

Design and Analysis of Algorithms

CSE 5311

Lecture 15 Dynamic Programming

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Dynamic programming

Design technique, like divide-and-conquer.

Example: *Longest Common Subsequence (LCS)*

- Given two sequences $x[1 \dots m]$ and $y[1 \dots n]$, find a longest subsequence common to them both.



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x : A B C B D A B

y : B D C A B A



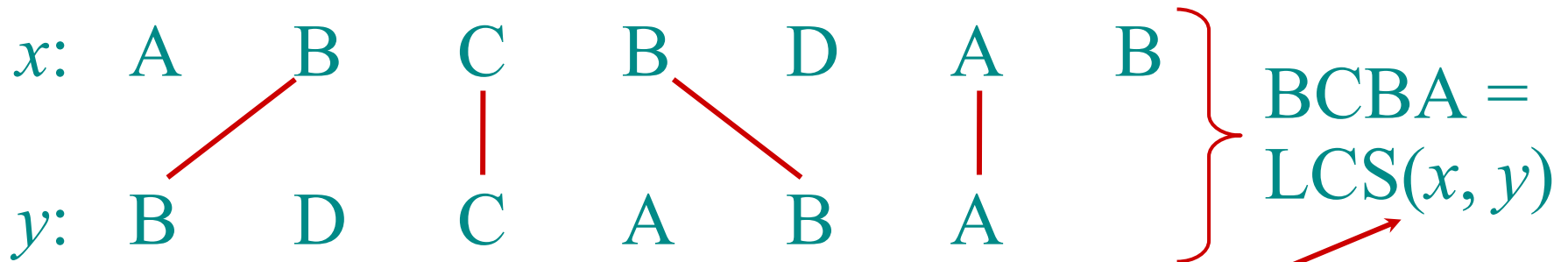
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functional notation,
but not a function



Brute-force LCS algorithm

Check every subsequence of $x[1 \dots m]$ to see if it is also a subsequence of $y[1 \dots n]$.



Brute-force LCS algorithm

Check every subsequence of $x[1 \dots m]$ to see if it is also a subsequence of $y[1 \dots n]$.

Analysis

- Checking = $O(n)$ time per subsequence.
- 2^m subsequences of x (each bit-vector of length m determines a distinct subsequence of x).

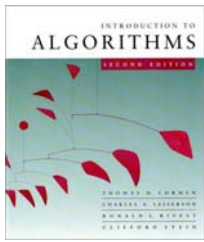
Worst-case running time = $O(n2^m)$
= exponential time.



Towards a better algorithm

Simplification:

1. Look at the *length* of a longest-common subsequence.
2. Extend the algorithm to find the LCS itself.

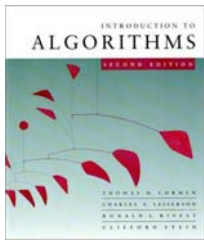


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Notation: Denote the length of a sequence s by $|s|$.

Strategy: Consider *prefixes* of x and y .

- Define $c[i, j] = |\text{LCS}(x[1 \dots i], y[1 \dots j])|$.
- Then, $c[m, n] = |\text{LCS}(x, y)|$.



Recursive formulation

Theorem.

$$c[i, j] = \begin{cases} c[i-1, j-1] + 1 & \text{if } x[i] = y[j], \\ \max \{c[i-1, j], c[i, j-1]\} & \text{otherwise.} \end{cases}$$

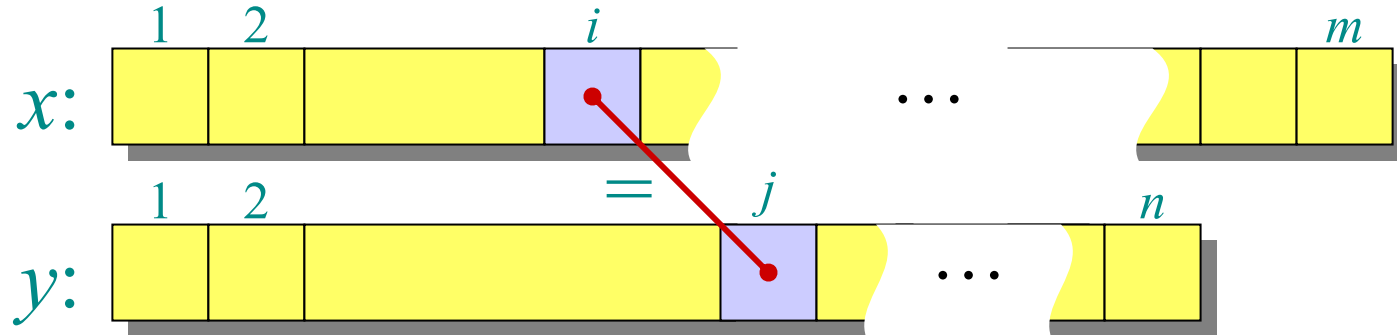


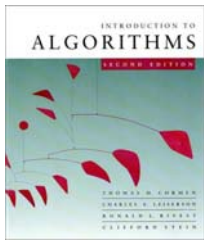
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Proof. Case $x[i] = y[j]$:



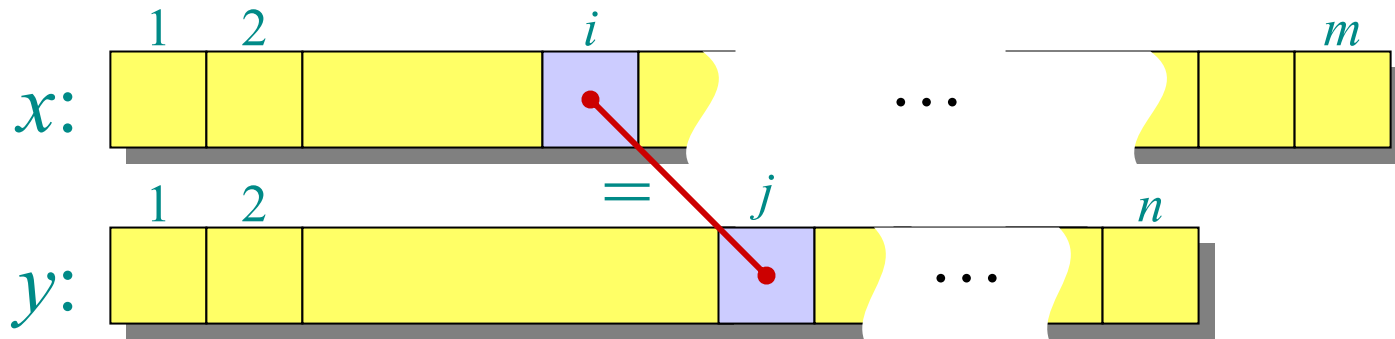


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Proof. Case $x[i] = y[j]$:



Let $z[1 \dots k] = \text{LCS}(x[1 \dots i], y[1 \dots j])$, where $c[i, j] = k$. Then, $z[k] = x[i]$, or else z could be extended. Thus, $z[1 \dots k-1]$ is CS of $x[1 \dots i-1]$ and $y[1 \dots j-1]$.



Proof (continued)

Claim: $z[1 \dots k-1] = \text{LCS}(x[1 \dots i-1], y[1 \dots j-1])$.

Suppose w is a longer CS of $x[1 \dots i-1]$ and $y[1 \dots j-1]$, that is, $|w| > k-1$. Then, **cut and paste**: $w \parallel z[k]$ (w concatenated with $z[k]$) is a common subsequence of $x[1 \dots i]$ and $y[1 \dots j]$ with $|w \parallel z[k]| > k$. Contradiction, proving the claim.



Proof (continued)

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Thus, $c[i-1, j-1] = k-1$, which implies that $c[i, j] = c[i-1, j-1] + 1$.

Other cases are similar. □



Dynamic-programming hallmark #1

Optimal substructure

*An optimal solution to a problem
(instance) contains optimal
solutions to subproblems.*



Dynamic-programming hallmark #1

Optimal substructure

An optimal solution to a problem (instance) contains optimal solutions to subproblems.

If $z = \text{LCS}(x, y)$, then any prefix of z is an LCS of a prefix of x and a prefix of y .



Recursive algorithm for LCS

```
LCS( $x, y, i, j$ )  
  if  $x[i] = y[j]$   
    then  $c[i, j] \leftarrow \text{LCS}(x, y, i-1, j-1) + 1$   
    else  $c[i, j] \leftarrow \max \{ \text{LCS}(x, y, i-1, j),$   
                                $\text{LCS}(x, y, i, j-1) \}$ 
```



