

Question 1

You and two of your friends live all in different cities. Each of you has a car and can start driving right now (after determining the meeting location). You drive on a road network, i.e., you have cities as vertices and two cities are connected via a directed edge if there is a road between them; the weight of the directed edge (u, v) is the time it takes you to get from u to v . You want to meet as soon as possible. How would you select a meeting location from one of your k favourite hang-out spots (also graph vertices) known to all of you? Which algorithm would you use and how is this done most efficiently? The more efficient the solution, the better the mark.

Solution:

Step 1: We create a MST for each of the three starting locations and store the cost for each person at each city. The most efficient way to do this is with Prim's Algorithm which runs in $O(|E| + V \log V) = O(V^2 + V \log V) = O(V^2)$ time.

Note: there is a linear time deterministic algorithm by Bernard Chazelle but it only works on undirected graphs (and therefore an incorrect answer). Karger, Klein & Tarjan have a randomized method which is linear expected time but the same worst case time as Prim's (and is not covered in this course). Dijkstra's is also an acceptable answer as it has the same run time.

Step 2: Since we want to meet as soon as possible, we want to choose the city where the last person to arrive arrives soonest:

Algorithm 1 Pick Meeting Location

Input: k meeting points

Output: Optimal meet location: $location$

```

1:  $cost \leftarrow \infty$ 
2:  $location \leftarrow \text{NULL}$ 
3: for  $v$  in  $k$  meeting points do
4:   if  $\max\{v.costs\} < cost$  then
5:      $cost \leftarrow \max\{v.costs\}$ 
6:      $location \leftarrow v$ 
7: return  $location$ 
```

The proofs are trivial (and omitted): Prim's has been proven in class, and the second part we iterate over all k points comparing it's max to the current min and updating accordingly.

Question 2

Give a bijection between well-formed (or valid) bracket sequences and full binary trees (see definition in class) so that you can count the number of such trees. Prove that it is a bijection.

To prove a bijection we need to show two things: That there are the same number of well formed bracket sequences $(2n)$ and full binary trees $(2n+1)$, and that there is one and only one sequence for a given tree.

From class we know that the number of well formed bracket sequences is C_n .

For full trees we will prove by induction that there is also C_n :

Base Case: $n = 0$: $C_0 = 1$ and there is only one possible tree with 1 node.

Inductive Hypothesis: A tree of size n leaf nodes has C_n possible constructions

Inductive Step: A tree with $n + 1$ leaf nodes has two sub trees, k nodes to the left, and $n - k$ nodes to the right. By IH, there are C_k possible configurations on the left and C_{n-k} possible configurations on the right. The total is then:

$$C_{n+1} = \sum_{k=1}^n C_k C_{n-k} = C_n$$

Therefore, for a full binary tree of size $2n + 1$ there are C_n possible constructions.

Mapping binary trees to bracket sequences:

This can be done with an Euler-Tour: On the first visit of a node, if it is a left child add "(" to the sequence, and if it is a right child add ")". The one-to-one relationship should be obvious: In order for a full binary tree to produce a different bracket sequence, the vertices must be visited in a different order. It also maintains the well ordered bracket sequence property as a left child is always visited before a right (by definition of an Euler tour).

Question 3

There are many algorithms for finding the longest common subsequence between two strings.

- Formally define the problem.
- Illustrate the problem via an example.
- Describe a brute force algorithm, prove its correctness and analyze its time complexity and space complexity.
- Describe a dynamic programming algorithm for the problem.
- Illustrate on an example of reasonable size how the algorithm works.
- Prove that it works correctly.

- Analyze its time and space complexity.

Formally define the problem: A subsequence is a string of characters contained within a larger string in the same order, but not necessarily contiguous. The problem is to find the largest string of characters that can be found in the two larger strings, such that the same characters of the subsequence appear in the same order in both strings.

Illustrate the problem via an example: Given the following input strings:

$S_1 = \text{'this is a string'}$

$S_2 = \text{'the second string'}$

The longest common subsequence is: 'th s string'.

Brute Force Algorithm:

Algorithm 2 Brute_Force(S_1, S_2)

Input: string: S_1, S_2

Output: string: *longest*

```
1: subsequences_1  $\leftarrow$  Get_All_Subsequences( $S_1$ )
2: subsequences_2  $\leftarrow$  Get_All_Subsequences( $S_2$ )
3: longest_length  $\leftarrow$  0
4: longest  $\leftarrow$  NULL
5: for sequence_1 in subsequences_1 do
6:   for sequence_2 in subsequences_2 do
7:     if sequence_1 = sequence_2 then
8:       if sequence_1.length > longest_length then
9:         longest_length  $\leftarrow$  sequence_1.length
10:        longest  $\leftarrow$  sequence_1
11: return longest
```

Analysis:

If S_1 is of length n and S_2 is of length m :

Time Complexity:

Lines 1 & 2) Creating the subsequences takes $O(2^n + 2^m)$ time

Lines 3 & 4) Constant time

Lines 5 - 7) Looping takes $O(2^n) * O(2^m)$ time. Each comparison takes $O(n * m)$ worse case.

