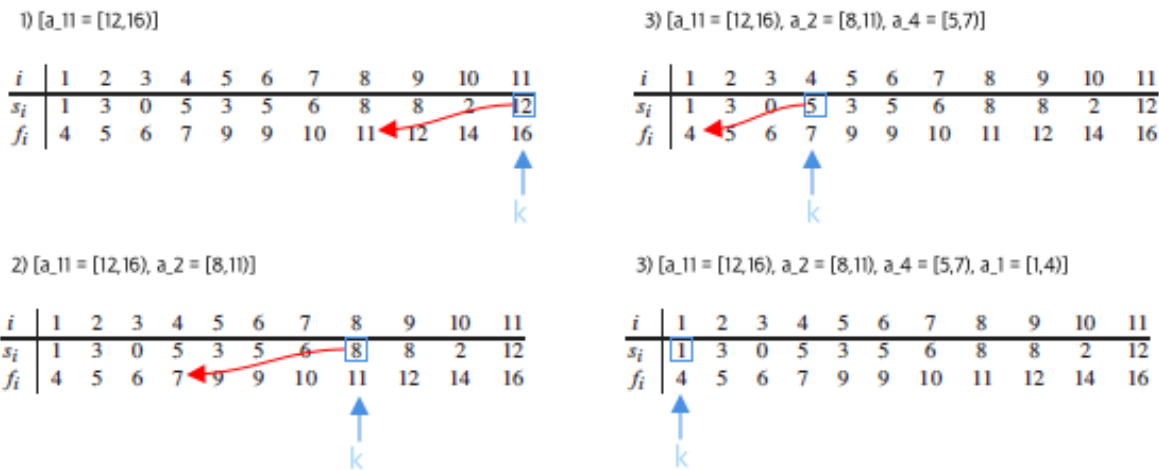


CSC373 Worksheet 2 Solution

July 27, 2020



1.

This approach is a greedy algorithm because algorithm

- 1) Has the greedy choice: selecting the last activity to start that is compatible with all previously selected activities
- 2) Has the greedy choice that is always part of optimal solution:

Claim:

Consider any nonempty subproblem S_k . Let a_m be an activity in S_k with the last activity to start that is compatible with all previously selected activities. Then a_m is included in some maximum-size subset of mutually compatible activities of S_k

Proof. Let A_k be a maximum-size subset of mutually compatible activities in S_k , and let a_j be the activity in A_k with the last activity to start that is compatible with all previously selected activities.

If $a_j = a_m$, we are done, since we have shown that a_m is the maximum-size subset of mutually compatible activities of S_k .

If $a_j \neq a_m$, let the set $A'_k = A_k = \{a_j\} \cup \{a_m\}$ be A_k but substituting a_m for a_j . The activities in A'_k are disjoint, which follow because the activities in A_k are disjoint, a_j is the first activity in A_k to finish, and $s_j \leq s_m$.

Since $|A'_k| = |A_k|$, we conclude that A'_k is a maximum-size subset of mutually compatible activities of S_k , and it includes a_m . \square

Notes:

- Greedy Algorithm
 - Always makes the choice that looks best at the moment
 - * Locally optimal solution leads to globally optimal solution
- Activity-selection Problem (Greedy algorithm using dynamic programming)
 - Goal: Selecting maximum size set of mutually compatible activities

Example:

i	1	2	3	4	5	6	7	8	9	10	11
s_i	1	3	0	5	3	5	6	8	8	2	12
f_i	4	5	6	7	9	9	10	11	12	14	16

- Suppose a set exists $S = \{a_1 = [s_1, f_1), a_2 = [s_2, f_2), \dots, a_n = [s_n, f_n)\}$
 - * a_i represents an i^{th} activity
 - * s_i represents starting time
 - * f_i represents finishing time
 - * $0 \leq s_i < f_i < \infty$
 - * a_1, \dots, a_n sorted in monotonically increasing order of finish time

i.e.