if $x[i] = y[j]$

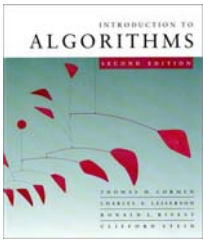
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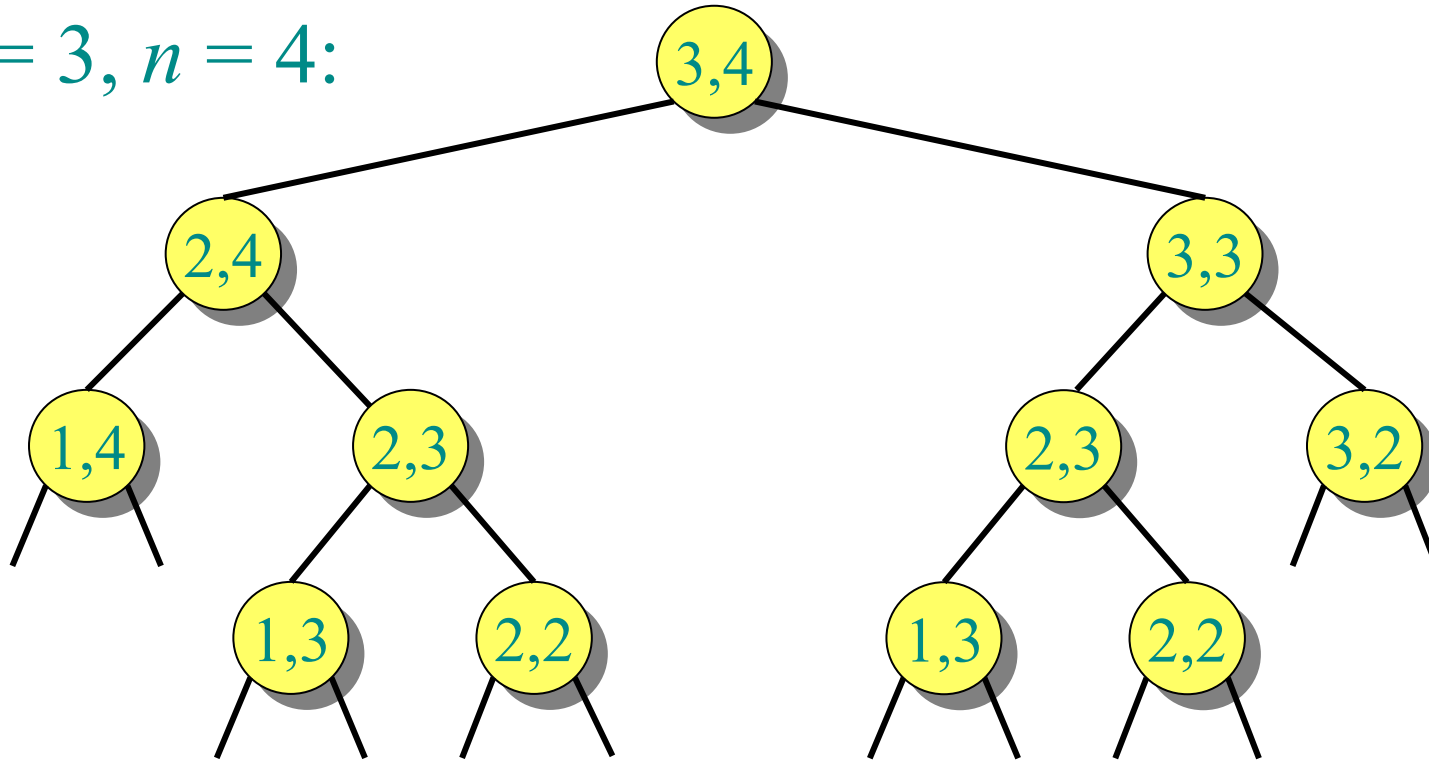
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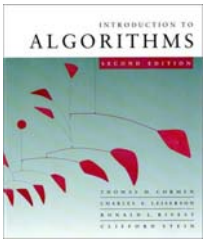
Worst-case: $x[i] \neq y[j]$, in which case the algorithm evaluates two subproblems, each with only one parameter decremented.



