

COMPSCI 311: Introduction to Algorithms

Lecture 15: Dynamic Programming

Dan Sheldon

University of Massachusetts Amherst

Dynamic Programming Recipe

- ▶ **Step 1:** Devise simple recursive algorithm
 - ▶ Flavor: make “first choice”, then recursively solve subproblem
- ▶ **Step 2:** Write recurrence for optimal value
- ▶ **Step 3:** Design bottom-up iterative algorithm

- ▶ Weighted interval scheduling: first-choice is binary
- ▶ Rod-cutting: first choice has n options
- ▶ Subset Sum: first choice is binary, but need to “add a variable” to recurrence

Subset Sum: Problem Formulation

- ▶ **Input**
 - ▶ Items $1, 2, \dots, n$
 - ▶ Weights w_i for all items (integers)
 - ▶ Capacity W
- ▶ **Goal:** select a subset S whose total weight is as large as possible without exceeding W .

Step 1: Recursive Algorithm, Binary Choice

Let O be optimal solution on items 1 through j . Is $j \in O$ or not?

SubsetSum(j)

if $j = 0$ **then return** 0

▷ **Case 1:** $j \notin O$

$v = \text{SubsetSum}(j - 1)$

▷ **Case 2:** $j \in O$

if $w_j \leq W$ **then**

$v = \max(v, w_j + \text{SubsetSum}(j - 1) ?)$

▷ else skip b/c can't fit w_j

return v

Clicker

```
SubsetSum(j)
  if j = 0 then return 0
  v = SubsetSum(j - 1)
  if w_j ≤ W then
    v = max(v, w_j + SubsetSum(j - 1)?)
  return v
```

- ▷ Case 1: $j \notin O$
- ▷ Case 2: $j \in O$

Is there a problem in Case 2?

- A. No, it is correct.
- B. Yes, you need to consider that the j^{th} item may be selected multiple times.
- C. Yes, if we take item j , the remaining capacity changes.

Second call to $\text{SubsetSum}(j - 1)$ no longer has capacity W .
Solution: must add extra parameter (problem dimension)

Step 1: Recursive Algorithm, Add a Variable

Find value of optimal solution O on items $\{1, 2, \dots, j\}$ when the remaining capacity is w

```
SubsetSum(j, w)
  if j = 0 then return 0
  ▷ Case 1: j ∉ O
  v = SubsetSum(j - 1, w)
  ▷ Case 2: j ∈ O
  if w_j ≤ w then
    v = max(v, w_j + SubsetSum(j - 1, w - w_j))
  return v
```

Step 2: Recurrence

- ▶ Let $\text{OPT}(j, w)$ be the maximum-weight subset of items $\{1, \dots, j\}$ whose weight does not exceed w

$$\text{OPT}(j, w) = \begin{cases} \text{OPT}(j - 1, w) & w_j > w \\ \max \left\{ \begin{array}{l} \text{OPT}(j - 1, w) \\ w_j + \text{OPT}(j - 1, w - w_j) \end{array} \right\} & w_j \leq w \end{cases}$$

- ▶ Base case: $\text{OPT}(0, w) = 0$ for all $w = 0, 1, \dots, W$.
- ▶ Questions
 - ▶ Do we need a base case for $\text{OPT}(j, 0)$? **No**
 - ▶ What is overall optimum to original problem? $\text{OPT}(n, W)$

From Recurrence to Iterative (“Turn the Crank”)

$$\text{OPT}(j, w) = \begin{cases} \text{OPT}(j - 1, w) & w_j > w \\ \max \left\{ \begin{array}{l} \text{OPT}(j - 1, w) \\ w_j + \text{OPT}(j - 1, w - w_j) \end{array} \right\} & w_j \leq w \end{cases}$$

What size memoization array? $M[j, w]$ for all values of j and w
 $M[0 \dots n, 0 \dots W]$

What order to fill entries? **base case first; RHS before LHS**
for j from $0 \rightarrow n$, for w from $0 \rightarrow W$

