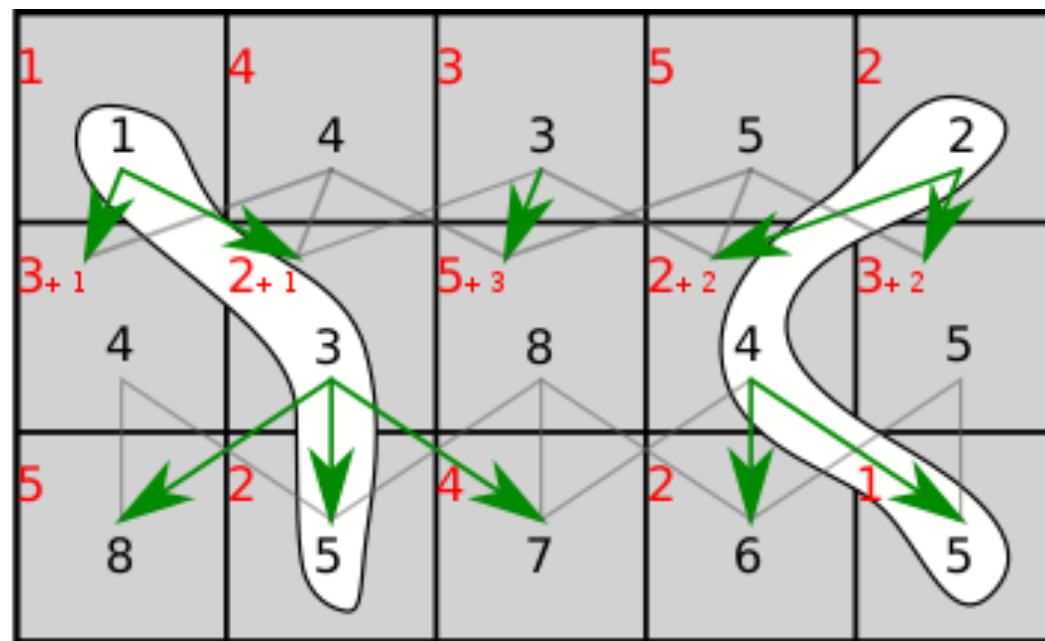


# Dynamic Programming III: Knapsack Problem

Algorithm  
Direction



# Admin

- Assignment 5 is due a day early
  - Office hours: M 2.00-3.30pm, T 3-5 pm
  - TA hours: today 3.30-5, 9-10 pm
  - TA hours: tomorrow 5-10 pm
  - Late work may not be graded in time
- **Midterm** next Friday (**April 2**); no class
- Exam be released 10.00 am Friday; can be taken in any 24 hour period between **10.00 am Friday to 10.00 am Sunday**

