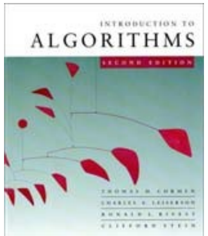
CS60020: Foundations of Algorithm Design and Machine Learning

Sourangshu Bhattacharya



Dynamic programming

Design technique, like divide-and-conquer.

Example: ***Longest Common Subsequence (LCS)***

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

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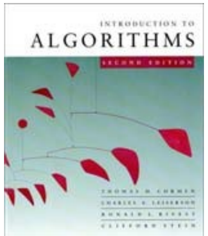

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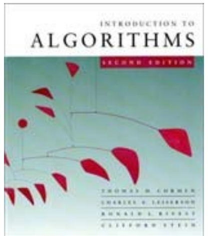

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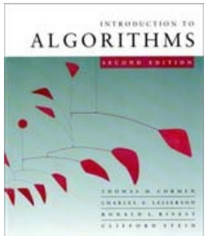
x: A B C B D A B

y: B D C A B A

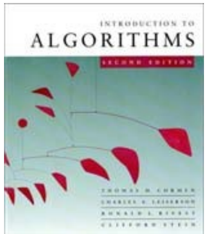
BCBA = LCS(x, y)

functional notation, but not a function



Brute-force LCS algorithm

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



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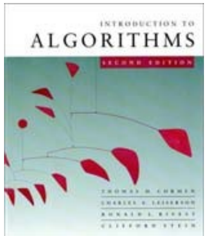
Analysis

- 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.



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Simplification:

1. Look at the *length* of a longest-common subsequence.
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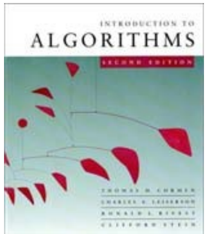
Notation: Denote the length of a sequence s by $|s|$.



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Simplification:

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

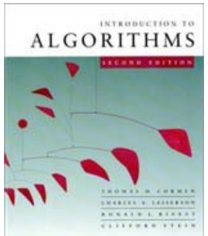
Strategy: Consider ***prefixes*** of x and y.

- Define $c[i, j] = |\text{LCS}(x[1 \,..\, i], y[1 \,..\, j])|$.
- 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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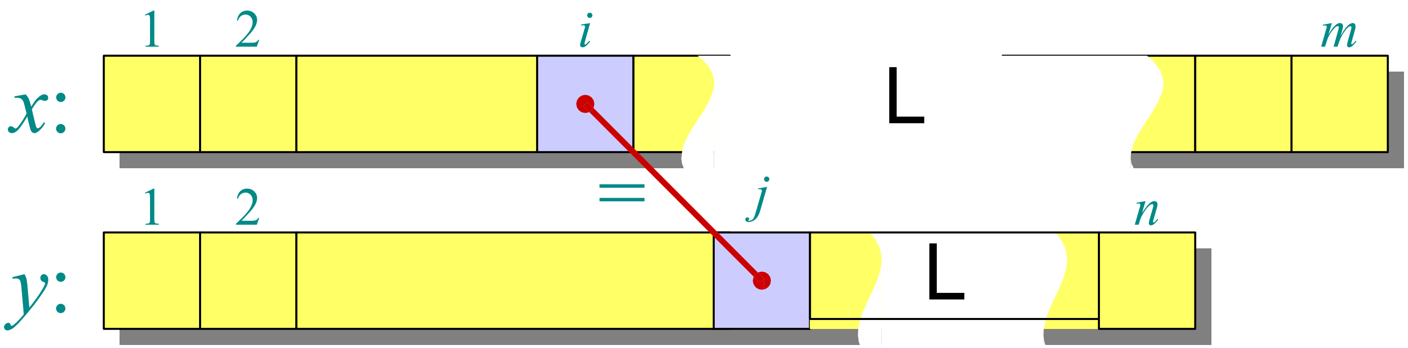
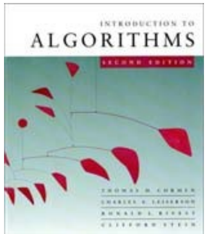
Proof. Case $x[i] = y[j]$:





