

Problem 1.

- a. The filled table is provided below.

i\D	0	1	2	3	4	5	6	7	8	9	10
0	0	0	0	0	0	0	0	0	0	0	0
1	0	0	4	4	4	4	4	4	4	4	4
2	0	0	4	4	7	7	7	7	7	7	7
3	0	0	4	6	7	10	10	13	13	13	13
4	0	0	4	6	7	10	10	13	13	15	15
5	0	0	4	6	7	10	10	13	13	15	17

Applying the `PrintOptKnapsack` procedure described in the lecture notes, we find items 1, 3, and 5 are in the optimal solution. Their weights are 2, 3, and 5 and their values are 4, 6, and 7. Hence the total weight is 10 and the total value is 17.

- b. We find that ACD is the LCS. The filled table is provided below. The numbers that are bolded represent the cells that the
- `PrintLCS`
- procedure goes through. The numbers that are red represent cells where we print
- X_i
- .

	j	0	1	2	3	4	5
i		Y_j	A	C	D	E	F
0	X_i	0	0	0	0	0	0
1	A	0	1	1	1	1	1
2	B	0	1	1	1	1	1
3	A	0	1	1	1	1	1
4	E	0	1	1	1	2	2
5	C	0	1	2	2	2	2
6	C	0	1	2	2	2	2
7	D	0	1	2	3	3	3

- c. We have
- $(d_0, d_1, d_2, d_3, d_4, d_5) = (1, 5, 2, 6, 1, 4)$
- . The minimum number of multiplications is 28. This is achieved via
- $((A \times B) \times (C \times D)) \times E$
- . The filled
- M
- matrix and
- S
- matrix are shown below.

M -matrix							
	j	i					
		1	2	3	4	5	
	5	28	42	20	42	0	
	4	24	22	12	0		
	3	22	60	0			
	2	10	0				
	1	0					

S -matrix							
	j	i					
		1	2	3	4	5	
	5	4	4	4	4	\perp	
	4	2	2	3	\perp		
	3	2	2	\perp			
	2	1	\perp				
	1	\perp					

Problem 2.

- We consider the algorithm presented in problem 2 of problem set #5. After running the algorithm, we have $A = \{0, 7, 8, 13, 17, 24\}$ and $S = \{N/A, 1, 1, 3, 3, 5\}$.

– We show how we fill the cell at $A[5]$. At this point, we will have $A = \{0, 7, 8, 13\}$ and $S = \{N/A, 1, 1, 3\}$. Let $i = 5$. We first set $A[i] = \infty$. We then iterate from $j = 1$ to $i - 1 = 4$. We attempt to find the lowest value out of $A[j] + C[j][5]$. We have

$$* j = 1 \longrightarrow A[1] + C[1][5] = 0 + 21 = 21,$$

$$* j = 2 \longrightarrow A[2] + C[2][5] = 7 + 13 = 20,$$

$$* j = 3 \longrightarrow A[3] + C[3][5] = 8 + 9 = 17,$$

$$* j = 4 \longrightarrow A[4] + C[4][5] = 13 + 8 = 21.$$

We see we get the lowest value when $j = 3$. As a result, we set $A[i] = 17$ and $S[i] = 3$ and have $A = \{0, 7, 8, 13, 17\}$ and $S = \{N/A, 1, 1, 3, 3\}$ after this step.

– We now show how we fill the cell at $A[6]$. Let $i = 6$. We first set $A[i] = \infty$. We then iterate from $j = 1$ to $i - 1 = 5$. We attempt to find the lowest value out of $A[j] + C[j][6]$. We have

$$* j = 1 \longrightarrow A[1] + C[1][6] = 0 + \infty = \infty,$$

$$* j = 2 \longrightarrow A[2] + C[2][6] = 7 + \infty = \infty,$$

$$* j = 3 \longrightarrow A[3] + C[3][6] = 8 + 17 = 25,$$

$$* j = 4 \longrightarrow A[4] + C[4][6] = 13 + 15 = 28,$$

$$* j = 5 \longrightarrow A[5] + C[5][6] = 17 + 7 = 24.$$

We see we get the lowest value when $j = 5$. As a result, we set $A[i] = 24$ and $S[i] = 5$ and have $A = \{0, 7, 8, 13, 17, 24\}$ and $S = \{N/A, 1, 1, 3, 3, 5\}$ after this step.

- $S = \{N/A, 1, 1, 3, 3, 5\}$, so renting from 1 to 3, 3 to 5, and 5 to 6 yields the minimum cost.

Problem 3.

