# CX2101 Algorithm Design and Analysis

Tutorial 4
Dynamic Programming
(Weeks 10-11)

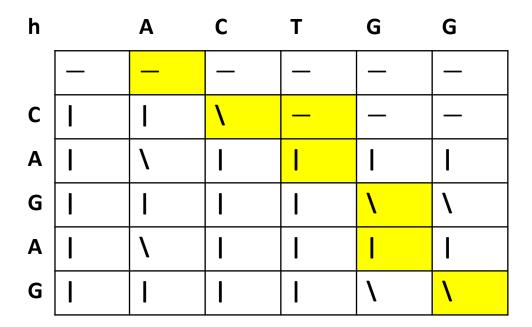
Find the length of the longest common subsequence and a longest common subsequence of CAGAG and ACTGG by the dynamic programming algorithm in the lecture notes.

	1	2	3	4	5
X	С	Α	G	Α	G
У	Α	C	H	G	G

C		Α	C	T	G	G	
	0	0	0	0	0	0	for i = 1 to n
C	0	0	1	1	1	1	for j = 1 to m
A	0	1	1	1	1	1	if x[i] == y[j] {
G	0	1	1	1	2	2	c[i][j] = c[i-1][j-1] + 1;
A	0	1	1	1	2	2	h[i][j] = '\';
G	0	1	1	1	2	3	c[i][j] = c[i-1][j];
h		Α	•	_	G	G	h[i][j] = ' '; }
		A	C	T	G	•	olcol
	_	  -	<u> </u>	<u> </u>	<u> </u>	<del>-</del>	else {
С	_  -	  - 	  -  \	  -  -	_ _ _	  -  -	c[i][j] = c[i][j-1];
C A	-    	  -       		  -  - 	  -  - 	  -  - 	•
_	-       	-       		  -  -   	  -       	  -       	c[i][j] = c[i][j-1];
A	-         	-		  -         	  -       	  -         	c[i][j] = c[i][j-1];

Dynamic Programming

CE2101/CZ2101



The subsequence:

C G G

The H-number H(n) is defined as follows:

H(0) = 1, and for n > 0:

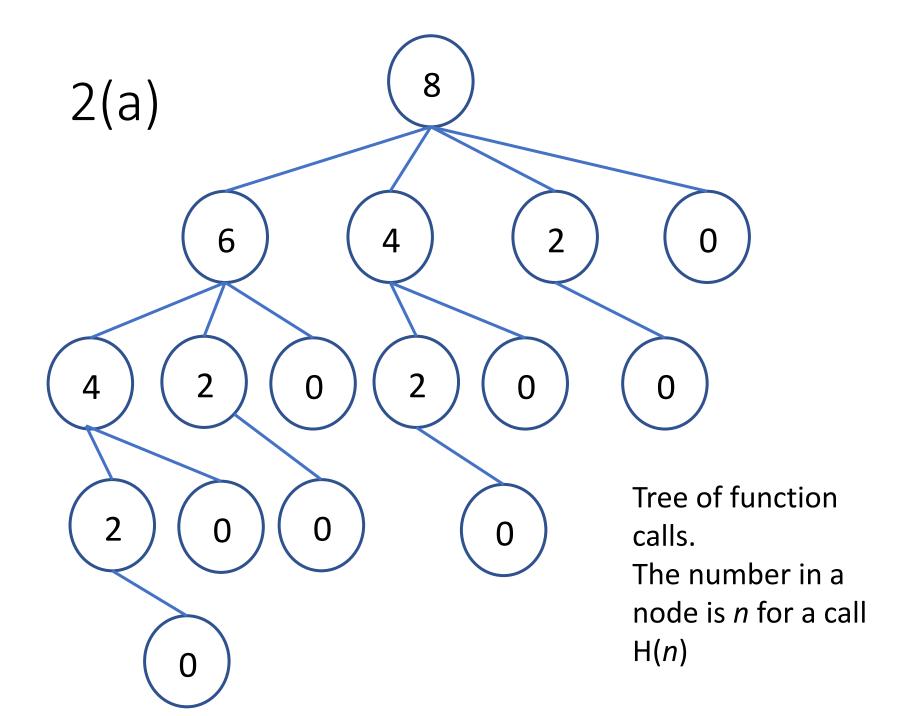
$$H(n) = H(n-1) + H(n-3) + H(n-5) + .... + H(0)$$
 when n is odd

$$H(n) = H(n-2) + H(n-4) + H(n-6) + .... + H(0)$$
 when n is even.