$$f_1 \leq f_2 \leq f_3 \leq \dots \leq f_{n-1} \leq f_n$$

- * a_i and a_j are **compatible**, if intervals $[s_i, f_i)$ and $[s_j, f_j)$ don't overlap

i.e

$$s_i \geq f_j \text{ and } s_j \geq f_i$$

- Steps
 1. Think about dynamic programming solution
 - * Construct optimal solution using two subproblems

S_{ij} : activities that start after activity a_i finishes and before activity a_j starts

i.e.

$$S_{19} = \{a_4 = [5, 7), a_6 = [5, 9), a_7 = [6, 10)\}$$

A_{ij} : maximum set of mutually compatible activities in S_{ij} (including a_k)

- $A_{ik} = A_{ij} \cap S_{ik}$
- $A_{kj} = A_{ij} \cap S_{kj}$
- $A_{ij} = A_{ik} \cup \{a_k\} \cup A_{kj}$
- So, $|A_{ij}| = |A_{ik}| + |A_{kj}| + 1$

- * Verify that optimal solution A_{ij} must include optimal solution to the two subproblems for S_{kj}

Let A'_{kj} be another mutually compatible activities in S_{kj} where $|A'_{kj}| > |A_{kj}|$.

Then we could use A'_{kj} in a solution to subproblem of S_{ij}

Then we have $|A_{ik}| + |A'_{kj}| + 1 > |A_{jk}| + |A_{kj}| + 1 = |A_{ij}|$ mutually compatible activities

This contradicts assumption that A_{ij} is an optimal solution

- * Verify that optimal solution A_{ij} must include optimal solution to the two subproblems for S_{ik}

The same applies for activities in S_{ik}

2. Observe that only one choice - greedy choice, and that when we make the greedy choice, only one subproblem remains

- * Steps

1. Make a greedy choice
 - Choose an activity that makes the most resource possible (intuition)
 - Choose an activity that finishes the earliest (intuition)
2. Solve a subproblem: Find activities that start after a_1 finishes
3. Verify that making greedy choices always arrive at optimal solution

Theorem 16.1 (Page 418):

Consider any non-empty subproblem S_k , and let a_m be an activity in S_k with the earliest finish time. Then a_m is included in some maximum-size

subset of mutually compatible activities of S_k

3. Develop recursive greedy solution



4. Convert the recursive algorithm into iterative one



2. • Greedy Choice

- Choose x_i that is greater than the current maximum as the upper bound of unit length closed interval
- Choose x_i that is smaller than the current minimum as the lower bound of unit length closed interval

Example:

$$\{0, 1, 2, 3, 4, 5\} \rightarrow [0, 5]$$

$$\{0, -1, 3, 5, 2\} \rightarrow [-1, 5]$$

- Optimal Substructure

Let I be the following instance of the problem: Let n be the number of items, and let x_i be the i^{th} point in the set.

Let $A = [x_{\min}, x_{\max}]$ be the solution. The greedy algorithm works by assigning $x_{\min} = \min(x_{\min}, x_n)$ and $x_{\max} = \max(x_{\max}, x_n)$, and then continuing by solving the subproblem

$$I' = (n - 1, \{x_1, \dots, x_{n-1}\}) \quad (1)$$

until $n = 0$.

We need to show that the strategy gives optimal solution.

Correct Solution:

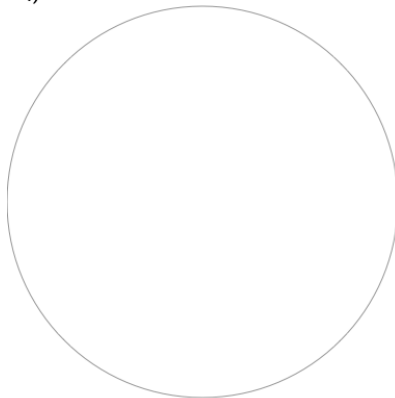
- 1) Consider the left-most interval.
- 2) Set the left most point x in the set as its value (since we know it must contain the leftmost point)
- 3) For any point that is within the unit distance of the point x (i.e. $[x, x + 1]$), remove the points since they are covered
- 4) Move to the next closest point not covered by the unit interval of x , and repeat until all points in the set are covered.
- 5) Since each step has a clearly optimal choice for where to put the leftmost interval, the final solution is optimal

Notes:

- I stopped because it's taking too much time.
- I struggled on this problem.

