

- LCS
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# **Sequence Alignment**



#### LCS

Recursive Approach Substructure Induction Summary

### **Longest Common Subsequence**

Given two strings, x of length m and y of length n, find a common non-contiguous subsequence that is as long as possible.

What is the complexity of the naive algorithm? How can we make this efficient?



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### **Recursive Approach**

LCS(i,j) means length of LCS only considering up to  $x_i$  and  $y_j$ 

$$LCS(i,j) = \begin{cases} 0, & \text{if } i = 0 \text{ or } j = 0\\ LCS(i-1,j-1) + 1, & \text{if } x_i = y_j\\ max(LCS(i-1,j), LCS(i,j-1)) & \text{otherwise} \end{cases}$$



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# **Optimal Substructure**

Prove global optimum uses optimal solutions of subproblems:

- Let z be an LCS(i,j) of length k What if subproblem of optimal solution were not optimal? Three cases:
  - If  $x_i = y_j$ , then  $z_k = x_i = y_j$  and  $LCS(i 1, j 1) = z_0..z_{k-1}$ . Not including  $z_k$  makes LCS suboptimal: contradiction! If  $z_0..z_{k-1}$  were not LCS, z could be longer, so not optimal: contradiction!
  - 2 If  $x_i \neq y_j$  and  $z_k \neq x_i$  then z is LCS(i-1,j)If longer exists, z would not be LCS: contradiction!
  - 3 If  $x_i \neq y_j$  and  $z_k \neq y_j$  then z is LCS(i, j-1)Similar case to 2



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# **Proof by Induction**

Proof structure:

- Prove base case is true (i, j = 1)
- Assume true for i 1 and j 1, prove true for i and j

If i, j = 1, then  $x_{i-1}$  and  $y_{j-1}$  are empty strings, so trivially true

We showed the second part of the proof already

Therefore, for any i, j, the subproblem of an optimal solution is optimal



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# **Summary of Dynamic Programming**

- optimal substructure: global optimum uses optimal solutions of subproblems
- 2 ordering of subproblems: solve 'smallest' first, build larger solutions from smaller
- 3 'overlapping' subproblems: polynomial number of subproblems, used multiple times
- independent subproblems: optimal solution of one subproblem doesn't affect optimality of another
  - top-down: memoization
  - bottom-up: compute table, then recover solution