- a) Give a recursive algorithm to compute H(n) for an arbitrary n as suggested by the recurrence equation given for H(n). Draw the tree that represents the recursive calls made when H(8) is computed.
- b) Draw the subproblem graph for H(8) and H(9).
- c) Write an iterative algorithm using the dynamic programming approach (bottom-up). What are the time and space required?

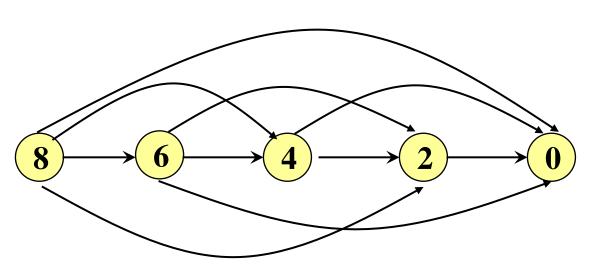
# Question 2(a)

```
int hn(int n) {
{ if (n == 0) return 1;
   else {
       S = 0;
       if (n \mod 2) j=n-1; else j=n-2;
       for (k = 0; k \le j; k = k+2)
           S += hn(k);
   return S;
```

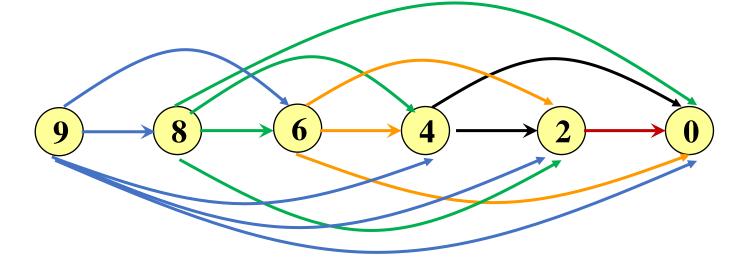


2(b)

The subproblem graph for H(8)



The subproblem graph for H(9)



```
int hn DP(int n)
2(c)
               // Make use of an array S[0..n]
                S[0]=1;
                for (i = 1; i<=n; i++) {
                    S[i] = 0;
                    if (i mod 2) j = i-1; else j=i-2;
                    while (i>=0) \{ S[i] += S[i]; i-=2; \};
                return S[n];
```

Space Complexity: O(n). Time complexity:  $O(n^2)$ 

The binomial coefficients can be defined by the recurrence equation:

$$C(n, k) = C(n - 1, k - 1) + C(n - 1, k)$$
 for  $n > 0$  and  $k > 0$   
 $C(n, 0) = 1$  for  $n > 0$   
 $C(0, k) = 0$ 

C(n, k) is also called "n choose k". This is the number of ways to choose k distinct objects from a set of n objects.

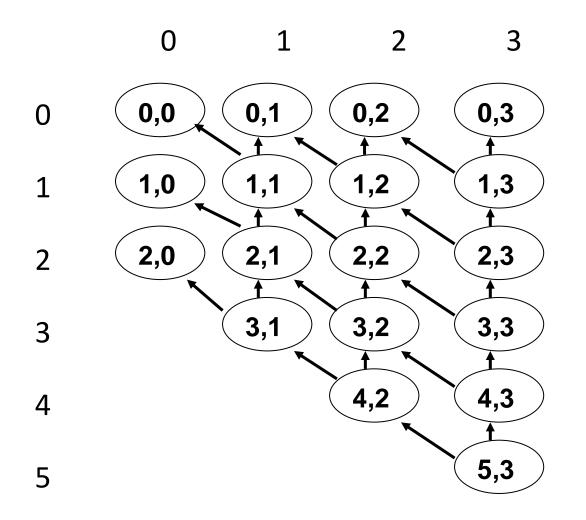
# 3(a)

