

## CS 25 - Algorithms

10/16/95

Last time (chap 16, 17)

- DP
- Greedy

Today (chap 17, 18)

- Greedy Alg.
- Amortized Analysis

Announcements

- X-hour

Dynamic programming is a technique that takes apart the problem into smaller pieces that can be solved independently.

It makes it easier to solve the whole problem.

And now to the results of dynamic programming.

Dynamic programming is best solution to the knapsack problem of the form:  
Given  $n$  items of different weights  $w_1, w_2, \dots, w_n$  and values  $v_1, v_2, \dots, v_n$ , find the solutions of maximum value  $v$  that can be put into a knapsack of capacity  $C$  by best combination of best weight  $w$  and maximum value  $v$ .

This is a classic programming problem because it is a good example of both finding best solution by indirect approach and the problem is similar to lot of other optimization problems.  
In simple words, if we want to solve this problem, we have to break it into smaller subproblems and solve them one by one. Then the final solution is obtained.

Similarly, we can solve many problems using the same approach.  
It is used in solving many problems.

As we saw in the last lecture, greedy algorithm can solve some problems but not all. If so, and they can't be solved by greedy algorithm, then dynamic programming can be used.

## Greedy algorithms

- Usually used to solve optimization problems

e.g. Multiple matrix multiplication (try to minimize # operations)  
LCS - longest common subsequence

- Key idea: Greedy algorithms always make the choice that looks best at the moment.
  - don't look ahead
  - don't consider future ramifications of current decisions
- \* makes a locally optimal vs. globally optimal decision
- In some sense, it's the opposite of dynamic programming.

Dynamic prog: Best solution to a problem is the best combination of the best solutions of some subproblems. Best solution of subproblem is best combination of best solution of some subsubproblems, etc.

Thus, dynamic programming works bottom up: first finding best solutions to smallest subproblems and then combining optimally to find best solutions to larger subproblems and so on until the best solution to the entire problem is obtained.

Greedy alg: Work top down, simply making the best decision at the moment and going on from there.

- Because of greedy decisions, greedy algorithms don't always obtain optimal solutions. But they often do, and they're simpler than dynamic prog.

## Elements of a greedy strategy

(How to tell if greedy strategy will work)

- 1) Greedy-choice property: A globally optimal solution can be arrived at by making locally optimal (greedy) choices.

e.g. In the A.S.P., while not every solution consists of greedy choices, we showed that  $\exists$  a solution composed of greedy choices.

- 2) Optimal substructure: An optimal solution to the problem contains optimal solutions to subproblems.

e.g. In the A.S.P., if the first activity of an optimal solution is removed, then the remaining activities are an optimal solution to the activities compatible with the removed activity.

## Greedy Methodology

1. Characterizing the "greedy choice"
2. Prove the greedy algorithm correct by induction
  - Show that  $\exists$  an opt. soln. which begins w/ greedy choice (base case)
  - Show that if  $\exists$  an opt. soln. which begins w/  $i$  greedy choices, then  $\exists$  opt. soln. which begins w/  $i+1$  greedy choices. (inductive step)

- each piece of the above proof will likely be by contradiction.

Example

## Fractional Knapsack

- $n$  items
- $H_i$ , item  $i$  has weight  $w_i$  and value  $v_i$
- knapsack holds  $W$  pounds

Goal: optimize value of items taken

Restriction:

- total weight cannot exceed  $W$
- can, however, take fractions of items  
(e.g. gold dust vs. gold ingots)

## Algorithm

- Sort items by  $q_i = v_i/w_i$  (quality)
- Take as much of best item as possible
- Repeat on items of successively lesser quality until knapsack full.
- R.T.  $\Theta(n \lg n)$  to sort,  $\Theta(n)$  to pick items :  $\Theta(n \lg n)$  total

Proof of correctness : (follows)

- In any solution to the fractional knapsack problem, consider the items taken in order of their quality  $z_i = v_i/w_i$ .