# Knapsack Problem

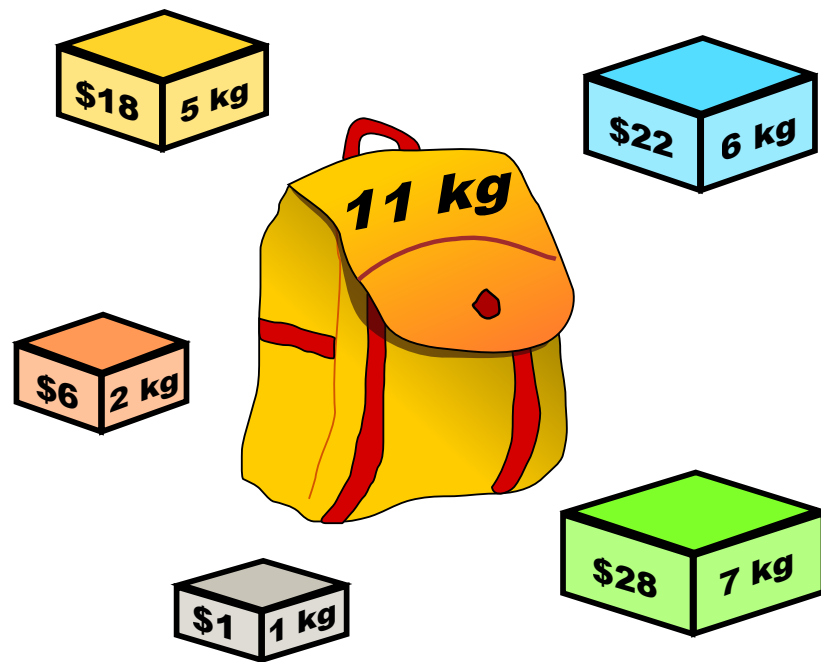
Reading: Chapter 6.4, KT

# Knapsack Problem

- **Problem.** Pack a knapsack to maximize total value
- There are  $n$  items, each with weight  $w_i$  and value  $v_i$
- Knapsack has total capacity  $C$
- For any set of items  $T$  they fit in the Knapsack iff
  - **Capacity constraint:**  $\sum_{i \in T} w_i \leq C$
- **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

# Knapsack Problem

- Does greedily picking the highest value item work?
- Does greedily picking the lowest weight item work?



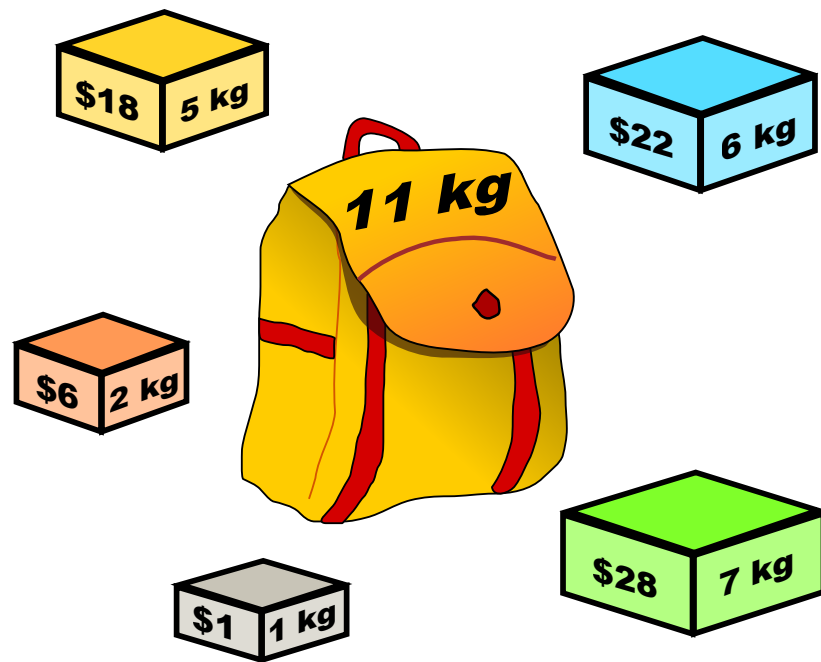
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by Dake

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

Knapsack instance  
(weight limit  $C = 11$  kg)

# Knapsack Problem

- Example (Knapsack capacity  $C = 11$ )
  - Optimal:  $\{3, 4\}$  has value \$40 (and weight 11)



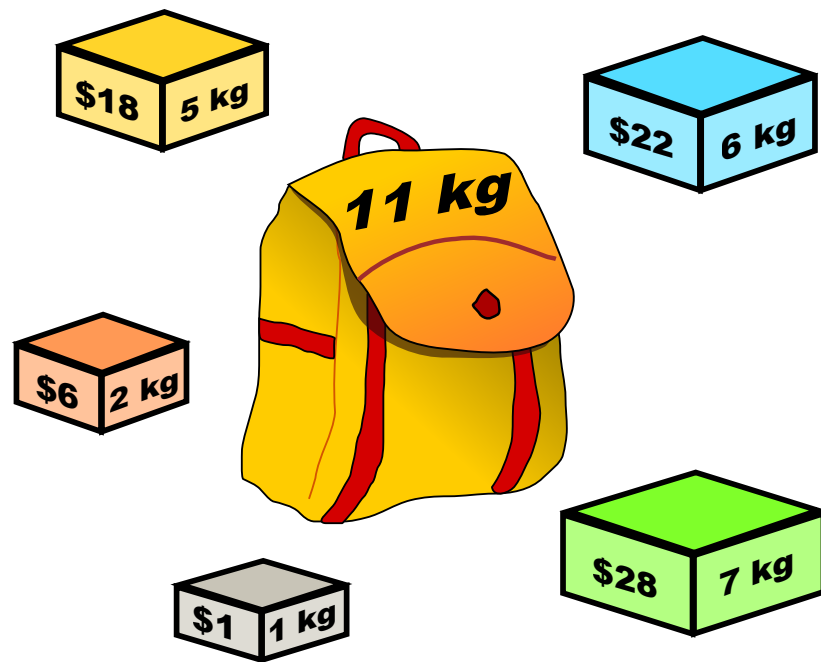
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**knapsack instance**  
**(weight limit  $W = 11$ )**