Give a recursive algorithm as suggested by the recurrence equation given for C(n, k).

```
int C(int n, int k)
{
    if (k == 0) return 1;
    if (n == 0) return 0;

    return C(n - 1, k - 1) + C(n - 1, k);
}
```

#### 3(b) Draw the subproblem graph for C(5, 3).



# 3(c)

Write a recursive algorithm using the dynamic programming approach (top-down) stating the data structure used for the dictionary.

```
Use dictionary: int dic[n+1][k+1]; // initialised to -1 in all entries
```

```
int C(int n, int k, int [] [] dic)
    int c1, c2;
    if (k == 0)
        dic[n][0] = 1;
        return 1; }
    if (n == 0) {
        dic[0][k] = 0;
        return 0; }
    if (dic[n-1][k-1] == -1)
        c1 = C(n-1, k-1);
    else c1 = dic[n - 1][k - 1];
    if (dic[n-1][k] == -1)
        c2 = C(n - 1, k);
    else c2 = dic[n-1][k];
    dic[n][k] = c1 + c2;
    return dic[n][k];
```

Time complexity: O(nk)
Space complexity: O(nk)

# 3(d)

Write an iterative algorithm using the dynamic programming approach (bottom-up).

```
Time complexity: O(nk)
int C(int n, int k, int [] [] dic)
                                             Space complexity: O(nk)
   int dic[n+1][k+1];
   For (i = 1; i \le k; i++) dic[0][i] = 0;
   For (i = 0; i \le n; i++) dic[i][0] = 1;
   For (i = 1; i <= n; i++)
        For (i = 1; i <= k; i++)
             dic[i][i] = dic[i-1][i-1] + dic[i-1][i];
   Return dic[n][k];
```

```
int C(int n, int k, int [] [] dic) // more optimized
    int dic[n+1][k+1];
    For (i = 1; i \le k; i++) dic[0][i] = 0;
    For (i = 0; i \le n-k; i++) dic[i][0] = 1;
    For (i = 1; i <= n; i++)
        For (j = max(i-(n-k), 1); j <= k; j++)
            dic[i][j] = dic[i-1][j-1] + dic[i-1][j];
    Return dic[n][k];
```

Suppose the dimensions of the matrices *A*, *B*, *C*, and *D* are 20x2, 2x15, 15x40, and 40x4, respectively, and we want to know how best to compute *AxBxCxD*. Show the arrays **cost**, **last**, and **multOrder** computed by Algorithms matrixOrder() in the lecture notes.

Array	y <b>d</b>			
20	2	15	40	4
0	1	2	3	4

Cost Last 

#### Array d

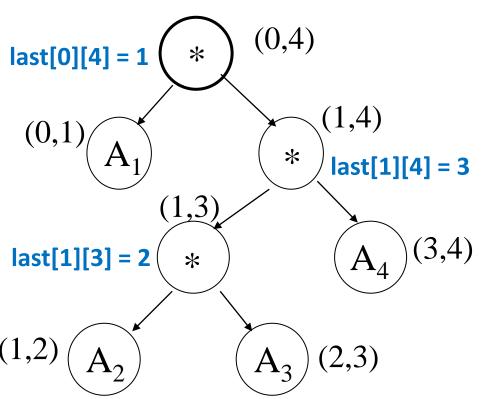
20 2	15	40	4	
------	----	----	---	--

```
Cost[0][3] = min(Cost[0][1]
+Cost[1][3] + d[0]*d[1]*d[3],
Cost[0][2] +Cost[2][3] +
d[0]*d[2]*d[3])
=min(1200+1600, 600+12000)
=2800
Cost[1][4] = min(Cost[1][2]
```

Cost[1][4] = min(Cost[1][2] +Cost[2][4] + d[1]\*d[2]\*d[4], Cost[1][3] +Cost[3][4] + d[1]\*d[3]\*d[4])