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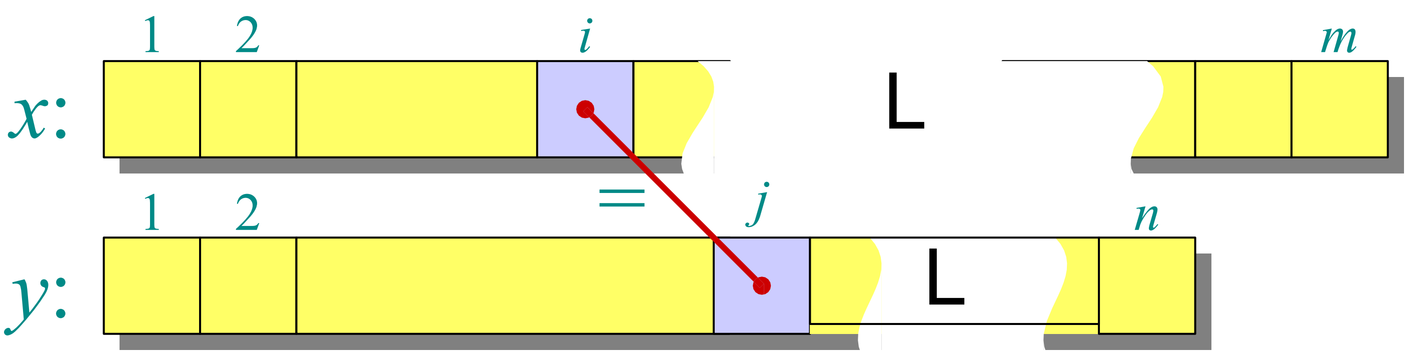
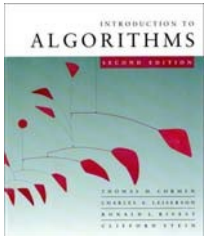


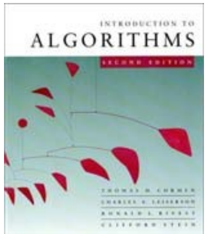
Let $z[1 \,.\,.\, k] = \text{LCS}(x[1 \,.\,.\, i], y[1 \,.\,.\, j])$, where $c[i, j] = k$. Then, $z[k] = x[i]$, or else z could be extended. Thus, $z[1 \,.\,.\, k-1]$ is CS of $x[1 \,.\,.\, i-1]$ and $y[1 \,.\,.\, j-1]$.



Proof (continued)

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

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



Proof (continued)

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

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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. $\square$

Dynamic-programming hallmark #1

Optimal substructure

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

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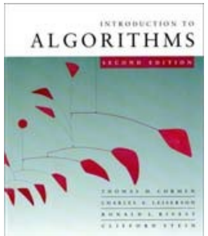
If $z = \text{LCS}(x, y)$, then any prefix of z is an LCS of a prefix of x and a prefix of y.



