

I. A “Recipe” for Dynamic Programming

1. Characterize the structure of an optimal solution, and recursively define the value of an optimal solution. In other word, come up with a **formula**
2. Compute the value of an optimal solution in a **bottom-up** fashion, and make use of the computed information (**memoization**)

Recap: Largest Common Subsequence Problem

II. Dynamic Programming VS Divide-and-conquer

Dynamic Programming	Divide-and-conquer
Subproblems overlap	Subproblems are disjoint , mostly smaller instances of the same type
Use a lookup table and traceback table (memoization)	Solve the subproblems recursively
Bottom-up (iteration)	Top-down (recursion)

In the context of subproblems sharing subsubproblems, divide-and-conquer algorithm does more work than necessary, repeatedly solving the common subsubproblems while dynamic-programming algorithm solves each subsubproblem just once and then saves its answer in a lookup table, thereby avoiding the work of recomputing the answer every time it solves each subsubproblem. We can conclude that dynamic programming is a good approach to **optimization problem**, such as *max* and *min*.

III. Dynamic Programming: Image Compression (Textbook Problem 15-8)

We are given a color picture consisting of an $m \times n$ array $A[1...m, 1...n]$ of pixels, where each pixel specifies a triple of red, green, and blue (RGB) intensities. Suppose that we wish to compress this picture slightly. Specifically, we wish to remove one pixel from each of the m rows, so that the whole picture becomes one pixel narrower (namely, $m \times n - 1$). To avoid disturbing visual effects, however, we require that the pixels removed in two adjacent rows be in the same or adjacent columns; the pixels removed form a “seam” from the top row to the bottom row where successive pixels in the seam are adjacent vertically or diagonally.

- (a) Show that the number of such possible seams grows at least exponentially in m , assuming that $n > 1$.
- (b) Suppose now that along with each pixel $A[i, j]$, we have calculated a real valued disruption measure $d[i, j]$ indicating how disruptive it would be to remove pixel $A[i, j]$. Intuitively, the lower a pixel’s disruption measure, the more similar the pixel is to its neighbors. Suppose further that we define the disruption measure of a seam to be the sum of the disruption measures of its pixels.

Give an algorithm to find a seam with the lowest disruption measure. How efficient is your algorithm?

(*Hint:* Let $distance[i, j]$ denote the value of the lowest disruption measure that starts with $A[i, j]$. How can you represent it in a formula?)