

CS141: Intermediate Data Structures and Algorithms

Greedy Algorithms

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- > Given a set of activities $S = \{a_1, a_2, ..., a_n\}$ where each activity *i* has a start time s_i and a finish time f_i , where 0 ≤ $s_i < f_i < \infty$.
- > An activity a_i happens in the half-open time interval [s_i , f_i].



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- > An activity a_i happens in the half-open time interval $[s_i, f_i]$.
- Activities compete on a single resource, e.g., CPU
- Two activities are said to be compatible if they do not overlap.
- The problem is to find a maximum-size compatible subset, i.e., a one with the maximum number of activities.

Example



a3[0,6)







+ 7

UCR

A Better Compatible Set



a3[0,6)



Participation Exercise



Name:

Student ID:

Two activities are said to be **compatible** if they **do not overlap**. For example, a1 and a8 are compatible activities. The subset that contains a2, a6, and a11 is a compatible subset of size 3, i.e., has three compatible activities. Find a **maximum-size compatible subset**, i.e., a one with the maximum number of activities, of the following set of activities.



An Optimal Solution



a3[0,6)



Another Optimal Solution



a3[0,6)





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 - > Brute force (naïve): all possible combinations \rightarrow O(2ⁿ)
 - > Can we do better?
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 - > Can we do better?
 - Divide line for D&C is not clear
- > Instead, can we make a greedy choice?
 - i.e., take the best choice so far, reduce the problem size, and solve a subproblem later
- Greedy choices
 - Longest first
 - Shortest first
 - Earliest start first
 - > Earliest finish first
 - **>** ...?



- > Greedy choice: shortest length first
 - > Why? To accommodate as much activities as possible



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> This greedy choice does not work



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- Greedy choice: earliest finish first
 - > Why? It leaves as much resource as possible for other tasks
- Is this choice correct? Does it guarantee an optimal solution?
 - > Can we find a counter example against this choice?
 - Not clear
 - > Let's try to prove its correctness, if we cannot, then it is wrong



- Is greedy choice enough to get optimal solution?
- Greedy choice property
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 - Prove that if a_m has the earliest finish time, it must be included in some optimal solution.
- > Assume a set S and a solution set A, where $a_m \notin A$
 - Let a_i is the activity with the earliest finish time in A (not in S)
 - > Compose another set $A' = A \{a_j\} \cup \{a_m\}$
 - A' still have all activities disjoint (as a_m has the global earliest finish time and A activities are already disjoint), and |A'|=|A|
 - > Then A' is an optimal solution
 - > Then a_m is always included in an optimal solution



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- > In the example:
 - > A ={a2, a4, a8, a11}, am= a1, aj= a2
 - A'={a1, a4, a8, a11}
 - > As a1 finishes before a2, then a1 is compatible with a4, a8, a11²⁵



- > Solution:
 - Include earliest finish activity a_m in solution A
 - > Remove all a_m's incompatible activities
 - > Repeat for the remaining earliest finish activity



a3[0,6)



↓ 27



a3[0,6)







a9[8,12)

















a1[1,4)





a1[1,4)





> Pseudo code?

{



Pseudo code? > findMaxSet(Array a, int n) - Sort "a" based on earliest finish time - result \leftarrow {} - for i = 1 to n validAi = true for j = 1 to result.size if (a[i] is incompatible with result[j]) validAi = false if (validAi) result ← result U a[i] - return result



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- Assume A is an optimal solution for S
 - Is A' = A-{a_i} an optimal solution for S' = S-{a_i and its incompatible activities}?
 - If A' is not an optimal solution, then there an optimal solution A'' for S' so that |A''| > |A'|
 - > Then B=A" U $\{a_i\}$ is a solution for S, |B|=|A"|+1, |A|=|A'|+1
 - > Then |B| > |A|, i.e., |A| is not an optimal solution, **contradiction**
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- > Why optimal substructure?
 - To guarantee it is correct to use solutions of subproblems after applying greedy choice



Elements of a Greedy Algorithm

- 1. Optimal Substructure
- 2. Greedy Choice Property



Solving the bigger problem include
 One choice (greedy) vs Multiple possible choices





- > Both have optimal substructure



- > Both have optimal substructure
- > Elements:

Greedy	DM
Optimal substructure	Optimal substructure
Greedy choice property	Overlapping subproblems







- > 0-1 Knapsack: Each item either included or not
- > Greedy choices:
 - > Take the most valuable \rightarrow Does not lead to optimal solution
 - > Take the most valuable per unit \rightarrow Works in this example



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 Greedy choice property: take the most valuable per weight unit



- Greedy choice property: take the most valuable per weight unit
- > Proof of optimality:
 - Given the set S ordered by the value-per-weight, taking as much as possible x_j from the item j with the highest value-per-weight will lead to an optimal solution X
 - > Assume we have another optimal solution X` where we take less amount of item j, say x_j ` < x_j .
 - > Since $x_j < x_j$, there must be another item k which was taken with a higher amount in X, i.e., $x_k > x_k$.
 - We create another solution X`` by doing the following changes in X`
 - Reduce the amount of item k by a value z and increase the amount of item j by a value z
 - The value of the new solution $V^{\ }=V^{\ }+z v_j/w_j-z v_k/w_k$ = $V^{\ }+z (v_j/w_j-v_k/w_k) \rightarrow v_j/w_j-v_k/w_k \ge 0 \rightarrow V^{\ }\ge V^{\ }$



> Optimal substructure



- > Optimal substructure
- Solution X with an optimal solution X with value V, we want to prove that the solution X^ˆ = X − x_j is optimal to the problem S^ˆ = S − {j} and the knapsack capacity W^ˆ = W − x_j
- Proof by contradiction
 - Assume that X` is not optimal to S`
 - There is another solution X`` to S` that has a higher total value V``
 V`
 - > Then $X \subset U\{x_j\}$ is a solution to S with value $V \subset x_j > V + x_j > V$
 - > Contradiction as V is the optimal value

Fknapsack (W, S, v's, w's) {

- Sort S based on vi/wi value
- rw = W
- result = { }
- for each si in S

```
if(wi <= rw)
```

result = result U si

```
rw = rw-wi
```

else

result = result U rw/wi * si





	a	b	С	d	е	f
Frequency (in thousands)	45	13	12	16	9	5
Fixed-length codeword	000	001	010	011	100	101
Variable-length codeword	0	101	100	111	1101	1100



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 - > Prefix codes give optimal data compression



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- Example: Message 'JAVA' a = "0", j = "11", v = "10" Encoded message "110100" Decoding "110100"



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- Example: Message 'JAVA' a = "0", j = "11", v = "10" Encoded message "110100" Decoding "110100"
- > In the table:

Encoding with fixed-length needs 300K bits Encoding with variable-length needs 224K bits





Fixed-length tree

Variable-length tree

f:5

e:9





Fixed-length tree

Variable-length tree

We need an algorithm to build the optimal variable-length tree



 $\operatorname{Huffman}(C)$

- $1 \quad n = |C|$
- $2 \quad Q = C$

- 3 **for** i = 1 **to** n 1
- 4 allocate a new node *z*.
 - z.left = x = EXTRACT-MIN(Q)
- 6 z.right = y = EXTRACT-MIN(Q)

$$z.freq = x.freq + y.freq$$

- 8 INSERT(Q, z)
- 9 return EXTRACT-MIN(Q) // return the root of the tree































 Details of optimal substructure and greedy choice property in the text book

Book Readings and Credits



- > Book Readings:
 - > 16.1 16.3
- > Credits to:
 - > Prof. Ahmed Eldawy notes