Which entry stores solution to overall problem? **Want $\text{OPT}(n, W)$: stored in $M[n, W]$**

Step 3: Iterative Algorithm

SubsetSum(n, W)

Initialize array $M[0..n, 0..W]$

Set $M[0, w] = 0$ for $w = 0, \dots, W$

for $j = 1$ to n **do**

for $w = 1$ to W **do**

if $w_j > w$ **then** $M[j, w] = M[j - 1, w]$

else $M[j, w] = \max(M[j - 1, w], w_j + M[j - 1, w - w_j])$

return $M[n, W]$

Running Time? $\Theta(nW)$.

Clicker

for $j = 1$ to n **do**

for $w = 1$ to W **do**

if $w_j > w$ **then** $M[j, w] = M[j - 1, w]$

else $M[j, w] = \max(M[j - 1, w], w_j + M[j - 1, w - w_j])$

Suppose we have n items, and the capacity W and weights w_j each have m decimal digits. Then the running time is:

- A. $\Theta(nm)$
- B. $\Theta(n \log_{10} m)$
- C. $\Theta(n10^m)$
- D. $\Theta(10^{nm})$

Polynomial vs. Pseudo-polynomial

If numbers have m digits, input size is $\Theta(nm)$, runtime is $\Theta(n10^m)$.

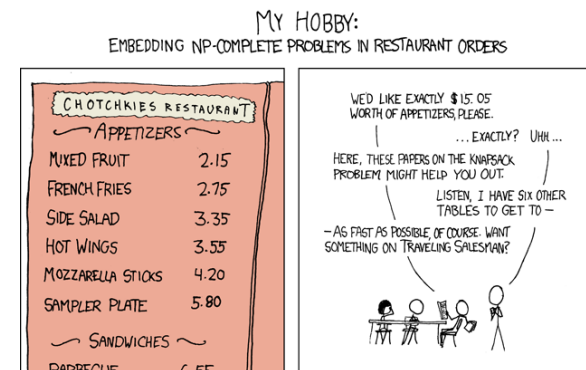
- ▶ **Polynomial time:** polynomial in input size (nm)
- ▶ **Pseudo-polynomial:** polynomial in number of items (n) and *magnitude* of numbers (10^m)

For numeric problems, input size is *log of magnitude* of the numbers. Poly-time algorithm should be polynomial in n and $\log W$.

Subset Sum:

- ▶ Our solution is pseudo-polynomial
- ▶ **No polynomial** algorithm is known

Subset Sum



Knapsack Problem

Same as subset sum, but now items have **value** in addition to weight

Input

- ▶ Items $1, 2, \dots, n$
- ▶ Weights w_i for all items (integers)
- ▶ Values v_i for all items (integers)
- ▶ Capacity W

Goal: select subset S whose total **value** is as large as possible without exceeding W .

Clicker

Recall subset-sum recurrence:

$$\text{OPT}(j, w) = \begin{cases} \text{OPT}(j-1, w) & w_j > w \\ \max \{ \text{OPT}(j-1, w), v_j + \text{OPT}(j-1, w - w_j) \} & w_j \leq w \end{cases}$$

How should the blue term be rewritten for the knapsack recurrence?

- A. $w_j + \text{OPT}(j-1, w - w_j)$
- B. $w_j + \text{OPT}(j-1, w - v_j)$
- C. $v_j + \text{OPT}(j-1, w - v_j)$
- D. $v_j + \text{OPT}(j-1, w - w_j)$

Clicker

Does our knapsack solution still work if the weights and/or values are real numbers instead of integers?

- A. It still works if both the values and weights are real numbers.
- B. It works if values are real numbers but weights are integers.
- C. It works if weights are real numbers but values are integers.
- D. It does not work if either the weights or values are real numbers.

Fractional knapsack problem allows partial objects (think grains, sand, fluid). Has simple **greedy** solution: choose highest value per weight.