Total time is $O(2^n * 2^m * n * m)$

Lines 9 - 11) Constant

Total time complexity: $O(n * m * 2^n * 2^m)$

Space:

There are 2^n subsequences of S_1 each taking $O(n)$ space.

There are 2^m subsequences of S_2 each taking $O(m)$ space.

Total Space: $O(n * 2^n + m * 2^m)$

Correctness:

Outer Loop:

Invariant: At the beginning of the i^{th} loop the longest of the first $i - 1$ subsequences is stored.

Initialization: Before entering the loop, no string is stored

Maintenance: During the i^{th} iteration, the i^{th} subsequence will be compared with all subsequences from the second string. If a longer matching string is found, the longest subsequence will be updated.

Termination: Upon completing the $(2^n)^{th}$ iteration, the longest subsequence will have been found.

Inner Loop:

Invariant: At the beginning of the j^{th} loop the longest matching of: 1) the first $j - 1$ subsequences of S_2 matching the i^{th} subsequence of S_1 , or 2) the $(i - 1)$ subsequence of S_1 matching any subsequence in S_2 , will have been stored.

Initialization: Before entering the loop, no comparisons have been made to the i^{th} subsequence of S_1

Maintenance: During the j^{th} iteration, the j^{th} subsequence from S_2 will be compared with the i^{th} subsequence from S_1 . If they match and are longer than the current longest, the longest subsequence will be updated.

Termination: Upon completing the $(2^m)^{th}$ iteration, all subsequences in S_2 will have been compared to the i^{th} subsequence of S_1 .

Note: This is one of several Brute Force algorithms. All should have roughly the same time/space complexity (remember recursive calls take space on the stack) **Describe a dynamic programming algorithm for the problem**

On Page 394 of the textbook, you can find the solution to this problem. It requires two 2d arrays, 1 for computing the length, and 1 for recreating the longest subsequence. They have been reproduced below:

```

LCS-LENGTH( $X, Y$ )
1   $m = X.length$ 
2   $n = Y.length$ 
3  let  $b[1..m, 1..n]$  and  $c[0..m, 0..n]$  be new tables
4  for  $i = 1$  to  $m$ 
5       $c[i, 0] = 0$ 
6  for  $j = 0$  to  $n$ 
7       $c[0, j] = 0$ 
8  for  $i = 1$  to  $m$ 
9      for  $j = 1$  to  $n$ 
10         if  $x_i == y_j$ 
11              $c[i, j] = c[i - 1, j - 1] + 1$ 
12              $b[i, j] = "\nwarrow"$ 
13         elseif  $c[i - 1, j] \geq c[i, j - 1]$ 
14              $c[i, j] = c[i - 1, j]$ 
15              $b[i, j] = "\uparrow"$ 
16         else  $c[i, j] = c[i, j - 1]$ 
17              $b[i, j] = "\leftarrow"$ 
18  return  $c$  and  $b$ 

```

Figure 1: LCS-Length creates two tables from which the LCS can be derived by running PRINT-LCS on the outputs

```

PRINT-LCS( $b, X, i, j$ )
1  if  $i == 0$  or  $j == 0$ 
2      return
3  if  $b[i, j] == "\nwarrow"$ 
4      PRINT-LCS( $b, X, i - 1, j - 1$ )
5      print  $x_i$ 
6  elseif  $b[i, j] == "\uparrow"$ 
7      PRINT-LCS( $b, X, i - 1, j$ )
8  else PRINT-LCS( $b, X, i, j - 1$ )

```

Figure 2: Will produce the LCS based on the output of LCS-Length

Illustrate on an example of reasonable size how the algorithm works:
Again from the textbook $S_1 = ABCBDAB$ & $S_2 = BDCABA$:

		j	0	1	2	3	4	5	6
			y_j B D C A B A						
i	x_i								
0			0	0	0	0	0	0	0
1	A		0	↑	↑	↑	↖1	←1	↖1
2	B		0	↖1	←1	←1	↑	↖2	←2
3	C		0	↑	↑	↖2	←2	↑	↑
4	B		0	↖1	↑	↑	↑	↖3	←3
5	D		0	↑	↖2	↑	↑	↑	↑
6	A		0	↑	↑	↑	↖3	↑	↖4
7	B		0	↖1	↑	↑	↑	↖4	↑

Figure 3: Example of the table based solution

Prove that it works correctly

By loop invariant:

Invariant: At the beginning of the $(i, j)^{th}$ loop $C[i-1, j-1]$ contains the length of the current longest subsequence and $B[i-1, j-1]$ points to the previous largest

Initialization: Before the loop C is empty with every value initialized to 0 and B is empty

Maintenance: If $S_1[i] = S_2[j]$, $C[i, j] = C[i-1, j-1] + 1$ and $B[i, j]$ points to $B[i-1, j-1]$. Otherwise $C[i, j] = \max\{C[i, j-1], C[i-1, j]\}$ and $B[i, j]$ points to the same max (and this the same character in one of the two strings), and the loop invariant is maintained.

