

# 4

## Dynamic Programming

Please read the 15-451 lecture notes on dynamic programming for the basic concepts, of top-down dynamic programming (or memoization), and bottom-up dynamic programming. (It also talks about dynamic programming on trees, etc.) These notes here are focused on the issues of reducing space usage for these DPs.

### 4.1 Longest Common Subsequence

Here is the naive bottom-up dynamic program to find the longest common subsequence (LCS) of two strings  $S$  and  $T$ . Define  $M$  to be a table with  $m + 1$  rows and  $n + 1$  columns, where  $M(i, j)$  computes the length of the longest common subsequence of the prefixes  $S_{1:i}$  and  $T_{1:j}$ .

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**Algorithm 6:** LCS-value( $S, T$ )

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```
6.1  $M(0, \star) = M(\star, 0) = 0$ 
6.2 for  $i = 1$  to  $m$  do
6.3   for  $j = 1$  to  $n$  do
6.4     if  $S_i = T_j$  then
6.5        $M(i, j) \leftarrow 1 + M(i - 1, j - 1)$ 
6.6     else
6.7        $M(i, j) \leftarrow \max(M(i - 1, j), M(i, j - 1))$ 
6.8 return  $M(m, n)$ 
```

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**Theorem 4.1.** Algorithm 6 computes the length of the longest common subsequence of two strings of length  $m, n$  in  $O(mn)$  time and space.

#### 4.1.1 Finding the LCS Itself

Having run Algorithm 6 to fill in the table, we can find the LCS itself in  $O(m + n)$  time by just “following the decisions” when filling the

```
[0 0 0 0 0 0 0 0 0 0 0]
[0 0 1 1 1 1 1 1 1 1 1]
[0 1 1 1 1 1 1 2 2 2 2]
[0 1 1 1 1 1 1 2 3 3 3]
[0 1 1 2 2 2 2 2 3 3 3]
[0 1 2 2 3 3 3 3 3 4 4]
[0 1 2 2 3 3 3 4 4 4 4]
[0 1 2 2 3 3 4 4 4 5 5]
[0 1 2 2 3 3 4 4 4 5 6]
```

Figure 4.1: The LCS of ACCTACAG and CATATACCAG.

table.

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**Algorithm 7:** LCS-Search( $S, T$ )
 

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```

7.1  $i \leftarrow m, j \leftarrow n$ 
7.2 while  $i > 0$  or  $j > 0$  do
7.3   if  $S_i = T_j$  then
7.4     output  $S_i$ 
7.5      $i \leftarrow i - 1, j \leftarrow j - 1$ 
7.6   else
7.7     if  $M(i, j) = M(i - 1, j)$  then  $i \leftarrow i - 1$  else  $j \leftarrow j - 1$ 

```

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(Exercise: One of the strings  $T$  has been accidentally deleted, but you still have the string  $S$ , and the table  $M(\cdot, \cdot)$ . Show how to output the LCS in  $O(m + n)$  time)

#### 4.2 Space-Efficiency

The above bottom-up algorithm for the LCS problem always takes  $O(mn)$  time and space. A very recent result shows that the quadratic runtime is necessary in general, but we can reduce the space usage. The crucial observations are simple: (a) we care only about the value of  $M(m, n)$ , and (b) the update rule for a cell  $M(i, j)$  depends only on  $M(i - 1, j - 1)$ ,  $M(i - 1, j)$  and  $M(i, j - 1)$ , which belong to the same row or previous row as the current cell  $(i, j)$  being filled in. Hence we can fill the table row-by-row, “keeping in mind” only rows  $i - 1$  and  $i$  when filling in row  $i$ . Formally, we define the table  $M$  to have only 2 rows and  $n + 1$  columns, and change the algorithm as follows:

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**Algorithm 8:** Low-Space LCS( $S, T$ )
 

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```

8.1  $M(0, \star) = M(\star, 0) = 0$ 
8.2 for  $i = 1$  to  $m$  do
8.3   for  $j = 1$  to  $n$  do
8.4     if  $S_i = T_j$  then
8.5        $M(i \bmod 2, j) \leftarrow 1 + M(i - 1 \bmod 2, j - 1)$ 
8.6     else
8.7        $M(i \bmod 2, j) \leftarrow$ 
8.8          $\max(M(i - 1 \bmod 2, j), M(i \bmod 2, j - 1))$ 
8.8 return  $M(m \bmod 2, n)$ 

```

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**Theorem 4.2.** Algorithm 8 computes the length of the longest common subsequence of two strings of length  $m, n$  in  $O(mn)$  time and  $O(\min(m, n))$  space

[0	0	0	0	0	0	0	0	0	0	0]
[0	0	1	1	1	1	1	1	1	1	1]
[0	1	1	1	1	1	1	2	2	2	2]
[0	1	1	1	1	1	1	2	3	3	3]
[0	1	1	2	2	2	2	2	3	3	3]
[0	1	2	2	3	3	3	3	3	4	4]
[0	1	2	2	3	3	3	4	4	4	4]
[0	1	2	2	3	3	4	4	4	5	5]
[0	1	2	2	3	3	4	4	4	5	6]

Figure 4.2: The LCS of ACCTACAG and CATATACCAG is ATACAG.

### 4.3 (Optional) Finding the LCS in Linear Space

How can we find the actual LCS using  $O(m + n)$  space: clearly the search algorithm given in Algorithm 7 will no longer work, since we don't have the entire table. Hence we need to be smarter: the lovely idea here can be called "guess the mid-point".

The main observation is this: there exists a value  $q$  such that

$$LCS(S_{1:m}, T_{1:n}) = LCS(S_{1:m/2}, T_{1:q}) + LCS(S_{m/2+1:m}, T_{q+1:n}). \quad (4.1)$$

I visualize this as follows: when we follow the optimal solution up from  $M(m, n)$  to  $M(0, 0)$ , this optimal solution must cross row  $m/2$  at some point—this point  $(m/2, q)$  must provide this partition. [Add a picture here.](#)

Now using Algorithm 8 on  $S_{1:m/2}$  and  $T$ , and on the *reversed* strings  $S_{m/2+1:m}$  and  $T$ , we can find the index  $q$  that achieves the equality (4.1). Now we can recurse on the two halves

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**Algorithm 9:** Low-Space LCS-Search( $S, T$ )

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- 9.1 run Algorithm 8 on  $S_{1:m/2}$  and  $T$ , and on reversed  $S_{m/2+1:m}$  and  $T$
  - 9.2 find  $q$  that satisfies equality (4.1)
  - 9.3 recurse on  $S_{1:m/2}, T_{1:q}$ , and on  $S_{m/2+1:m}, T_{q+1:n}$ .
- 

**Theorem 4.3.** *Algorithm 9 runs in time  $O(mn)$  and space  $O(m + n)$ .*

*Proof.* For the runtime, note that the first line of the algorithm runs in  $O(mn)$  time, using Theorem 4.2. Now a linear-time scan can find the value  $q$  that minimizes the sum  $LCS(S_{1:m/2}, T_{1:q}) + LCS(S_{m/2+1:m}, T_{q+1:n})$ . Now for the inductive proof, assume that the runtime of the recursive calls is at most  $c(m/2)q + c(m/2)(n - q) = c(m/2)n$ . Summing this all up, we get at most  $cmn$ .  $\square$

This idea is essentially that used by Savitch for his classical result relating log-space computation to non-deterministic log-space.