsack Problem Knapsack Problem and Memory Functions Summary | Given a sequence of integers, find the longest <i>increasing</i> sequence. Example 1: 5, 2, 8, 6, 3, 6, 9, 7 (the longest increasing subsequences is: 2, 3, 6, 9)  How do we solve this problem using dynamic programming?  Key observation: Convert the numbers into a DAG!  Example 2: 3, 5, 1, 3, 11, 19, 4, 17, 21, 9, 13, 18 |
|---|---|
|   | Algorithm 0.2: LIS(A)   |

#### **Binomial Coefficient**

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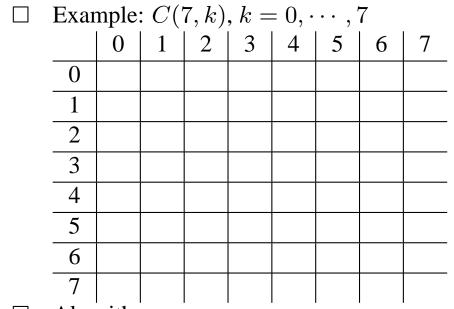
- $\Box (x+y)^n = C(n,0)x^n + \dots + C(n,k)x^{n-k}y^k + \dots + C(n,n)y^n$
- $\square$  Now, our problem is how to compute C(n,k) for all  $k=0\cdots n$  efficiently
- $\square$  We know that  $C(n,k) = \frac{n!}{k!(n-k)!}$ , which is the combination size of picking k elements from n elements.
- Brute force algorithm: Compute  $C(n,0), C(n,1), C(n,2), \cdots C(n,n)$  individually
- ☐ But we know that the same computations are repeated many times!
- $\square$  In fact, we know that C(n,k) = C(n-1,k-1) + C(n-1,k)
- ☐ This idea has been discovered many many years ago in China, India, Iran, and Italy, etc, but one of its most famous names is Pascal's Triangle named after Blaise Pascal, a french mathematician



(image of Blaise Pascal 1623–1662)

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□ Algorithm

**Algorithm 0.3:** BINOMIAL(n)

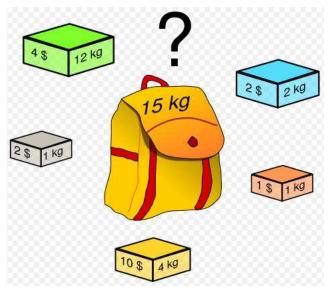
 $\Box$  Time complexity

## **Knapsack Problem**

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Knapsack Problem
Knapsack Problem
Knapsack Problem
Knapsack Problem
Summary

 $\square$  Knapsack Problem: Given n objects, each object has weight w and value v, and a knapsack of capacity W, find most valuable items that fit into the knapsack



- ☐ Brute force approach
  - generate a list of all potential solutions
  - evaluate potential solutions one by one
  - when search ends, announce the solution(s) found
- $\square$  What is the time complexity of the brute force algorithm?

## **Knapsack Problem**

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- ☐ Dynamic programming approach
  - Assume that we want to compute the optimal solution S(w,i) for capacity w < W with i items
  - Assume that we know the optimal solutions S(w', i') for all  $w' \le w$  and  $i' \le i$
  - Option 1: **Don't add** the k-th item to the bag, then S(w,i) = S(w,i-1)
  - Option 2: **Add** the k-the item to the bag, then  $S(w,i) = S(w-w_i,i-1) + v_i$

| $\overline{w}$                   | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 |
|----------------------------------|---|---|---|---|---|---|---|---|---|----|----|----|----|----|----|
| 12kg, \$4                        |   |   |   |   |   |   |   |   |   |    |    |    |    |    |    |
| 1kg, \$2                         |   |   |   |   |   |   |   |   |   |    |    |    |    |    |    |
| 2kg, \$2                         |   |   |   |   |   |   |   |   |   |    |    |    |    |    |    |
| 1kg, \$2<br>2kg, \$2<br>1kg, \$1 |   |   |   |   |   |   |   |   |   |    |    |    |    |    |    |
| 4kg, \$10                        |   |   |   |   |   |   |   |   |   |    |    |    |    |    |    |

 $\Box$  Time complexity?

### **Knapsack Problem and Memory Functions**

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Summary

- □ So far, we look at four DP-based algorithms, all of them are bottom-up approaches.
   □ We can in fact design DP-based algorithms using top-down (recursive) approach.
  - One important benefit of top-down approach is that we can avoid solving unnecessary subproblems

| w   | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 |
|---|---|---|---|---|---|---|---|---|---|----|----|----|----|----|----|
| 12kg, \$4                                     |   |   |   |   |   |   |   |   |   |    |    |    |    |    |    |
| 1kg, \$2                                      |   |   |   |   |   |   |   |   |   |    |    |    |    |    |    |
| 2kg, \$2                                      |   |   |   |   |   |   |   |   |   |    |    |    |    |    |    |
| 1kg, \$1                                      |   |   |   |   |   |   |   |   |   |    |    |    |    |    |    |
| 1kg, \$2<br>2kg, \$2<br>1kg, \$1<br>4kg, \$10 |   |   |   |   |   |   |   |   |   |    |    |    |    |    |    |

☐ Algorithm

```
\begin{aligned} &\textbf{Algorithm 0.4: } \text{ NAPSK}(w,i) \\ &\textbf{if } V[w,i] < 0 \\ &\textbf{then } value \leftarrow \text{NAPSK}(w,i-1) \\ &\textbf{else } w < W[i] \\ &\textbf{then } value \leftarrow \max\{\text{NAPSK}(w,i-1),\text{NAPSK}(w-W[i],i-1) + V[i]\} \\ &V[w,i] \leftarrow value \\ &\textbf{return } (V[w,i]) \end{aligned}
```

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- ☐ Things you need to know about dynamic programming (dp)
  - programming in dp (and linear programming) is a mathematical term, which means optimization or planning, i.e. it should not be confused with "computer programming" or "programming language"
  - dp solves problems with overlapping sub-problems
  - dp solves problems which have **optimal substructure**, i.e., its optimal solution can be constructed from optimal solutions of its sub-problems
  - dp stores the results of sub-problems for later reuse
  - dp works by converting a problem into a set of sub-problems and representing these sub-problems as a DAG.
- ☐ Next week: Dynamic Programming 2
  - Edit distance (string matching)
  - Chain matrix multiplication
  - All pairs shortest distance