Recursive algorithm for LCS

LCS(x, y, i, j)
    if $x[i] = y[j]$
        then $c[i, j] \leftarrow \text{LCS}(x, y, i-1, j-1) + 1$
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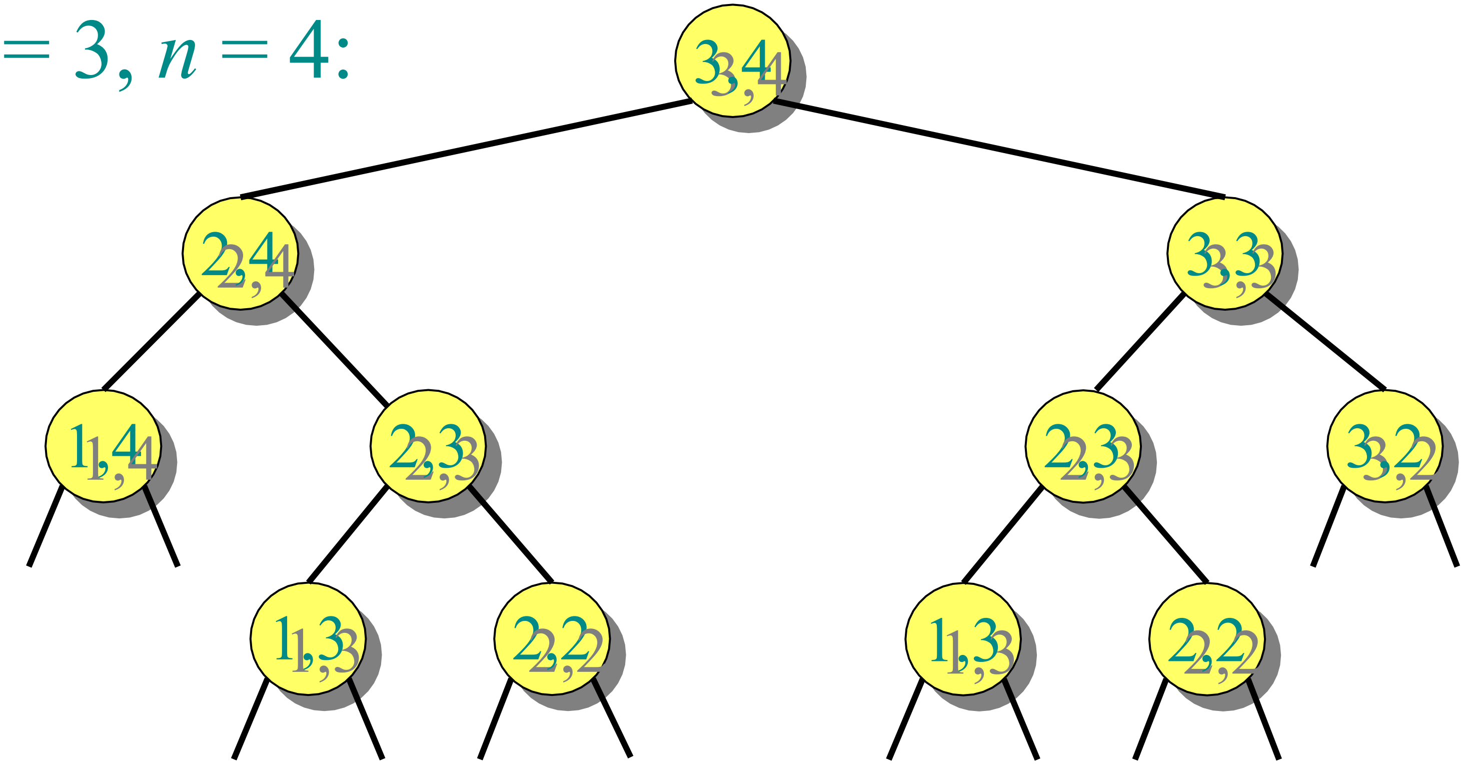
Worst-case: $x[i] \neq y[j]$, in which case the algorithm evaluates two subproblems, each with only one parameter decremented.

Recursion tree

$m = 3, n = 4$:



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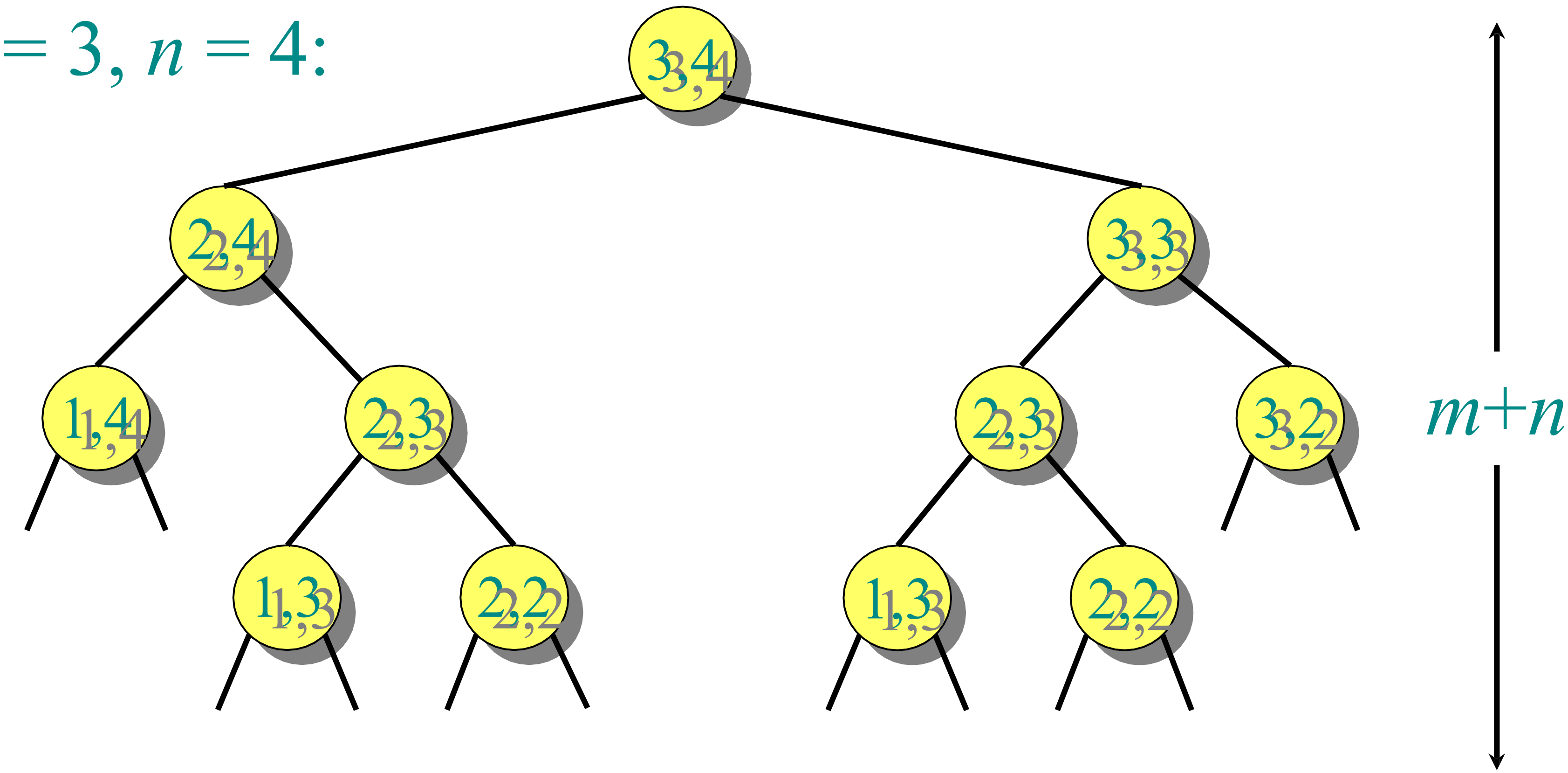

Height $= m + n \Rightarrow$ work potentially exponential.