Base Case:  $\exists$  an opt. soln. that begins with a greedy choice.

PF

- W.l.o.g., assume items are numbered according to their order as sorted by quality. Thus,  $z_1 \geq z_2 \geq z_3 \dots$
- W.l.o.g., assume  $z_i > z_{i+1} \forall 1 \leq i < n$ . (Otherwise, "combine" items with identical qualities.)
- Consider any opt. sol.  $S$ :
  - if  $S$  begins w/greedy choice (i.e., takes as much of Item 1 as possible), then done. ✓
  - if not, then  $S$  must take a positive amount of some other item  $k > 1$

$\Rightarrow \exists$  some weight  $u > 0 \Rightarrow$  we can construct a new sol.  $S'$  which takes  $u$  less of Item  $k$  and  $u$  more of Item 1. ( $u = \min \{ \text{Amount of Item } k \text{ taken}, \text{Amount of Item 1 remaining} \}$ )

$$\begin{aligned} \text{Value}(S') &= \text{Value}(S) - u \frac{v_k}{w_k} + u \frac{v_1}{w_1} \\ &= \text{Value}(S) + u(v_{w_1} - v_k/w_k) \\ &> \text{Value}(S) \quad \text{since } u > 0 \text{ and } z_1 > z_k \end{aligned}$$

$\Rightarrow S$  is not optimal  $\times$ .

(In a greedy hotel, else O(n lg n) time)

Inductive Step: If  $\exists$  an opt. soln. which begins with  $i-1$  greedy choices, then  $\exists$  an opt. soln. which begins with  $i$  greedy choices.

PF

(Virtually identical to previous proof; leave as an exercise.)

W.l.o.g., assume  
solution sorted  
by quality

Greedy:  


Others:  


Another exampleActivity Selection Problem

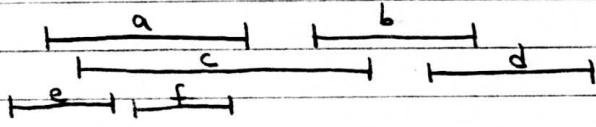
- Set  $S$  of  $n$  activities

$s_i$  = start time of activity  $i$

$f_i$  = finish time of activity  $i$

- find maximum subset  $A$  of compatible activities.

e.g. Given  $n$  activities that need <sup>speaking</sup> same auditorium, what is most activities you can schedule?



best: {  
e f b  
e f d}

greedy decision : pick the <sup>compatible</sup> activity with the earliest finishing time so that you have maximum possible remaining time to schedule other activities.

Greedy - Activity - Selector ( $s, f$ )