# Exponential Possibilities

- Given  $S$  items, how many subsets of items are there total?
  - $2^S$ : exponential possibilities
- Dynamic programming trades off space for time, and through memoization gives an efficient solution



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$i$	$v_i$	$w_i$
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**knapsack instance**  
**(weight limit  $W = 11$ )**

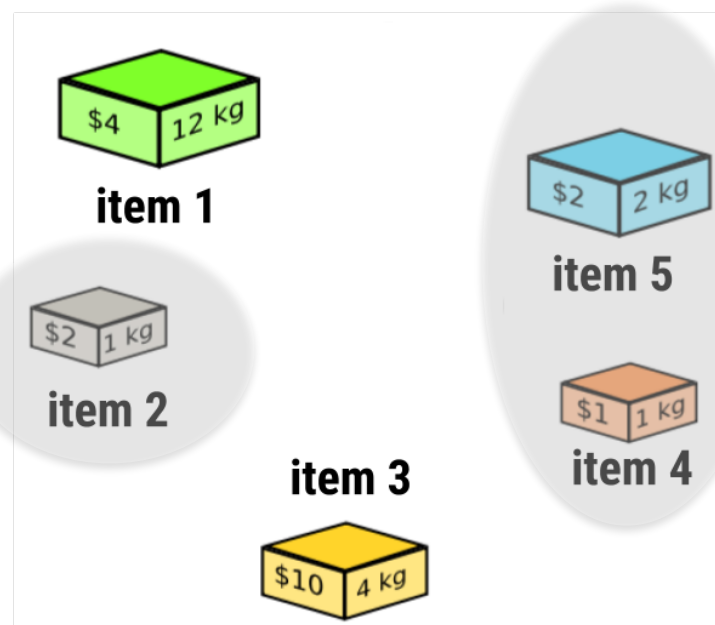
# Towards a Subproblem

- Idea 1: Keep track of capacity
  - **Subproblem.** Let  $T[c]$  denote the value of the optimal solution that uses capacity  $\leq c$ .
- Optimal solution:  $T[C]$
- How do come up with a recurrence?
- Not obvious with just capacities

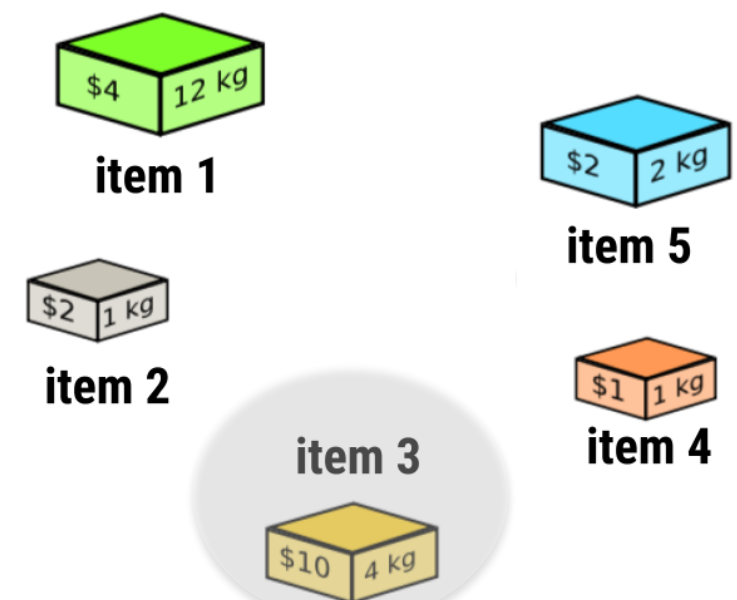


# Subproblems and Optimality

- When items are selected we need to fill the remaining capacity optimally
- Subproblem associated with a given remaining capacity can be solved in different ways