- I had trouble understanding the meaning of unit interval
 - I felt there is missing knowledge regarding optimal substructure
 - I felt tunnel visioned to provide one interval that covers all
- I had difficulty arguing why the algorithm is correct
 - i.e. How can i generate a claim?
- Unit length
 - $[1, 25, 2.25]$ includes all x_i such that $1.25 \leq x_i \leq 2.25$.
- Greedy-choice property and optimal substructure to problem are the two key ingredients
- Summary of Steps for Greedy Algorithm
 1. Determine the optimal structure of the problem
 2. Develop a recursive solution.
 3. Show that if we make the greedy choice, then only one subproblem remains
 4. Prove that it is always safe to make the greedy choice
 5. Develop a recursive algorithm that implements the greedy strategy
 6. Convert the recursive algorithm to an iterative algorithm
- Criteria for Greedy Algorithm
 1. Greedy-choice property
 - Exists if we can assemble a globally optimal solution by making a locally optimal (greedy) choices
 2. Optimal Substructure
 - Exists if an optimal solution to the problem contains within it optimal solutions to subproblems.
- Greedy vs Dynamic Programming
 - 0-1 Knapsack Problem

1)



Capacity: 50 lbs
Current: 50lbs

0-1 Knapsack Problem

item 1
weight: 10 lbs
worth: \$60
value: \$6/lbs

item 2
weight: 20 lbs
worth: \$100
value: \$5/lbs

item 3
weight: 30 lbs
worth: \$120
value: \$4/lbs

2)



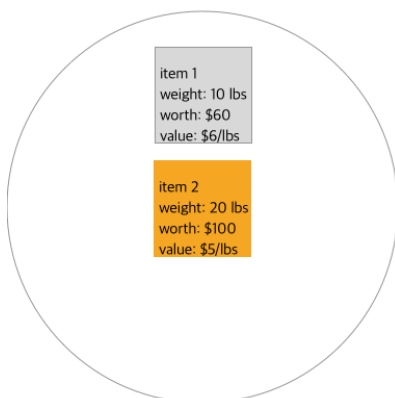
Capacity: 50 lbs
current: 40 lbs

item 1
weight: 10 lbs
worth: \$60
value: \$6/lbs

item 2
weight: 20 lbs
worth: \$100
value: \$5/lbs

item 3
weight: 30 lbs
worth: \$120
value: \$4/lbs

3)



Capacity: 50 lbs
current: 20 lbs

item 1
weight: 10 lbs
worth: \$60
value: \$6/lbs

item 2
weight: 20 lbs
worth: \$100
value: \$5/lbs

item 3
weight: 30 lbs
worth: \$120
value: \$4/lbs

Uh oh. This is not greedy!

– Fractional Knapsack Problem

1)



Capacity: 50 lbs
Current: 50lbs

Fractional Knapsack Problem

item 1
weight: 10 lbs
worth: \$60
value: \$6/lbs

item 2
weight: 20 lbs
worth: \$100
value: \$5/lbs

item 3
weight: 30 lbs
worth: \$120
value: \$4/lbs

2)



Capacity: 50 lbs
current: 40 lbs

item 1
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worth: \$60
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item 2
weight: 20 lbs
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item 3
weight: 30 lbs
worth: \$120
value: \$4/lbs

3)



Capacity: 50 lbs
current: 20 lbs

item 1
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worth: \$60
value: \$6/lbs

item 2
weight: 20 lbs
worth: \$100
value: \$5/lbs

item 3
weight: 30 lbs
worth: \$120
value: \$4/lbs

item 2
weight: 20 lbs
worth: \$100
value: \$5/lbs

4)