$n \leftarrow \text{length}[s]$

$A \leftarrow \{1\}$

$j \leftarrow 1$

for  $i \leftarrow 2$  to  $n$

do if  $s_i \geq f_j$

then  $A \leftarrow A \cup \{i\}$

$j \leftarrow i$

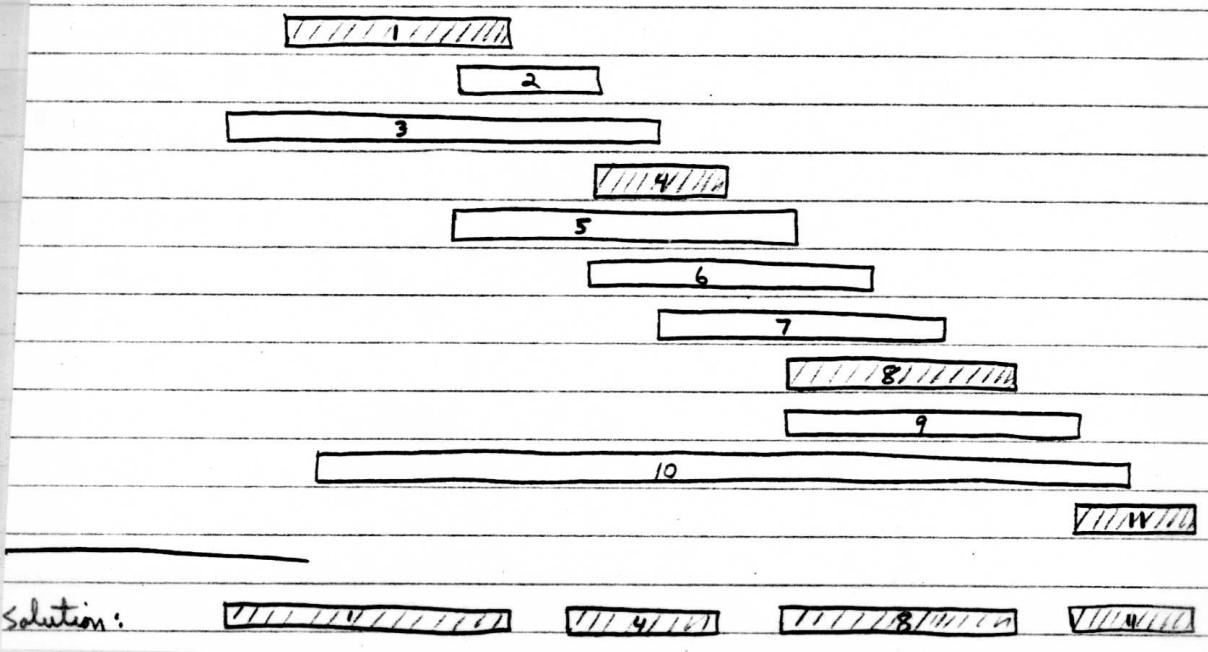
return  $A$

% assume activities sorted by finishing time,  
% e.g.  $f_1 \leq f_2 \leq \dots \leq f_n$

Running time -  $O(n)$  if already sorted, else  $O(n \lg n)$  to sort.

Example

(Shade activities in as they are selected)  
(draw all 11 activities first...)



Solution:

Proof of correctness

- Let  $S = \{1, 2, \dots, n\}$  be a set of activities to schedule, ordered by finish times (i.e.,  $f_1 \leq f_2 \leq \dots \leq f_n$ )

$$\text{Greedy: } G = \{g_1, g_2, g_3, \dots\}$$

$$\text{Opt: } A = \{a_1, a_2, a_3, \dots\}$$

Base Case:  $\exists$  an optimal solution that begins with a greedy choice (i.e. activity  $g_1$ ).

Proof: Let  $A \subseteq S$  be an optimal solution, and order the activities in  $A$  by their finish time.

Suppose activity  $g_1$  is the first activity in this order.

$$A = \{a_1, a_2, a_3, \dots\}$$

If  $a_1 = g_1$ , done ✓

If  $a_1 \neq g_1$ , then  $(A - \{a_1\}) \cup \{g_1\}$  is an optimal solution (since  $f_{g_1} \leq f_{a_1}$ )

Inductive Step: If  $\exists$  an opt. soln. that begins with  $i$ -th greedy choice, then  $\exists$  an opt. soln. that begins w/  $i$ -th g.c.

$$A = \{g_1, g_2, g_3, \dots, g_i, a_{i+1}, \dots\}$$

Proof: Let  $A \subseteq S$  be such an opt. soln. and let  $a_i$  be the  $i$ -th item picked (in sorted order)

If  $a_i = g_i$ , done ✓

If  $a_i \neq g_i$ , then  $a_i > g_i$  and  $g_i$  not picked. (why?) (Considering soln. in sorted order by  $f_i$ )

$\Rightarrow (A - \{a_i\}) \cup \{g_i\}$  is an opt. soln. (why?) ( $f_{g_i} < f_{a_i}$  if  $a_i > g_i$ )

Greedy:  
 $G = \{g_1, g_2, \dots, g_n\}$   
(sorted order)