

NPTEL MOOC

PROGRAMMING, DATA STRUCTURES AND ALGORITHMS IN PYTHON

Week 8, Lecture 3

Madhavan Mukund, Chennai Mathematical Institute

<http://www.cmi.ac.in/~madhavan>

Longest common subword

- * Given two strings, find the (length of the) longest common subword
 - * “secret”, “secretary” — “secret”, length 6
 - * “bisect”, “trisection” — “isection”, length 5
 - * “bisect”, “secret” — “sec”, length 3
 - * “director”, “secretary” — “ec”, “re”, length 2

More formally ...

- * Two strings $u = a_0a_1\dots a_{m-1}$, $v = b_0b_1\dots b_{n-1}$
- * If $a_ia_{i+1}\dots a_{i+k-1} = b_jb_{j+1}\dots b_{j+k-1}$ for some i and j , u and v have a common subword of length k
- * Aim: Find the length of the longest common subword of u and v

Brute force

- * $u = a_0a_1\dots a_{m-1}$ and $v = b_0b_1\dots b_{n-1}$
- * Try every pair of starting positions i in u , j in v
 - * Match $(a_i, b_i), (a_{i+1}, b_{i+1}), \dots$ as far as possible
 - * Keep track of the length of the longest match
- * Assuming $m > n$, this is $O(mn^2)$
 - * mn pairs of positions
 - * From each starting point, scan can be $O(n)$

Inductive structure

- * $a_i a_{i+1} \dots a_{i+k-1} = b_j b_{j+1} \dots b_{j+k-1}$ is a common subword of length k at (i,j) iff
 - * $a_i = b_j$ and
 - * $a_{i+1} \dots a_{i+k-1} = b_{j+1} \dots b_{j+k-1}$ is a common subword of length $k-1$ at $(i+1, j+1)$
- * $LCW(i,j)$: length of the longest common subword starting at a_i and b_j
 - * If $a_i \neq b_j$, $LCW(i,j)$ is 0, otherwise $1+LCW(i+1, j+1)$
 - * Boundary condition: when we have reached the end of one of the words

Inductive structure

- * Consider positions 0 to m in u , 0 to n in v
 - * m, n means we have reached the end of the word
- * $LCW(m, j) = 0$ for all j
- * $LCW(i, n) = 0$ for all i
- * $LCW(i, j) = 0$, if $a_i \neq b_j$,
 $1 + LCW(i+1, j+1)$, if $a_i = b_j$

Subproblem dependency

- * $LCW(i,j)$ depends on $LCW(i+1,j+1)$
- * Last row and column have no dependencies
- * Start at bottom right corner and fill by row or by column

		0	1	2	3	4	5	6
		s	e	c	r	e	t	.
0	b							
1	i							
2	s							
3	e							
4	c							
5	t							
6	.							

Subproblem dependency


- * $LCW(i,j)$ depends on $LCW(i+1,j+1)$
- * Last row and column have no dependencies
- * Start at bottom right corner and fill by row or by column



		0	1	2	3	4	5	6
		s	e	c	r	e	t	.
0	b							
1	i							
2	s							
3	e							
4	c							
5	t							
6	.							

Subproblem dependency


- * $LCW(i,j)$ depends on $LCW(i+1,j+1)$
- * Last row and column have no dependencies
- * Start at bottom right corner and fill by row or by column



		0	1	2	3	4	5	6
		s	e	c	r	e	t	.
0	b							0
1	i							0
2	s							0
3	e							0
4	c							0
5	t							0
6	.	0	0	0	0	0	0	0

Subproblem dependency


- * $LCW(i,j)$ depends on $LCW(i+1,j+1)$
- * Last row and column have no dependencies
- * Start at bottom right corner and fill by row or by column



		0	1	2	3	4	5	6
		s	e	c	r	e	t	.
0	b						0	0
1	i						0	0
2	s						0	0
3	e						0	0
4	c						0	0
5	t						1	0
6	.	0	0	0	0	0	0	0

Subproblem dependency


- * $LCW(i,j)$ depends on $LCW(i+1,j+1)$
- * Last row and column have no dependencies
- * Start at bottom right corner and fill by row or by column



		0	1	2	3	4	5	6
		s	e	c	r	e	t	.
0	b					0	0	0
1	i					0	0	0
2	s					0	0	0
3	e					1	0	0
4	c					0	0	0
5	t					0	1	0
6	.	0	0	0	0	0	0	0