Cost[0][4] = min (Cost[0][1] +Cost[1][4] + d[0]\*d[1]\*d[4], Cost[0][2] +Cost[2][4] + d[0]\*d[2]\*d[4], Cost[0][3] +Cost[3][4] + d[0]\*d[3]\*d[4])

# Computation of MultOrder is not examinable



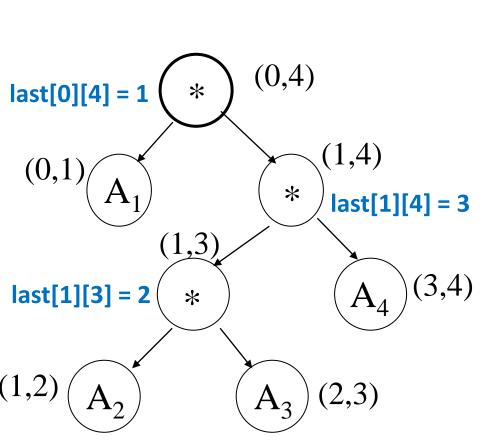
	0	1	2	3	4
0			1	1	1
1				2	3
2					3
3					
4					

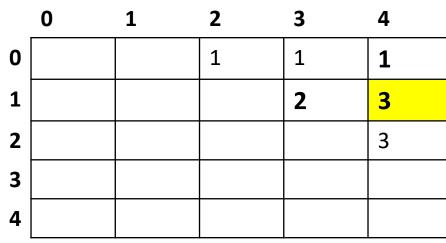
last

Starting from last[0][4] = 1 Output to MultOrder; Continue with last[1][4] then last[0][1]

#### multOrder

	1
--	---

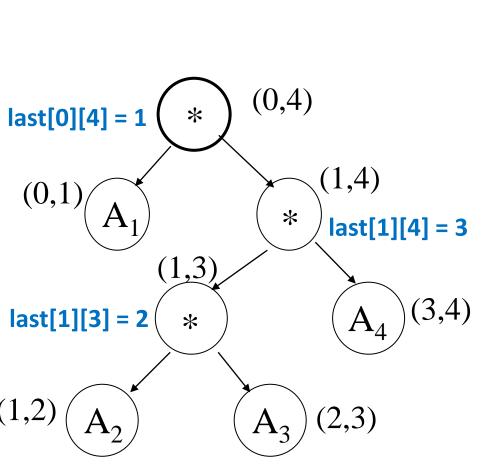


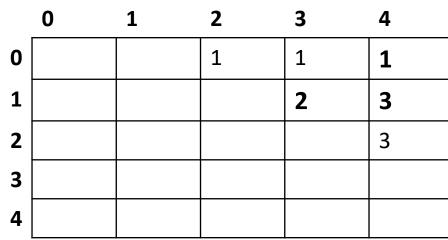


last[1][4] = 3
Output to MultOrder;
Continue with last[3][4]
then last[1][3]