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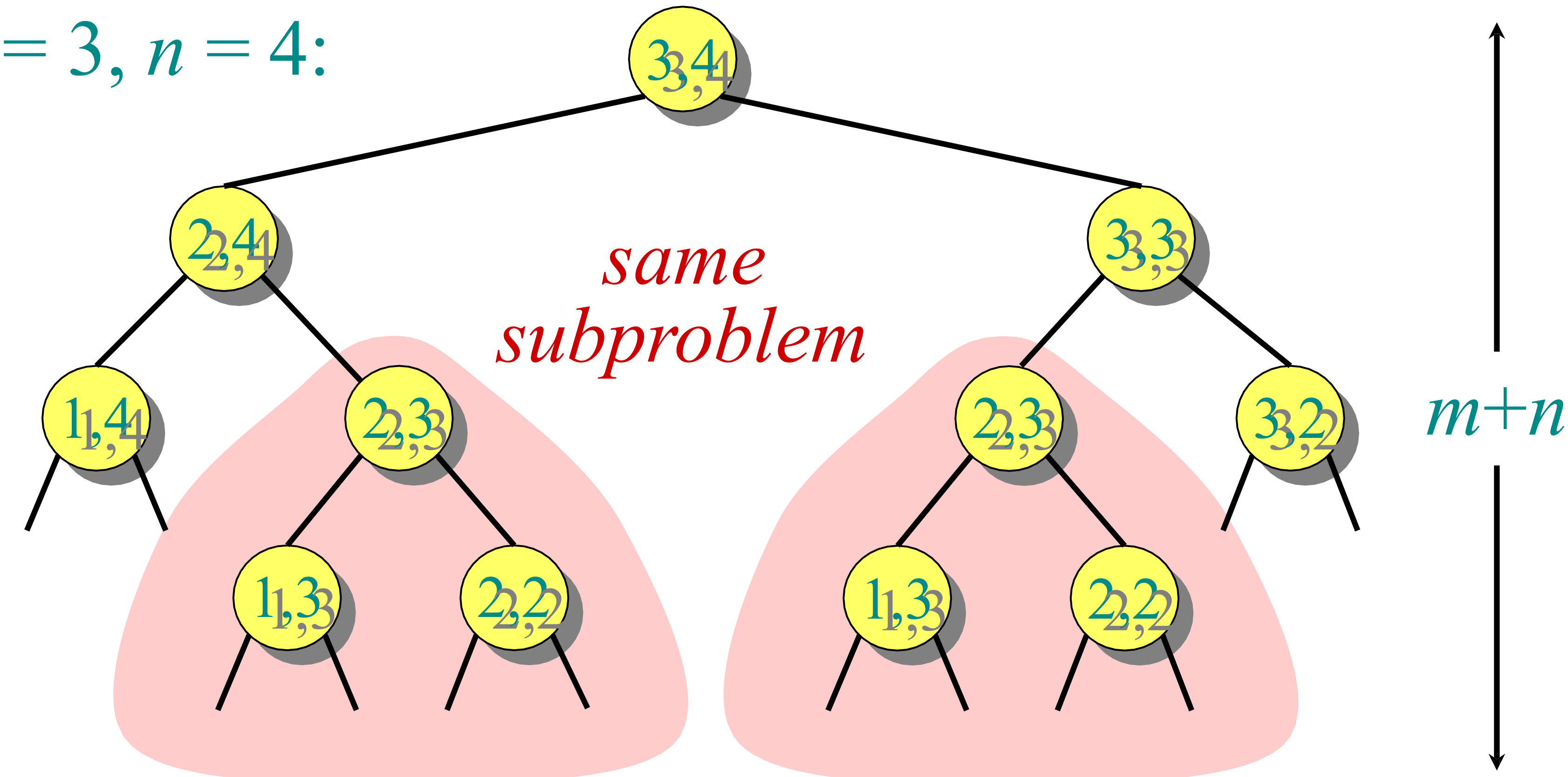

Height $= m + n \Rightarrow$ work potentially exponential., but we're solving subproblems already solved!

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

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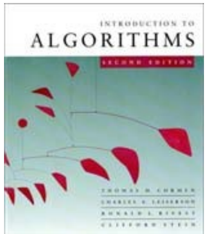
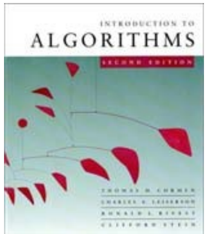
The number of distinct LCS subproblems for two strings of lengths m and n is only mn.



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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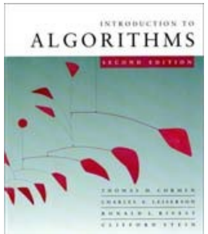

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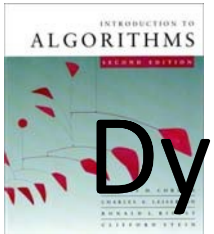
Time $= \Theta(mn) =$ constant work per table entry.
Space $= \Theta(mn)$.



Dynamic-programming algorithm

IDEA:

Compute the table bottom-up.

		A	B	C	B	D	A	B
	0	0	0	0	0	0	0	0
B	0	0	1	1	1	1	1	1
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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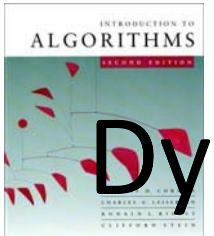

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Reconstruct LCS by tracing backwards.

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B	0	0	1	1	1	1	1	1
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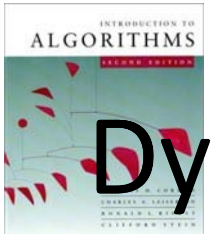

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Space = $\Theta(mn)$.

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

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