Subproblem dependency


- * $LCW(i,j)$ depends on $LCW(i+1,j+1)$
- * Last row and column have no dependencies
- * Start at bottom right corner and fill by row or by column



		0	1	2	3	4	5	6
		s	e	c	r	e	t	.
0	b				0	0	0	0
1	i				0	0	0	0
2	s				0	0	0	0
3	e				0	1	0	0
4	c				0	0	0	0
5	t				0	0	1	0
6	.	0	0	0	0	0	0	0

Subproblem dependency


- * $LCW(i,j)$ depends on $LCW(i+1,j+1)$
- * Last row and column have no dependencies
- * Start at bottom right corner and fill by row or by column



		0	1	2	3	4	5	6
		s	e	c	r	e	t	.
0	b			0	0	0	0	0
1	i			0	0	0	0	0
2	s			0	0	0	0	0
3	e			0	0	1	0	0
4	c			1	0	0	0	0
5	t			0	0	0	1	0
6	.	0	0	0	0	0	0	0

Subproblem dependency


- * $LCW(i,j)$ depends on $LCW(i+1,j+1)$
- * Last row and column have no dependencies
- * Start at bottom right corner and fill by row or by column



		0	1	2	3	4	5	6
		s	e	c	r	e	t	.
0	b		0	0	0	0	0	0
1	i		0	0	0	0	0	0
2	s		0	0	0	0	0	0
3	e		2	0	0	1	0	0
4	c		0	1	0	0	0	0
5	t		0	0	0	0	1	0
6	.	0	0	0	0	0	0	0

Subproblem dependency


- * $LCW(i,j)$ depends on $LCW(i+1,j+1)$
- * Last row and column have no dependencies
- * Start at bottom right corner and fill by row or by column



		0	1	2	3	4	5	6
		s	e	c	r	e	t	.
0	b	0	0	0	0	0	0	0
1	i	0	0	0	0	0	0	0
2	s	3	0	0	0	0	0	0
3	e	0	2	0	0	1	0	0
4	c	0	0	1	0	0	0	0
5	t	0	0	0	0	0	1	0
6	.	0	0	0	0	0	0	0

Reading off the solution

- * Find (i,j) with largest entry
- * $LCW(2,0) = 3$
- * Read off the actual subword diagonally



		0	1	2	3	4	5	6
		s	e	c	r	e	t	.
0	b	0	0	0	0	0	0	0
1	i	0	0	0	0	0	0	0
2	s	3	0	0	0	0	0	0
3	e	0	2	0	0	1	0	0
4	c	0	0	1	0	0	0	0
5	t	0	0	0	0	0	1	0
6	.	0	0	0	0	0	0	0

Reading off the solution

- * Find (i,j) with largest entry
- * $LCW(2,0) = 3$
- * Read off the actual subword diagonally

		0	1	2	3	4	5	6
		s	e	c	r	e	t	.
0	b	0	0	0	0	0	0	0
1	i	0	0	0	0	0	0	0
2	s	3	0	0	0	0	0	0
3	e	0	2	0	0	1	0	0
4	c	0	0	1	0	0	0	0
5	t	0	0	0	0	0	1	0
6	.	0	0	0	0	0	0	0

LCW(u,v), DP

```
def LCW(u,v): # u[0..m-1], v[0..n-1]
    for r in range(len(u)+1):
        LCW[r][len(v)+1] = 0 # r for row
    for c in range(len(v)+1):
        LCW[len(u)+1][c] = 0 # c for col
    maxLCW = 0
    for c in range(len(v)+1,-1,-1):
        for r in range(len(u)+1,-1,-1):
            if u[r] == v[c]:
                LCW[r][c] = 1 + LCW[r+1][c+1]
            else:
                LCW[r][c] = 0
            if LCW[r][c] > maxLCW:
                maxLCW = LCW[r][c]
    return(maxLCW)
```


Complexity

- * Recall that the brute force approach was $O(mn^2)$
- * The inductive solution is $O(mn)$ if we use dynamic programming (or memoization)
 - * Need to fill an $O(mn)$ size table
 - * Each table entry takes constant time to compute

Longest common subsequence

- * Subsequence: can drop some letters in between
- * Given two strings, find the (length of the) longest common subsequence
 - * “secret”, “secretary” — “secret”, length 6
 - * “bisect”, “trisect” — “isect”, length 5
 - * “bisect”, “secret” — “sect”, length 4
 - * “director”, “secretary” — “ectr”, “retr”, length 4

LCS

- * LCS is longest path we can find between non-zero LCW entries, moving right and down