- a. The general idea of our algorithm is to apply the **LCS** algorithm discussed in class. However, instead of using two different strings, we will simply call the **LCS** algorithm with some string X and the reverse of X . Let us define $Y = \langle x_n \dots x_1 \rangle = \langle y_1 \dots y_m \rangle$ as the reverse of X . We get the recursion

$$\text{LSP}(\langle x_1 \dots x_n \rangle, \langle y_1 \dots y_m \rangle) = \max \left\{ \begin{array}{l} \text{LSP}(\langle x_1 \dots x_{n-1} \rangle, \langle y_1 \dots y_m \rangle), \\ \text{LSP}(\langle x_1 \dots x_n \rangle, \langle y_1 \dots y_{m-1} \rangle), \\ (\text{if } x_n = y_m) \ 1 + \text{LSP}(\langle x_1 \dots x_{n-1} \rangle, \langle y_1 \dots y_{m-1} \rangle). \end{array} \right\}$$

All recursive calls live in a small domain: the first i characters of X and the first j characters of Y .

- b. We define $D[i][j]$ to hold the result of the (i, j) -recursion call. For each $0 \leq i \leq n$ and $0 \leq j \leq n$ (where n is the length of the input string X), $D[i][j]$ is the length of the longest common subsequence of $\langle x_1 \dots x_n \rangle$ and $\langle x_n \dots x_1 \rangle$. We have

$$D[i][j] = \max \left\{ \begin{array}{l} D[i-1][j], \\ D[i][j-1], \\ (\text{if } x_i = y_j) \ 1 + D[i-1][j-1]. \end{array} \right\}$$

The dimension of the table will be $n \times n$. The cell at $D[n][n]$ will store the value of an optimal solution.

- c. The pseudocode for **LongestSubPalindrome** is provided below. It prints and returns the length of the longest sub-palindrome. Note that it uses the **LCS** algorithm discussed in the lecture slides as a helper function. The code is written in Lua. Note that the **local** keyword is used to create a new variable. **{}** is used to create a new array. Other Lua-specific functions are explained in comments throughout the code.

```

1  function LCS(X, Y)
2      local n = X:len() -- Get the length of X
3      local m = Y:len() -- Get the length of Y
4
5      local D = {}
6
7      for i = 0, n do
8          D[i] = {}
9
10         for j = 0, m do
11             D[i][j] = 0
12         end

```

```

13     end
14
15     for i = 1, n do
16         for j = 1, m do
17             D[i][j] = D[i - 1][j]
18
19             if D[i][j - 1] > D[i][j] then
20                 D[i][j] = D[i][j - 1]
21             end
22
23             -- sub(i, i) gets the ith character of X
24             -- sub(j, j) gets the jth character of Y
25             if X:sub(i, i) == Y:sub(j, j) and D[i - 1][j - 1] + 1 > D[i][j] then
26                 D[i][j] = D[i - 1][j - 1] + 1
27             end
28         end
29     end
30
31     return D
32 end
33
34 function LongestSubPalindrome(X)
35     local n = X:len() -- Get the length of X
36     local m = n
37     local D = LCS(X, X:reverse()) -- reverse() reverses X
38     print(D[n][m])
39     return D
40 end

```

As discussed in the lecture notes, `LCS` runs in $O(n+m+nm)$ time where n is the length of the first string and m is the length of the second string. Our algorithm `LongestSubPalindrome` calls `LCS` with some string X and the reverse of X . If X has length n , then the reverse of X also has length n . This means we are calling `LCS` with two strings of length n meaning we can conclude the running time is in $O(2n + n^2) \in O(n^2)$.

d. The pseudocode for `PrintLongestSubPalindrome` is provided below.

```

1 function PrintLongestSubPalindrome(D, i, j, X)
2     if i > 0 and j > 0 then
3         if D[i][j] == D[i - 1][j - 1] + 1 then
4             PrintLongestSubPalindrome(D, i - 1, j - 1, X)
5             print(X:sub(i, i))
6         elseif D[i][j] == D[i - 1][j] then
7             PrintLongestSubPalindrome(D, i - 1, j, X)
8         else
9             PrintLongestSubPalindrome(D, i, j - 1, X)
10        end

```

```

11     end
12 end

```

Notice that the algorithm is almost exactly the same as the algorithm derived for `PrintLCS` in the lecture notes. The algorithm travels at most n cells up and n cells left in D . As a result, we can conclude the running time is in $O(n)$.

- e. (i) The filled table is shown below.

	j	0	1	2	3	4	5	6
i		Y_j	e	d	q	q	e	q
0	X_i	0	0	0	0	0	0	0
1	p	0	0	0	0	0	0	1
2	e	0	1	1	1	1	1	1
3	q	0	1	1	2	2	2	2
4	q	0	1	1	2	3	3	3
5	d	0	1	2	2	3	3	3
6	e	0	1	2	2	3	4	4

- (ii) The sub-palindrome generated is `eqqe`. We first used the `LongestSubPalindrome` algorithm to generate D , then used the `PrintLongestSubPalindrome` algorithm with D , $i = 6$, $j = 6$, and $X = \text{"peqqde"}$ to output the letters of the palindrome.