Termination: At the end of the $(i, j)^{th}$ iteration $C[i, j]$ contains the length of the longest subsequence and $B[i, j]$ points to either the next character, or the same.

Time Complexity:

Since there are two nested loops of length n and m and constant work being done within the nesting, the overall time complexity is $O(n * m)$

$$m[3, 5] = \min \begin{cases} m[3, 3] + m[4, 5] + 2 * 12 * 50 = 4200 \\ m[3, 4] + m[5, 5] + 2 * 5 * 50 = 620 \end{cases}$$

$$m[2, 3] = m[2, 2] + m[3, 3] + 10 * 2 * 12 = 240$$

The optimal parameterization is then:

$$(A_1 \cdot A_2) \cdot (((A_3 \cdot A_4) \cdot A_5) \cdot A_6)$$

Question 5

Consider the enclosed graph $G = (V, E)$ on n vertices. Apply DFS to it (starting at node 1) and describe the intervals $[pre, post]$ for all nodes. List all back-edges and cross-edges.

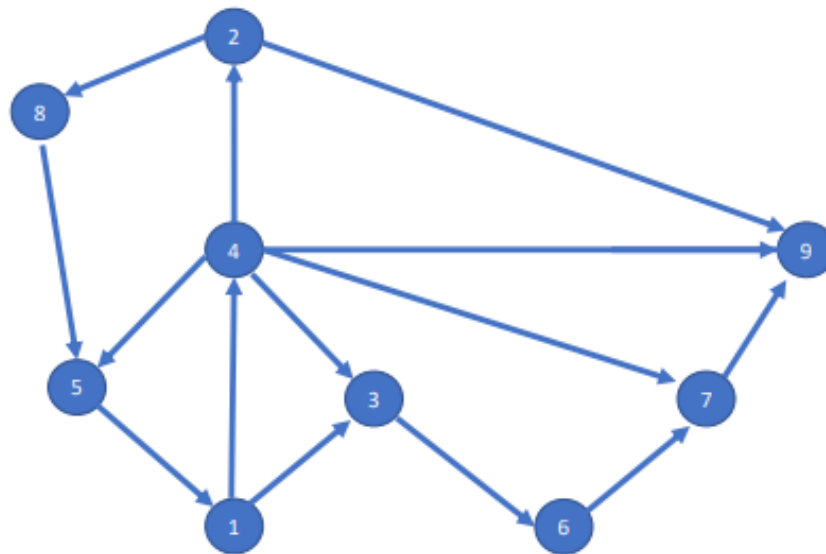


Figure 5: The input graph for Question 5

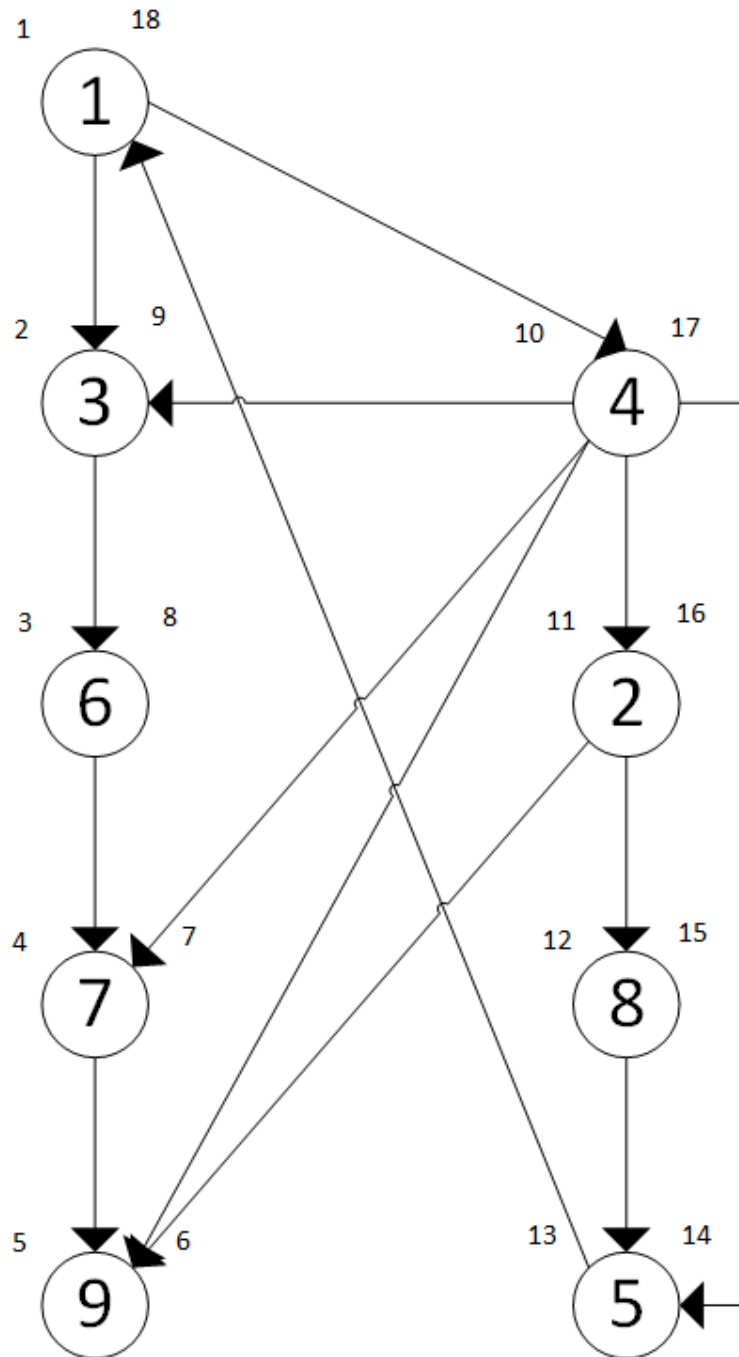


Figure 6: Result of DFS on the input graph

Edge Types:

Edge	Type
13	Tree
14	Tree
28	Tree
29	Cross
36	Tree
43	Cross
47	Cross
45	Forward
49	Cross
51	Back