		0	1	2	3	4	5	6
		s	e	c	r	e	t	.
0	b	0	0	0	0	0	0	0
1	i	0	0	0	0	0	0	0
2	s	3	0	0	0	0	0	0
3	e	0	2	0	0	1	0	0
4	c	0	0	1	0	0	0	0
5	t	0	0	0	0	0	1	0
6	.	0	0	0	0	0	0	0

Applications

- * Analyzing genes
 - * DNA is a long string over A,T,G,C
 - * Two species are closer if their DNA has longer common subsequence
- * UNIX diff command
 - * Compares text files
 - * Find longest matching subsequence of lines

Inductive structure

u	a ₀	a ₁	a ₂	a _{m-1}
v	b ₀	b ₁	b ₂	...	b _{n-1}	

- * If $a_0 = b_0$,
$$\text{LCS}(a_0 \dots a_{m-1}, b_0 \dots b_{n-1}) = 1 + \text{LCS}(a_1 a_2 \dots a_{m-1}, b_1 b_2 \dots b_{n-1})$$
 - * Can force (a_0, b_0) to be part of LCS
- * If not, a_0 and b_0 cannot both be part of LCS
 - * Not sure which one to drop
 - * Solve both subproblems $\text{LCS}(a_1 a_2 \dots a_{m-1}, b_0 b_1 \dots b_{n-1})$ and $\text{LCS}(a_0 a_1 \dots a_{m-1}, b_1 b_2 \dots b_{n-1})$ and take the maximum

Inductive structure

u	a_i	a_{i+1}	a_{i+2}	a_{m-1}
v	b_j	b_{j+1}	b_{j+2}	b_{n-1}

- * $\text{LCS}(i,j)$ stands for $\text{LCS}(a_i a_{i+1} \dots a_{m-1}, b_j b_{j+1} \dots b_{n-1})$
- * If $a_i = b_j$, $\text{LCS}(i,j) = 1 + \text{LCS}(i+1, j+1)$
- * If $a_i \neq b_j$, $\text{LCS}(i,j) = \max(\text{LCS}(i+1, j), \text{LCS}(i, j+1))$
- * As with LCW, extend positions to m, n
 - * $\text{LCS}(m, j) = 0$ for all j
 - * $\text{LCS}(i, n) = 0$ for all i

Subproblem dependency

- * $LCS(i,j)$ depends on $LCS(i+1,j+1)$ as well as $LCS(i+1,j)$ and $LCS(i,j+1)$
- * Dependencies for $LCS(m,n)$ are known
- * Start at $LCS(m,n)$ and fill by row, column or diagonal

The diagram illustrates the subproblem dependencies for the Longest Common Subsequence (LCS) problem between the strings "secret" and "bits". It features a grid where the top row and left column are labeled with the characters of the strings. The top row labels are 0, 1, 2, 3, 4, 5, 6, and the left column labels are b, i, s, e, c, t, . (representing the characters of "bits"). The grid cells are colored light blue. Yellow arrows indicate the dependencies for calculating the LCS value at each cell (i,j). The arrows point from the cell (i+1, j+1) to (i, j), from (i+1, j) to (i, j), and from (i, j+1) to (i, j). For example, the cell (3,3) (containing 'e' from "secret" and 'e' from "bits") has arrows pointing to (4,4) (containing 'c' from "secret" and 'c' from "bits"), (4,3) (containing 'c' from "secret" and 'e' from "bits"), and (3,4) (containing 'e' from "secret" and 'c' from "bits").

		0	1	2	3	4	5	6
		s	e	c	r	e	t	.
0	b							
1	i							
2	s							
3	e							
4	c							
5	t							
6	.							

Subproblem dependency


- * $LCS(i,j)$ depends on $LCS(i+1,j+1)$ as well as $LCS(i+1,j)$ and $LCS(i,j+1)$
- * Dependencies for $LCS(m,n)$ are known
- * Start at $LCS(m,n)$ and fill by row, column or diagonal



		0	1	2	3	4	5	6
		s	e	c	r	e	t	.
0	b							
1	i							
2	s							
3	e							
4	c							
5	t							
6	.							