3. *Proof.* Let T be a binary tree corresponding to an optimal prefix code and suppose that T is not full. Let node n have a single child x . Let T' be the tree obtained by removing n and replacing it by x . Let m be leaf node which is descendent of x . Then we have:

My work:

$$B(T') \leq \sum_{c \in C \setminus \{m\}} c.freq \cdot d_T(c) + m.freq \cdot d_{T'}(m) \quad (1)$$

$$= \sum_{c \in C \setminus \{m\}} c.freq \cdot d_T(c) + m.freq \cdot (d_T(m) - 1) \quad (2)$$

$$< \sum_{c \in C \setminus \{m\}} c.freq \cdot d_T(c) + m.freq \cdot d_T(m) \quad (3)$$

$$= \sum_{c \in C} c.freq \cdot d_T(c) \quad (4)$$

$$= B(T) \quad (5)$$

which contradicts the fact that T was optimal. Therefore every binary tree corresponding to an optimal prefix code is full

□

Notes:

- Optimal Substructure

- A problem is said to have optimal substructure if an optimal solution can be constructed from optimal solutions of its subproblems.

- Huffman Codes

- Is an algorithm that uses greedy algorithm for lossless (without loss of data) data compression
- Has two types of codewords

	a	b	c	d	e	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

- * Fixed Length Code
 - has codeword with the same length
- * Variable Length
 - has codeword that may be of different lengths
- Constructs optimal prefix codes
 - * Means no codeword is a prefix of some other codewords

e.g.

The following is not prefix codes

a - 110

b - 1101

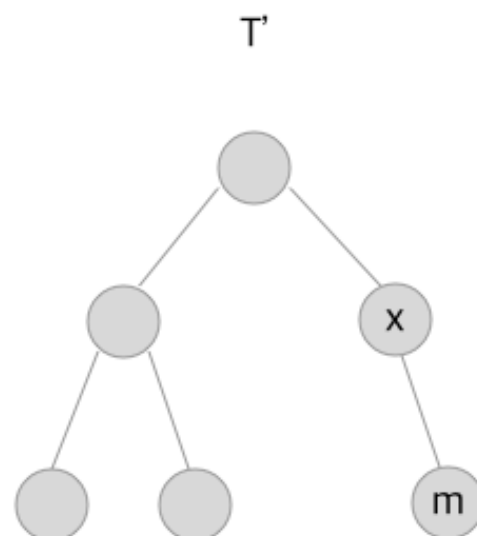
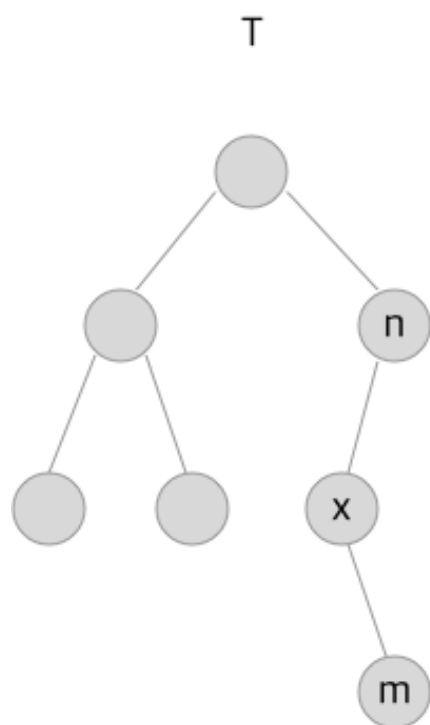
e.g.

The following is prefix codes

a - 110

b - 111

- Realized that I should learn with the solution. Otherwise, it will take too much time.
- Learned that the author used another but very similar tree T' to show the cost of bits in T is not minimum, which is the condition of prefix codes.
- Learned that the solution feels very similar to the proof of optimal substructure on page 416.
- Learned that the tree T and T' looks as follows:



4. Notes

- Constructing Huffman Code
 1. Take the 2 chars with the lowest frequency
 2. Make a 2 leaf node tree from them