67	Tree
79	Tree
85	Tree

Suppose you have a graph in which, after a DFS traversal, every pair of intervals $[pre, post]$ have a non-empty intersection. What can you conclude about the graph (if anything)?

If for every pair of intervals $[pre, post]$ have a non-empty intersection, we can conclude that there are no cross edges. (see slide 33 in graphProblems in the Class slides).

Question 6

Consider the following linear program:

$$\begin{array}{ll}
 \text{minimize:} & 2x_1 + 3x_2 \\
 \text{subject to:} & x_1 + 1.5x_2 \leq 10 \\
 & x_1 - x_2 \leq 3 \\
 & x_2 \leq 3 \\
 & x_1, x_2 \geq 0
 \end{array}$$

- Show the feasible region by plotting the constraints on the (x_1, x_2) -Cartesian coordinate system.
- Using your feasible region, find the optimal solution for this linear program. Is this the only solution? If yes, then explain why. If no, then state how many optimal solutions are there and justify your answer.

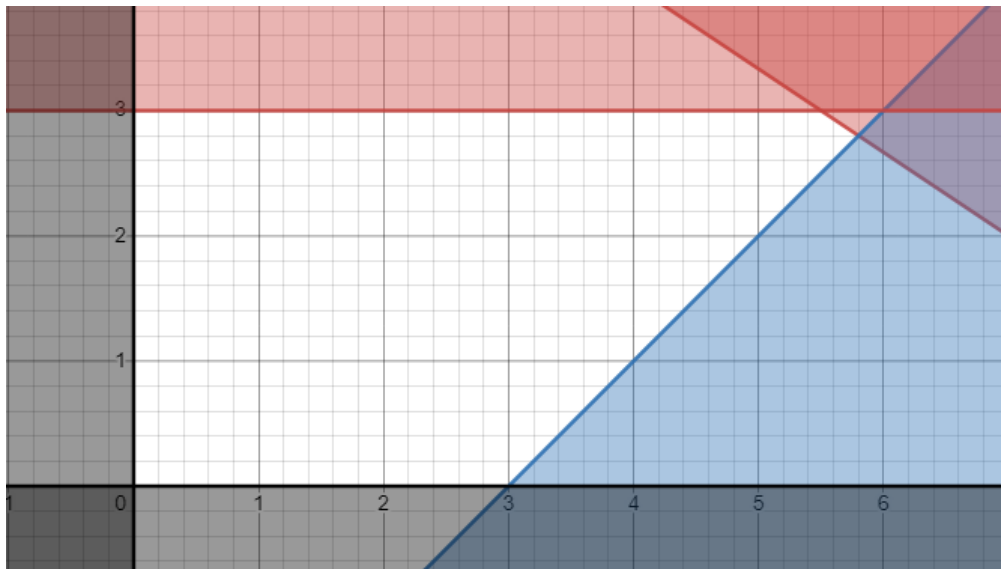


Figure 7: Feasibility region shown in white

As the LP asked us to minimize, there is only one possible solution at $x_1 = x_2 = 0$.