Greedy Algorithms

Algorithms

Greedy Algorithms

- Many algorithms run from stage to stage
	- At each stage, they make a decision based on the information available
- A Greedy algorithm makes decisions
	- At each stage, using locally available information, the greedy algorithm makes an optimal choice

- Sometimes, greedy algorithms give an overall optimal solution
- Sometimes, greedy algorithms will not result in an optimal solution but often in one good enough

Divisible Items Knapsack Problem

- Given a set of items *S*
	- Each item has a weight *w*(*x*)
	- Each item has a value $v(x)$
- Select a subset *M* ⊂ *S*
	- Constraint:

$$
\sum_{x \in M} w(x) < W
$$

Objective Function:

$$
\sum_{x \in M} v(x) \longrightarrow \max
$$

Divisible Items Knapsack Problem

- Order all items by impact
	- \bullet **impact** $(x) =$ *v*(*x*) *w*(*x*)
- In order of impact (highest first), ask whether you want to include the item
	- And you include it if the sum of the weights of the items already selected is smaller than *W*

- Set of activities $S = \{a_1, a_2, ..., a_n\}$
	- Each activity has a start time and a finish time
		- $0 \le s_i < f_i < \infty$
	- Each activity needs to use your facility
	- Only one activity at a time
	- Make the rental agreements that maximize the number of rentals

- Two activities a_i and a_j are compatible iff a_i and a_j
	- $[s_i, f_i) \cap [s_j, f_j] = \emptyset$

• This means that activity $i < j$ finishes before activity j

• Example:

- A compatible set is $\{A_1, A_5, A_8, A_{10}\}$
- Another compatible set is $\{A_3, A_9\}$

- Optimal rental with a dynamic programming algorithm
	- Subproblems: Define S_{ik} to be the set of activities that start after a_i finishes and finish before a_k starts

$$
S_{1,8} = \{a_5\}
$$

- We want to find an optimal rental plan for *Sik*
	- Assume that there is an optimal solution that contains activity $a_j \in S_{i,k}$
	- By selecting a_j , we need to decide what to do with the time before $\vec{a_j}$ starts and after $\vec{a_j}$ finishes
	- These sets are S_{ij} and S_{jk}

- Assume that a_j is part of an optimal solution $A_{i,k}$ for $S_{i,k}$
	- Then $A_{i,k}$ is divided into the ones that end before a_j and the ones that start after *aj*

•
$$
A_{i,j} = A_{i,k} \cap S_{i,k} \quad A_{j,k} = A_{i,k} \cap S_{j,k}
$$

$$
A_{i,k} = A_{i,j} \cup \{a_j\} \cup A_{j,k}
$$

- Clearly, $A_{i,j}$ is an optimal solution for $S_{i,j}$
- $A_{j,k}$ is an optimal solution for $S_{j,k}$
- For if not, we could construct a better solution for *Si*,*k*

- We can therefore solve recursively the problem for $S_{i,k}$ by looking at all possible activities for *aj*
	- Define $C[i, k] =$ Max number of compatible activities in $S_{i,k}$
	- Then:

 $C[i, k] = \max(0, \max(C[i, j] + C[j, k] + 1 | a_i \in S_{i,k}))$

• The 0 is necessary because there might be no activity in $S_{i,k}$

• The recursion leads to a nice dynamic programming problem

$$
C[i, k] = \max(0, \max\left(C[i, j] + C[j, k] + 1 \mid a_j \in S_{i,k}\right))
$$

• But can we do better?

- Start out with the initial problem
	- Select the activity that finishes first
		- this would be a_1
	- This leaves most space for all other activities
		- Call S_1 the set of activities compatible with a_1
			- These are those starting after a_1
		- Similarly, call $\ S_{k}^{-}$ the set of activities starting after

• Theorem: For any non-empty problem S_k let a_m be the activity with the smallest end time. Then a_m is contained in an optimal solution

- Proof:
	- Let A_k be a solution
		- $\bullet\;$ i.e. the maximum sized compatible subset in S_k
		- Let $a_1 \in A_k$ be the activity with earliest finish time
		- If $a_m = a_1$ then we are done

• Theorem: For any non-empty problem S_k let a_m be the activity with the smallest end time. Then a_m is contained in an optimal solution

- Proof:
	- Otherwise replace a_1 with a_m in A_k

$$
\bullet \qquad A'_k = A_k - \{a_1\} \cup \{a_m\}
$$

- Since a_m is the first to finish, this is a set of compatible activities
- Therefore, there exists an optimal solution with a_m

- Result of the Theorem:
	- We can find an optimal solution (but not necessarily all optimal solutions) by always picking the first one to finish.

• Example

- Select a_1
- Exclude a_2 , a_3 , and a_4 as incompatible
- Choose a_5 , a_8 , and a_{10} for the complete solution

Greedy Algorithms

- Greedy algorithms
	- Determine the optimal substructure
	- Develop a recursive solution
	- Show that making the greedy choice is best
	- Show that making the greedy choice leads to a similar subproblem
	- Obtain a recursive algorithm
	- Convert the recursive algorithm to an iterative algorithm

- How to make change for a given amount using minimum number of coins with denominations $\ \{1, a_2, a_3, \, ... , a_n\}$
	- Some sets of coins allow a greedy solution
		- Always choose biggest coin smaller than amount
		- ${1,5,10,20,50}$
		- \bullet {1,5,10,50,100,200,1000}
	- Others are not regular, i.e. the greedy solution is not always best
		- $\{1,6,7\}$
		- Why is this not regular?

 $12 = 7 + 1 + 1 + 1 + 1 + 1 = 6 + 6$

- Dynamic Programming approach
	- Common subproblem structure?

- Let $x_1 + x_2 a_2 + x_3 a_3 + ... + x_n a_n = M$ be an optimal way to make change with $x_1 + x_2 + x_3 + \ldots + x_n$ coins.
- Then this is also an optimal way to make change for *N*

 $y_1 + y_2 a_2 + y_3 a_3 + \ldots + y_n a_n = N$, $y_1 \le x_1, y_2 \le y_2, \ldots, y_n \le x_n$

• Proof?

- Because of the common sub-problem property, we can use dynamic programming
- Easiest organized by limiting the number of coins
	- Let the values of the coins be

 $1 = a_1 < a_2 < a_3 < \dots < a_n$

• For all amounts $m \leq M$ let $d_k(m)$ be the minimum number of coins using denominations $\ a_1, a_2, ..., a_k$

• What is the recursive formula?

 $d_k(m) = \min\{d_{k-1}(m - a_k) + 1, d_{k-1}(m - 2a_k) + 2, d_{k-1}(m - 3a_k) + 3, \ldots, d_{k-1}(m - 2a_k)\}$ *m ak* $\left\lfloor a_k \right\rfloor + \left\lfloor a_k \right\rfloor$ *m ak* \bigcup

• Solve the coin problem for $\{1,6,7\}$ and amount 25