Dynamic Programming III: Knapsack Problem

## Admin

- Next Monday will be an activity day
  - Practice dynamic programming w.r.t. graphs
  - Use any extra time in activity period to work on problem set & ask questions

Further Reading: Chapter 6.4, KT

**Problem**. Pack a knapsack to maximize the total item value

• There are *n* items, each with weight  $w_i$  and value  $v_i$ :

$$I = \{(v_1, w_1), \dots, (v_n, w_n)\}$$

- Knapsack has total capacity  ${\it C}$
- For any set of items T they fit in the Knapsack iff

$$\sum_{i \in T} w_i \le C$$

• Goal: Find subset S of items that fit in the knapsack (satisfy the capacity constraint) and maximize the total value:

$$\sum_{i\in S} v_i$$

• Assumption. All weights and values are non-negative integers

Let's first explore greedy solutions to the problem.

Consider the following problem instance:

• Ideas for what to be greedy about?



i	Vi	Wi
1	\$1	1 kg
2	\$6	2 kg
3	\$18	5 kg
4	\$22	6 kg
5	\$28	7 kg

Idea 1: Pick the most expensive stuff we can!

• Algorithm: greedily pick the highest value item that fits.



Creative Commons Attribution-Share Alike 2.5 by Dake Total value: \$35 Utilized capacity: 10 kg

i	Vi	Wi
1	\$1	1 kg
2	\$6	2 kg
3	\$18	5 kg
4	\$22	6 kg
5	\$28	7 kg

Idea 2: Pick the lightest stuff we can!

• Algorithm: greedily pick the lowest weight item that fits.

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Total value: \$25 Utilized capacity: 9 kg

<i>i</i>	Vi	Wi
1	\$1	1 kg
2	\$6	2 kg
3	\$18	5 kg
4	\$22	6 kg
5	\$28	7 kg

Idea 3: Pick the heaviest stuff we can!

• Algorithm: greedily pick the highest weight item that fits.



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Total value: \$35 Utilized capacity: 10 kg

i	Vi	Wi
1	\$1	1 kg
2	\$6	2 kg
3	\$18	5 kg
4	\$22	6 kg
5	\$28	7 kg

Other ideas?

Spoiler: Greedy doesn't work! What is optimal in this instance?

• Optimal packing is  $\{i_3, i_4\}$ : value \$40 (and weight 11)

How many packings muse we consider in an **exhaustive** search?



i	$v_i$	Wi
1	\$1	1 kg
2	\$6	2 kg
3	\$18	5 kg
4	\$22	6 kg
5	\$28	7 kg

### **Exponential Possibilities**

Given S items, how many subsets of items are there in total?

- $2^{S}$ : there are an exponential number of possibilities
- Dynamic programming trades of space for time, and through memoization, we get an (interestingly) efficient solution!



i	Vi	Wi
1	\$1	1 kg
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3	\$18	5 kg
4	\$22	6 kg
5	\$28	7 kg

## Recipe for a Dynamic Program

- Formulate the right subproblem. The subproblem must have an optimal substructure
- Formulate the recurrence. Identify how the result of the smaller subproblems can lead to that of a larger subproblem
- State the base case(s). The subproblem thats so small we know the answer to it immediately!
- State the final answer. (In terms of the subproblem)
- Choose a memoization data structure. Where are you going to store already computed results? (Usually a table)
- Identify evaluation order. Identify the dependencies: which subproblems depend on which ones? Using these dependencies, identify an evaluation order
- Analyze space and running time. As always!

### Towards a Subproblem

Previously, our DP has tracked a value instead of a set.

- Idea 1: Keep track of current capacity c, where  $0 \le c \le C$
- Subproblem. Let T[c] denote the value of the optimal solution that uses capacity  $\leq c$ .
- Optimal solution: T[C]
- **Recurrence**: Not obvious with just capacities.
  - Why is this a challenge?

# Subproblems and Optimality

When items are selected, we need to fill the remaining capacity optimally

• Challenge: the subproblem associated with a given remaining capacity can be solved in different ways



- In both cases, remaining capacity: 11 kg, but items left are different
  - Using just capacity might not be enough. Perhaps a 2D table can capture capacity AND items?

### Subproblem: Optimal Substructure

### Subproblem

#### **Subproblem**

OPT(i, c): value of optimal solution using items  $\{1, 2, ..., i\}$  with total capacity  $\leq c$ , for  $1 \leq i \leq n, 0 \leq c \leq C$ 

**Final answer** 



### Base Cases

 $n \times C$ : Are there any rows/columns can we fill immediately?