Recursion tree

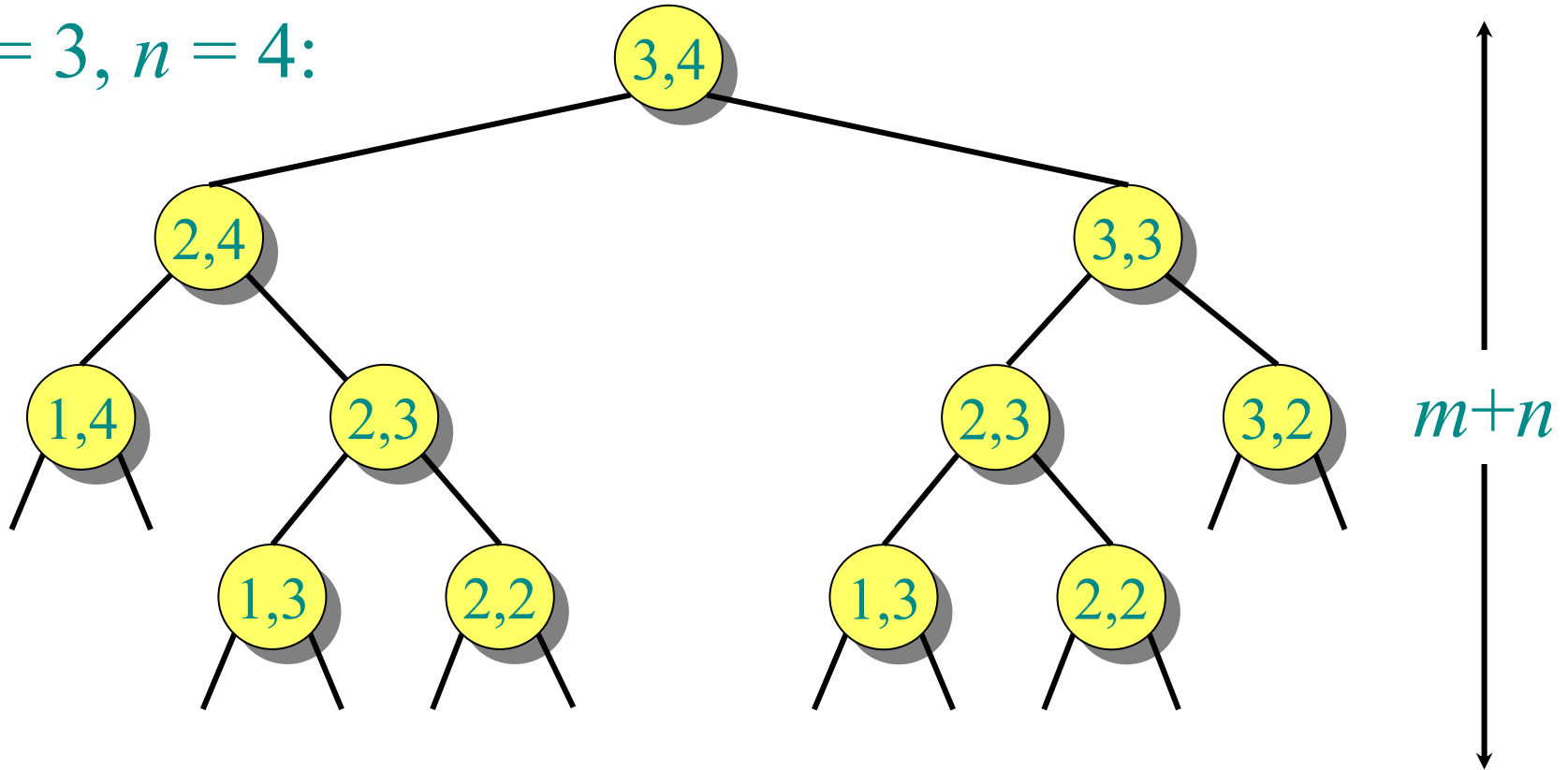
$m = 3, n = 4$:



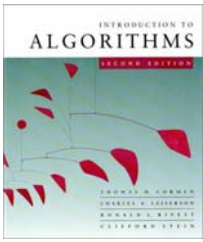


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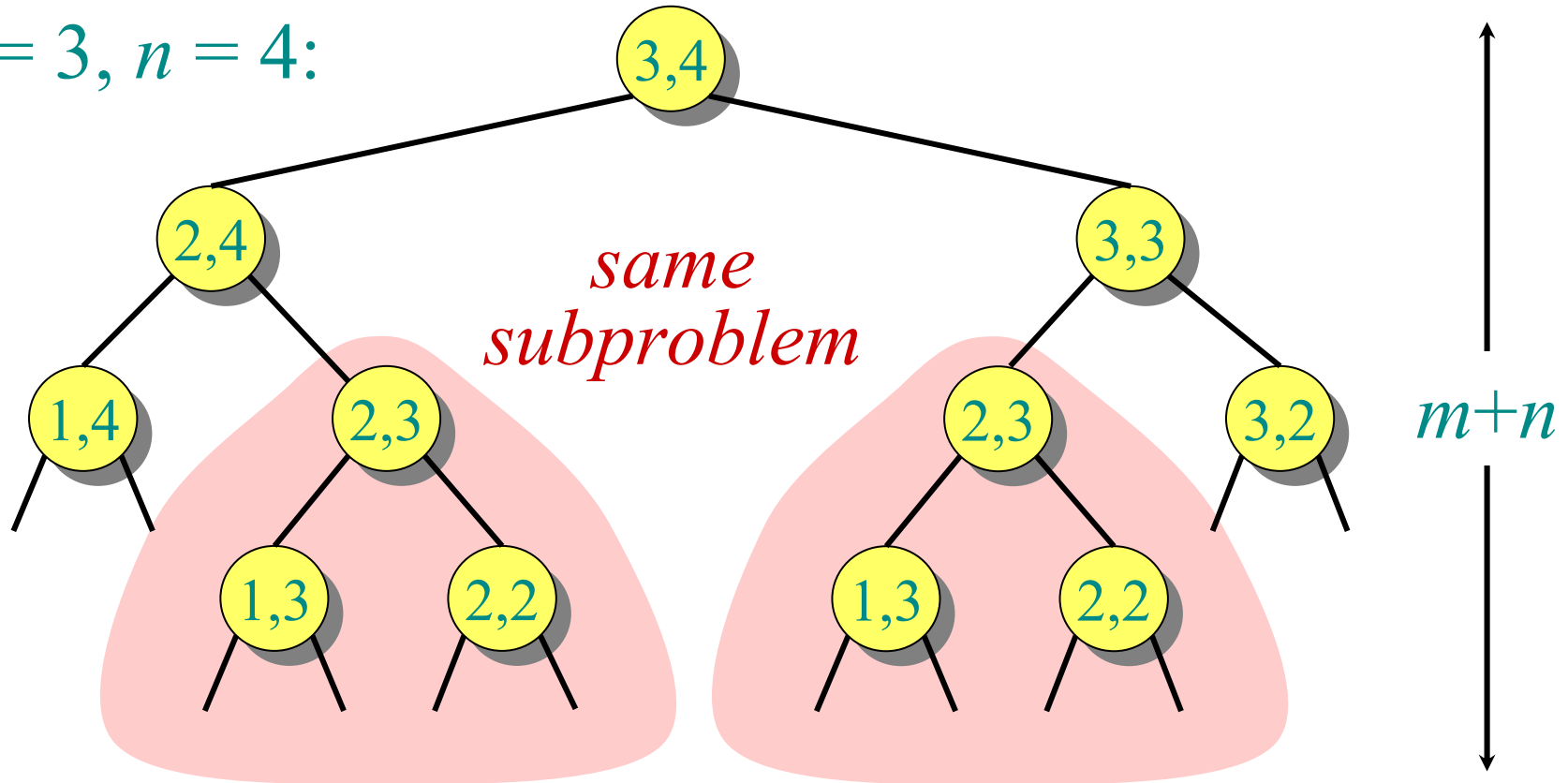


Height = $m + n \Rightarrow$ work potentially exponential.



Recursion tree

$m = 3, n = 4$:



Height = $m + n \Rightarrow$ work potentially exponential,
but we're solving subproblems already solved!



Dynamic-programming hallmark #2

Overlapping subproblems

A recursive solution contains a “small” number of distinct subproblems repeated many times.



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Overlapping subproblems

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The number of distinct LCS subproblems for two strings of lengths m and n is only mn .



Memoization algorithm

Memoization: After computing a solution to a subproblem, store it in a table. Subsequent calls check the table to avoid redoing work.



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Time = $\Theta(mn)$ = constant work per table entry.

Space = $\Theta(mn)$.

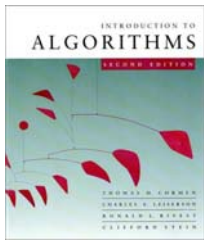


Dynamic-programming algorithm

IDEA:

Compute the table bottom-up.

		A	B	C	B	D	A	B
B	0	0	0	0	0	0	0	0
D	0	0	1	1	1	2	2	2
C	0	0	1	2	2	2	2	2
A	0	1	1	2	2	2	3	3
B	0	1	2	2	3	3	3	4
A	0	1	2	2	3	3	4	4



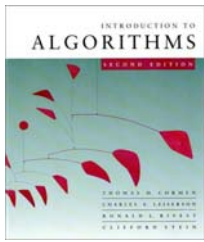
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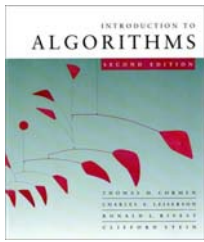
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Reconstruct LCS by tracing backwards.

	A	B	C	B	D	A	B
B	0	0	1	1	1	1	1
D	0	0	1	1	2	2	2
C	0	0	1	2	2	2	2
A	0	1	1	2	2	3	3
B	0	1	2	2	3	3	4
A	0	1	2	2	3	4	4



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Exercise:

$O(\min\{m, n\})$.

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