

Knapsack and Dynamic Programming

6.1000 LECTURE 21

FALL 2025

Announcements

- Pset 5 checkoff due today
- Pset 6 due 12/1, Monday after Thanksgiving
- No office hours on 11/26, Wednesday before Thanksgiving
- No office hours on 12/10, last day of classes
- Instructor office hours on 12/11, Thursday before finals

Recall: Knapsack problems



- You have limited strength, so there is a maximum weight knapsack that you can carry
- You want to take more stuff than you can carry
- How do you choose what to take vs. leave behind?
 - Want to optimize “value” of things to take
- Two variants
 - Continuous or fractional knapsack problem
 - 0/1 knapsack problem

Straightforward

Much more interesting

Quanta are
infinitesimal
relative to
available space



versus



Quanta are
large relative to
available space

Greedy solutions

- Repeatedly pick the best item among what's available
 - Once you pick, you have to commit, no backtracking
- Continuous knapsack
 - Pick as much of the most value-dense item as possible
- 0/1 knapsack
 - Must take an entire object or leave it behind
 - Possible greedy metrics: by value, by weight, by density
 - None are guaranteed to yield optimal solution

Enumeration of item combinations

- Optimal solution
 - Enumerate all possible item selections
 - For each, check whether it satisfies the capacity constraint
 - Among those that do, keep the one with the most value
- How to enumerate
 - Approach 1: recursively generate
 - generate all combinations for **items[1:]**
 - collect each combo both with and without **item[0]**
 - Approach 2: read off binary digits
 - let ***n*** be **len(items)**
 - generate binary representations of **0** through **$2^n - 1$**
 - each is an ***n***-character string of **0**'s and **1**'s
 - each **1** selects the item at that index

Runtime performance of enumeration

- 2^n combinations, grows exponentially in number of items
 - $2^{10} \sim 10^3$, $2^{20} \sim 10^6$, $2^{30} \sim 10^9$
 - Processor speeds $\sim 10^9$ Hz (cycles per second)
 - $\sim 10^3$ cycles to process each combination
- Solution times become user-unfriendly around $n \sim 25$
 - Each increment in n will **double** the size of the solution space to consider
 - Not scalable
 - Are we doomed to rely on greedy solutions?



Pruning branches in decision tree

- While generating the combinations, keep track of remaining capacity as we go descend branches in the decision tree
- If taking the next object would cause our selection to go over capacity, do not consider that branch
- Testing result
 - Can solve up to $n \sim 35$ in less than a minute
 - Better, but still not practical
- In-class exercise
 - Decision-tree implementation makes list copies when slicing
 - Rewrite so that it recurses on ***index of next item*** to consider, rather than on list of remaining items



Avoid re-solving overlapping subproblems

- Consider items $A, B, C, D, \dots$ with weights $2, 3, 2, 1, \dots$ and capacity **20**
- After going down the branch $+A, +B, -C$, need to solve a subproblem for items $D, E, \dots$ with capacity **15**
- After going down the branch $-A, +B, +C$, need to solve the **exact same subproblem!**
- ***Idea (dynamic programming)***
 - Remember the result the first time
 - Recognize if we re-encounter, use saved result

Dynamic programming

- Broadly applicable algorithm strategy
 - Principles were invented by Richard Bellman in the 1950s
 - Name was chosen for “marketing”
 - “programming” in the sense of “creating a schedule/solution”
 - “dynamic” because it sounds cool
 - https://en.wikipedia.org/wiki/Dynamic_programming#History_of_the_name
- **Correctness requirement: optimal substructure**
 - optimal solutions involve optimal solutions to subproblems
- **Efficiency requirement: overlapping subproblems**
 - different subproblems rely on the same subproblems
 - how efficient depends on amount of subproblem overlap