- What about the first column corresponding to item 1?

OPT(1, c): Value of optimal solution that uses item 1 and has total capacity at most c

• For  $i = 1; c \in \{1, 2, \dots, C\}$  we can fill out the first column as:

OPT(1, 
$$c$$
) =  $v_1$  if  $c \ge w_1$   
OPT(1,  $c$ ) = 0 if  $c < w_1$   
Item 1 fits, add its value  $v_1$   
Item 1 does not fit, value of empty knapsack is 0

### Base Cases

Are there any rows/columns can we fill immediately?

- What about the first row corresponding to capacity 0?
- OPT(*i*, 0): Value of optimal solution that uses first *i* items and has total capacity at most 0
- For i = 1, 2, ..., n we can fill out the first row as:

$$OPT(i, 0) = 0$$

Items  $1 \dots i$  do not fit, value of empty knapsack is 0

## **Optimal Substructure**

- OPT(*i*, *c*): Let us try to construct the optimal solution that uses items {1,2,...,*i*} and capacity at most *c*
- What are the possibilities for the last  $i^{th}$  item:
  - Either item i is in the optimal solution or not
  - We must consider both cases
- Case 1. Suppose item *i* is not in the optimal solution, what is the optimal way to solve the remaining problem?

• 
$$OPT(i, c) = OPT(i - 1, c)$$

Item *i* is left out, use best solution that considers items 1...(i - 1)for the same capacity

## **Optimal Substructure**

- OPT(*i*, *c*): Let us try to construct the optimal solution that uses items {1,2,...,*i*} and capacity at most *c*
- What are the possibilities for the last  $i^{th}$  item:
  - Either item i is in the optimal solution or not
  - We must consider both cases
- **Case 2.** Suppose item *i* is in the optimal solution, what is the recurrence of the optimal solution?
  - $OPT(i, c) = v_i + OPT(i 1, c w_i)$ 
    - This case only possible if  $c \ge w_i$

### Final Recurrence

For  $1 \le i \le n$  and  $1 \le c \le C$ , we have:

$$OPT(i, c) = \max\{OPT(i - 1, c), v_i + OPT(i - 1, c - w_i)\}$$

- Memoization structure: We store OPT[i, c] values in a 2-D array or table using space O(nC)
- Evaluation order: In what order should we fill in the table?
  - Row-major order (row-by-row)

## Working Through An Example

$$OPT(1, c) = v_1 \text{ if } c \ge w_1$$

$$OPT(1, c) = 0 \text{ if } c < w_1$$

$$OPT(i, c) = 0$$

$$OPT(i, c) = 0$$

$$OPT(i, c) = 0$$

$$OPT(i, c) = max\{OPT(i - 1, c), v_i + OPT(i - 1, c - w_i)\}$$



i	Vi	Wi
1	\$1	1 kg
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i

knapsack instance (weight limit W = 11)

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#### c=0 c=1 c=2 c=3 c=4 c=5 c=6 c=7 c=8 c=9 c=10 c=11

i=1	0	1	1	1	1	1	1	1	1	1	1	1
i=2	0	1	6	7	7	7	7	7	7	7	7	7
i=3	0	1	6	7	7	18	19	24	25	25	25	25
i=4	0	1	6	6	6	18	22	24	28	28	28	40
i=5	0	1	6	6	6	18	22	28	29	34	34	40

# Running Time

- Time to fill out a single table cell? O(1)
- How many cells are there in our table? O(nC)
- Total cost? O(nC)

# Running Time

- Is O(nC) polynomial? By which I mean polynomial in the size of the input
- What is the input? n items, plus the integer C
  - We need O(n) size to store n items
  - How much space to store integer C?  $\log_2 C$  bits
- So, is O(nC) polynomial in the input size?
  - No! One table dimension depends on <u>value</u> of input, not size needed to represent it:  $C = 2^{\log_2 C}$
  - "Pseudopolynomial" polynomial in the *value* of the input

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  - Kleinberg Tardos Slides by Kevin Wayne (<u>https://www.cs.princeton.edu/~wayne/kleinberg-tardos/pdf/04GreedyAlgorithmsl.pdf</u>)
  - Jeff Erickson's Algorithms Book (<u>http://jeffe.cs.illinois.edu/</u> <u>teaching/algorithms/book/Algorithms-JeffE.pdf</u>)
  - Shikha Singh