Partial Selection #1



Partial Selection #2

- In both cases, remaining capacity: 11 but items left are different

Subproblem:  
Optimal Substructure

# Subproblem

- **Subproblem**

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

- **Final answer**

$\text{OPT}(n, C)$

# Base Cases

- Let us think about which rows/columns can we fill initially
- $\text{OPT}(i, 0)$ : Value of optimal solution that uses first  $i$  items and total capacity at most 0
- $\text{OPT}(0, c)$ : Value of optimal solution that uses zero items and total capacity at most  $c$

$$\text{OPT}(i, 0) = 0 \text{ for } 0 \leq i \leq n$$

$$\text{OPT}(0, c) = 0 \text{ for } 0 \leq c \leq C$$

# Optimal Substructure

- $\text{OPT}(i, c)$ : Imagine the optimal solution that uses items  $\{1, 2, \dots, i\}$  and capacity at most  $c$
- What are the possibilities for the last  $i$ th item:
  - Either it is in the optimal solution or not, we consider both cases
- **Case 1.** Suppose it is **not** in the optimal solution, what is the optimal way to solve the remaining problem?
  - $\text{OPT}(i, c) = \text{OPT}(i - 1, c)$

# Optimal Substructure

- $\text{OPT}(i, c)$ : Imagine the optimal solution that uses items  $\{1, 2, \dots, i\}$  and capacity at most  $c$
- What are the possibilities for the last  $i$ th item:
  - Either it is in the optimal solution or not, we consider both cases
- **Case 2.** Suppose it **is** in the optimal solution, what is the recurrence of the optimal solution?
  - $\text{OPT}(i, c) = v_i + \text{OPT}(i - 1, c - w_i)$  (assuming  $c \geq w_i$ , if not, this case is not possible)

# Final Recurrence

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

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

- **Memoization structure:** We store  $\text{OPT}[i, c]$  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)

# Running Time

- Takes  $O(1)$  to fill out a cell,  $O(nC)$  total cells
- Is this polynomial? By which I mean polynomial in the *size of the input*
- How large is the input to knapsack?
  - Store  $n$  items, plus need to store  $C$
  - $O(n + \log C)$
- Is  $O(nC)$  polynomial?
  - No!
  - “Pseudopolynomial” - polynomial in the *value* of the input
- To think about: does this work if the weights are not integers?



# 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 that's so small we know the answer to it!
- **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!

# Partitioning Books

Reading: [Linked on GLOW](#)

# Dynamic Programming Practice

- Suppose we have to scan through a shelf of books, and this task can be split between  $k$  workers
- We do not want to reorder/rearrange the books, so instead we divide the shelf into  $k$  regions
- Each worker is assigned one of the regions
- What is the fairest way to divide the shelf up?



# DP: Dividing Work

- Suppose we have to scan through a shelf of books, and this task can be split between  $k$  workers
- We do not want to reorder/rearrange the books, so instead we divide the shelf into  $k$  regions
- Each worker is assigned one of the regions
- What is the fairest way to divide the shelf up?
- If the books are equal length, we can just give each worker the same number of books
- What if books are not equal size?
  - How can we find the fairest partition of work?

# The Linear Partition Problem

- **Input.** A input arrangement  $S$  of nonnegative integers  $\{s_1, \dots, s_n\}$  and an integer  $k$
- **Problem.** Partition  $S$  into  $k$  ranges such that the maximum sum over all the ranges is minimized

- **Example.**

- Consider the following arrangement

100 200 300 400 500 600 700 800 900

- Suppose  $k = 3$ , where should we partition to minimize the maximum sum over all ranges?