#### multOrder

3	1
---	---

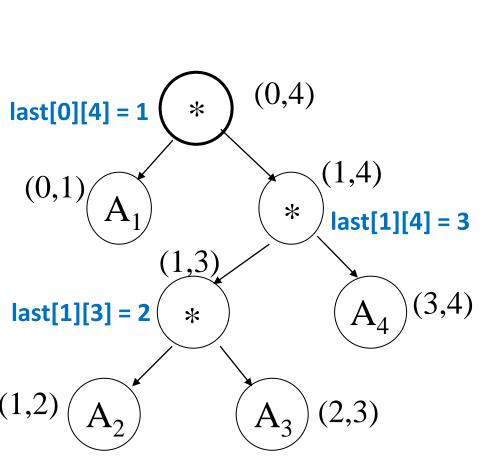


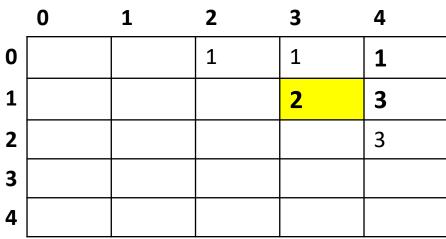


last[3][4] is a single matrix: Do nothing

#### multOrder

	2	1
	3	

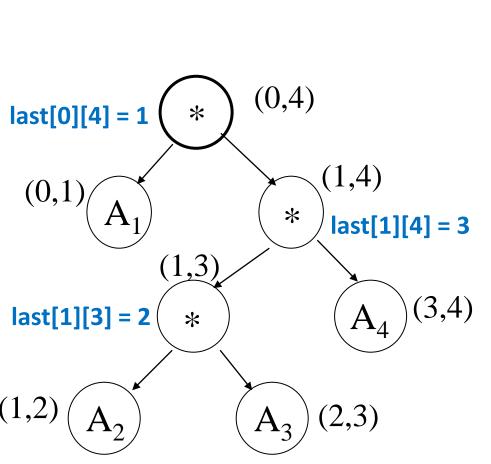


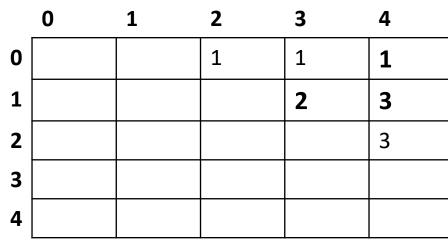


last[1][3] = 2
Output to MultOrder;
Continue with last[2][3]
then last[1][2]

#### multOrder

-	i		·
		_	_
	7	3	1
	~	5	

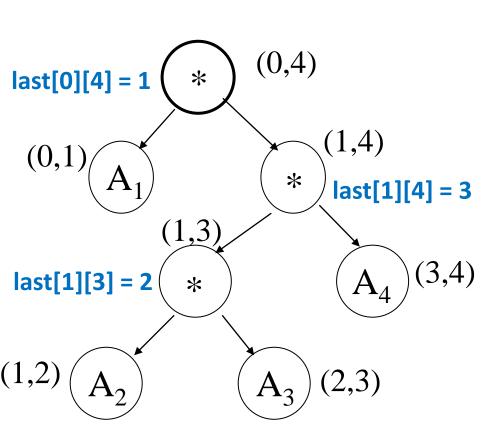


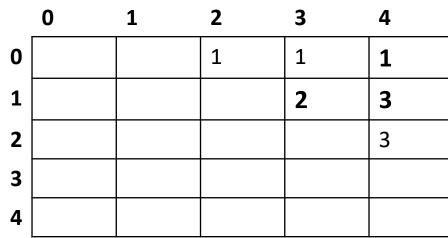


last[2][3] is a single matrix:
Do nothing
last[1][2] is a single matrix:
Do nothing

#### multOrder

1 2	2	1
<b>Z</b>	3	





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last[0][1] is a single matrix: Do nothing

So the best sequence is  $(A1 \times ((A2 \times A3) \times A4))$ 

#### multOrder

2 3 1

Construct an example with only three or four matrices where the worst multiplication order does at least 100 times as many element-wise multiplications as the best order.

Let the dimensions of A, B and C be 100x1, 1x100, 100x1 respectively.

Best order: A(BC) – the no. of multiplications is 200

Worst order: (AB)C – the no. of multiplications is 20000

We have a knapsack of size 10 and 4 objects. The sizes and the profits of the objects are given by the table below. Find a subset of the objects that fits in the knapsack that maximizes the total profit by the dynamic programming algorithm in the lecture notes.

р	10	40	30	50
S	5	4	6	3

C = 10

profit

0 1 2 3 4

0	0	0	0	0	0
1	0	0	0	0	0
2	0	0	0	0	0
3	0	0	0	0	50
4	0	0	40	40	50
5	0	10	40	40	50
6	0	10	40	40	50
7	0	10	40	40	90
8	0	10	40	40	90
9	0	10	50	50	90
10	0	10	50	70	90

р	10	40	30	50
W	5	4	6	3

```
for r = 1 to C
   for c = 1 to n
       profit[r][c] = profit[r][c-1];
       if (w[c] \leq r)
          if (profit[r][c] <</pre>
       profit[r-w[c]][c-1] + p[c]
              profit[r][c] =
                 profit[r-w[c]][c-1]
                 + p[c]
```