Subproblem dependency


- * $LCS(i,j)$ depends on $LCS(i+1,j+1)$ as well as $LCS(i+1,j)$ and $LCS(i,j+1)$
- * Dependencies for $LCS(m,n)$ are known
- * Start at $LCS(m,n)$ and fill by row, column or diagonal



		0	1	2	3	4	5	6
		s	e	c	r	e	t	.
0	b							0
1	i							0
2	s							0
3	e							0
4	c							0
5	t							0
6	.	0	0	0	0	0	0	0

Subproblem dependency


- * $LCS(i,j)$ depends on $LCS(i+1,j+1)$ as well as $LCS(i+1,j)$ and $LCS(i,j+1)$
- * Dependencies for $LCS(m,n)$ are known
- * Start at $LCS(m,n)$ and fill by row, column or diagonal



		0	1	2	3	4	5	6
		s	e	c	r	e	t	.
0	b						0	0
1	i						0	0
2	s						0	0
3	e						0	0
4	c						0	0
5	t						1	0
6	.	0	0	0	0	0	0	0

Subproblem dependency


- * $LCS(i,j)$ depends on $LCS(i+1,j+1)$ as well as $LCS(i+1,j)$ and $LCS(i,j+1)$
- * Dependencies for $LCS(m,n)$ are known
- * Start at $LCS(m,n)$ and fill by row, column or diagonal



		0	1	2	3	4	5	6
		s	e	c	r	e	t	.
0	b					1	0	0
1	i					1	0	0
2	s					1	0	0
3	e					1	0	0
4	c					1	0	0
5	t					1	1	0
6	.	0	0	0	0	0	0	0

Subproblem dependency


- * $LCS(i,j)$ depends on $LCS(i+1,j+1)$ as well as $LCS(i+1,j)$ and $LCS(i,j+1)$
- * Dependencies for $LCS(m,n)$ are known
- * Start at $LCS(m,n)$ and fill by row, column or diagonal



		0	1	2	3	4	5	6
		s	e	c	r	e	t	.
0	b				1	1	0	0
1	i				1	1	0	0
2	s				1	1	0	0
3	e				1	1	0	0
4	c				1	1	0	0
5	t				1	1	1	0
6	.	0	0	0	0	0	0	0

Subproblem dependency


- * $LCS(i,j)$ depends on $LCS(i+1,j+1)$ as well as $LCS(i+1,j)$ and $LCS(i,j+1)$
- * Dependencies for $LCS(m,n)$ are known
- * Start at $LCS(m,n)$ and fill by row, column or diagonal



		0	1	2	3	4	5	6
		s	e	c	r	e	t	.
0	b			2	1	1	0	0
1	i			2	1	1	0	0
2	s			2	1	1	0	0
3	e			2	1	1	0	0
4	c			2	1	1	0	0
5	t			1	1	1	1	0
6	.	0	0	0	0	0	0	0

Subproblem dependency


- * $LCS(i,j)$ depends on $LCS(i+1,j+1)$ as well as $LCS(i+1,j)$ and $LCS(i,j+1)$
- * Dependencies for $LCS(m,n)$ are known
- * Start at $LCS(m,n)$ and fill by row, column or diagonal



		0	1	2	3	4	5	6
		s	e	c	r	e	t	.
0	b		3	2	1	1	0	0
1	i		3	2	1	1	0	0
2	s		3	2	1	1	0	0
3	e		3	2	1	1	0	0
4	c		2	2	1	1	0	0
5	t		1	1	1	1	1	0
6	.	0	0	0	0	0	0	0

Subproblem dependency

- * $LCS(i,j)$ depends on $LCS(i+1,j+1)$ as well as $LCS(i+1,j)$ and $LCS(i,j+1)$
- * Dependencies for $LCS(m,n)$ are known
- * Start at $LCS(m,n)$ and fill by row, column or diagonal



		0	1	2	3	4	5	6
		s	e	c	r	e	t	.
0	b	4	3	2	1	1	0	0
1	i	4	3	2	1	1	0	0
2	s	4	3	2	1	1	0	0
3	e	3	3	2	1	1	0	0
4	c	2	2	2	1	1	0	0
5	t	1	1	1	1	1	1	0
6	.	0	0	0	0	0	0	0

Recovering the sequence

- * Trace back the path by which each entry was filled
- * Each diagonal step is an element of the LCS
 - * “sect”

		0	1	2	3	4	5	6
		s	e	c	r	e	t	.
0	b	4	3	2	1	1	0	0
1	i	4	3	2	1	1	0	0
2	s	4	3	2	1	1	0	0
3	e	3	3	2	1	1	0	0
4	c	2	2	2	1	1	0	0
5	t	1	1	1	1	1	1	0
6	.	0	0	0	0	0	0	0

LCS(u,v), DP

[illegible]

Complexity

- * Again $O(mn)$ using dynamic programming (or memoization)
- * Need to fill an $O(mn)$ size table
- * Each table entry takes constant time to compute