

HOME WORK - IProblem 1 : 15.1.3

Consider a modification of the rod cutting problem in which, in addition to a price p_i , for each rod, each cut incurs a fixed cost of c . The revenue associated with the solution is now the sum of the prices of the pieces minus the costs of making the cuts. Give a dynamic programming algorithm to solve this modified problem.

MEMOIZED - CUT - ROD - AUX(p, n, r)

1. if $r[n] \geq 0$
2. return $r[n]$
3. if $n == 0$
4. $q = 0$
5. else $q = -\infty$
6. for $i = 1$ to n
7. $q = \max(q, p[i] + \text{MEMOIZED - CUT - ROD - AUX}(p, n - i, r))$
8. $r[n] = q$
9. return q

BOTTOM-UP-CUT-ROD (p, n)

1. let $r[0..n]$ be a new array
2. $r[0] = 0$
3. for $j = 1$ to n
4. $q = -\infty$
5. for $i = 1$ to j
6. $q = \max(q, p[i] + r[j-i])$
7. $r[j] = q$
8. return $r[n]$

Now, when we consider the cost cutting c
we have to replace line 7 in MEMOIZED-CUT-ROD
-Aux(p, n, r) with

$$q = \max(q, p[i] + \text{Memoized-cut-rod-Aux}(p, n-i, r, c) - c)$$

And, line 6 in BOTTOM-UP-CUT-ROD with

$$q = \max(q, p[i] + r[j-i] - c)$$

\Rightarrow We can observe that there's no cutting cost
for $i=1$ & $i=n$. When there's no cut, no cutting
cost is incurred.

Problem 3 15.3-3

Consider the variant of the matrix chain multiplication problem in which goal is to parenthesize the sequence of matrices so as to maximize, rather than minimize, the number of scalar multiplications. Does this problem exhibit optimal substructure?

Yes, this problem exhibits optimal substructure. The concept of optimal substructure is to find a parenthesization which is most optimal and it is not possible to find a less costly way to parenthesize.

Consider that best case parenthesization is just two set of matrix chains. To maximize scalar multiplications, we must find the optimal substructure, in this case, the highest cost, once we reach that there's no costlier way.

Problem 4 15-2

Give a recursive formula, pseudocode for computing the length of the longest palindrome, correctness justification, and the running time of your algorithm. Also give the pseudo code on how to construct the longest Palindrome.

Let us consider 'x' as a string which a set of characters. And let us consider $x[i, \dots, j]$ as a substring of string 'x'. We can find a palindrome of minimum length 2 when $x[i] = x[j]$. If it's not same then we begin to check further comparing $x[i+1, \dots, j]$ and $x[i, \dots, j-1]$

Let us consider maximum length of palindrome as $L(i, j)$

$$\text{So, } L(i, j) = \begin{cases} L(i+1, j-1) + 2 & x[i] = x[j] \\ \max\{L(i+1, j), L(i, j-1)\} & \text{otherwise} \end{cases}$$

Pseudocode:

LONGEST - PALINDROME ($x[1, \dots, n]$)

// Input: String : $L[i, j]$ is a 2-D array

// output: length of longest palindrome

1. for $i = 1$ to n

2. $L[i, i] = 1$

→ for each character.

3. for $i = 1$ to n

4. for $s = 1$ to $n-i$

5. $j = s+i$

6. $L[s, j] = \text{PALINDROME-COST}(\text{~~cost~~})(L, x, s, j)$

7. $L[j, s] = \text{PALINDROME-COST}(\text{~~cost~~})(L, x, j, s)$

8. return $L[1, n]$

NOTE:

$L[i, j]$ stores longest palindrome in $x[i, \dots, j]$.

Recursion :

PALINDROME - COST (L, x, i, j)

// input: Array L from the LONGEST-PALINDROME

// output: cost of L[i, j]

1. if $i = j$
2. return L[i, j]
3. else if $x[i] = x[j]$
4. if $i+1 < j-1$
5. return L[i+1, j-1] + 2
6. else
7. return 2 → when single character
8. else
9. return max (L[i+1, j], L[i, j-1])

Complexity :

→ first for loop → $O(n)$ time

→ second for loop → $O(n-i) \rightarrow O(n)$ time

∴ total running time of algorithm: ~~$O(n^2)$~~
is $O(n^2)$

Correctness justification:

Initialization: We consider a string that has one or more characters in it.

Maintainance: It holds true for first iteration and returns the length of ~~a~~ palindrome if when there is only one character. If it is more than one character, the longest subpalindrome is calculated. Line 4-7 calculates the length of longest palindrome subsequence.

Termination: When the loop terminates, after it's ~~run~~ compiled for all the characters in the string. We get the length of the longest sub sequence palindrome and we can tell that the algorithm is correct.

Problem 2 : Consider a variation of the longest subsequence (LCS) problem, which we call a string similarity score (SSS). For two strings S_1 & S_2 , each matching character in a subsequence alignment gives a score of 3, while each character in S_1 or S_2 that is not matched, gives a penalty score of -1. For example, ACCTC and CATGCTC have an SSS of $4 \times 3 - 4 = 8$, since an LCS has length 4 & there are one and three unmatched characters in S_1 & S_2 respectively.

Modify the original LCS dynamic programming algorithm to compute the SSS of two strings 4 ~~algorithmically~~ directly. That is, your algorithm must not compute the LCS first and then calculate the SSS from the LCS.

Solution:

STRING-SIMILARITY-SCORE(x, y)

1. $m = x.length$
2. $n = y.length$
3. let $score[0...m, 0...n]$ be new tables
4. for $i = 1$ to m
5. $score[i, 0] = -i$
6. for $j = 1$ to n
7. $score[0, j] = -j$
8. for $i = 1$ to m
9. for $j = 1$ to n
10. if $x_i == y_j$
11. $score[i, j] = score[i-1, j-1] + 3$
12. else if $score[i-1, j] > score[i, j-1]$
13. $score[i, j] = score[i-1, j] - 1$
14. else $score[i, j] = score[i, j-1] - 1$
15. return $score[m, n]$

$$score(i, j) = \begin{cases} -j & \text{if } i=0 \\ -i & \text{if } j=0 \\ score[i-1, j-1] + 3 & \text{if } i, j > 0 \text{ \& } x_i = y_j \end{cases}$$