100 200 300 400 500 | 600 700 | 800 900

# Optimal Substructure

- Notice that the  $k$ th partition starts after we place the  $(k - 1)$ st “divider”
- Let us try to construct an optimal solution. Where can we place the *last* divider?
  - Between some elements, suppose between  $i$ th and  $(i + 1)$ st element where  $1 \leq i \leq n - 1$
  - What is the cost of placing the last divider here? Max of:
    - Cost of the last partition  $\sum_{j=i+1}^n s_j$
    - Cost of the optimal way to partition the elements to the “left”  
— **this is a smaller version of the same problem!**
- **Question:** Can you come up with the **subproblem** for the dynamic program?

# Dividing Work: DP Algorithm

- **Subproblem.**  $M[i, j]$  be the minimum cost over all partitions of first  $i$  books into  $j$  partitions,  $1 \leq i \leq n$ ,  $1 \leq j \leq k$
- **Base cases.**
  - $M[1, j] = s_1$  for all  $1 \leq j \leq k$
  - $M[i, 1] = \sum_{t=1}^i s_t$  for all  $1 \leq i \leq n$
- **Recurrence.**
  - Dictates how we go from one subproblem to the next
  - Now we have a two dimensional table so we also need to think about which order to go in (what the dependencies are...)

# Dividing Work: DP Algorithm

- **Subproblem.**  $M[i, j]$  be the minimum cost over all partitions of first  $i$  books into  $j$  partitions,  $1 \leq i \leq n$ ,  $1 \leq j \leq k$
- **Base cases.**
  - $M[1, j] = s_1$  for all  $1 \leq j \leq k$
  - $M[i, 1] = \sum_{t=1}^i s_t$  for all  $1 \leq i \leq n$
- **Recurrence.**  $M[i, j] = \min_{1 \leq i' \leq i} \max\{M(i', j-1), \sum_{t=i'+1}^i s_t\}$
- **Final solution.**  $M[n, k]$
- **Memoization structure.** Two-dimensional array.
- **Evaluation order.** ?

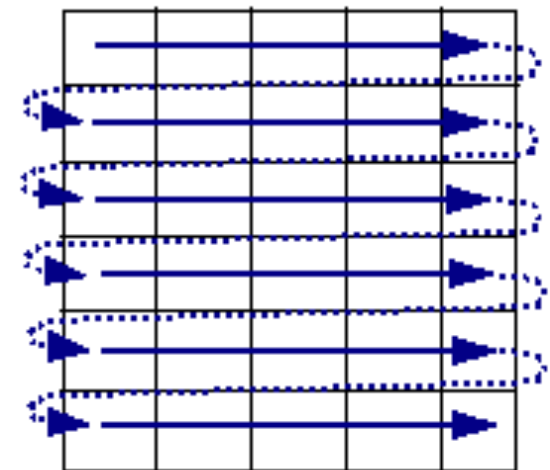


# Evaluation Order

- What do we need filled in so that we can fill in  $M[i, j]$ ?
- For all  $i' < i$ , need  $M[i', j - 1]$
- Plan: fill in all  $M[i, 1]$ , then all  $M[i, 2]$  (in increasing order of  $i$ ), then all  $M[i, 3]$ , and so on
- Let's draw out  $M$  where each value of  $j$  is a row of  $M$

# Dividing Work: Final Pieces

- Evaluation order.
  - To fill out one cell, we need to take min over the values to the left in the previous row
  - Thus, we fill out rows one-by-one
  - Called row major order
- Running time?
  - Size of table:  $O(k \cdot n)$
  - How long to compute a single cell?
    - Depends on  $n$  other cells
  - $O(n^2 \cdot k)$  time



Row-major order

# Running Time

- Running time
  - Size of table:  $O(k \cdot n)$
  - How long to compute a single cell?
    - Depends on  $n$  other cells
  - $O(n^2 \cdot k)$  time
- Is this a polynomial running time?
- How big can  $k$  get?
  - At most  $n$  non-empty partitions of  $n$  elements
  - $O(n^3)$  algorithm in the worst case

# Acknowledgments

- Some of the material in these slides are taken from
  - Kleinberg Tardos Slides by Kevin Wayne (<https://www.cs.princeton.edu/~wayne/kleinberg-tardos/pdf/04GreedyAlgorithmsI.pdf>)
  - Jeff Erickson's Algorithms Book (<http://jeffe.cs.illinois.edu/teaching/algorithms/book/Algorithms-JeffE.pdf>)