# CS3383 Unit 3 Lecture 1: Longest Common Subsequence 

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## Outline

Dynamic Programming
Longest Common Subsequence

## Ordering Subproblems

## Ordered Subproblems

In order to solve our problem in a single pass, we need

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- An ordered set of subproblems $L(i)$
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- In hotel problem, (topological) ordering by time
- Often, by a recurrence relation
- For example the Longest Common Subsequence problem.


## LCS definition

## $T, O U, R L A K E$ <br> Given two strings (sequences), find a maximum length <br> subsequence common to both?

## Recursive formula for the length

$$
\begin{aligned}
& c[i, j]:=|\operatorname{LCS}(x[0 \ldots i-1], y[0 \ldots j-1])| \\
& c[i, j]= \begin{cases}c[i-1, j-1]+1 & \text { if } x[i-1]=y[j-1] \\
\max (c[i, j-1], c[i-1, j]) & \text { otherwise }\end{cases}
\end{aligned}
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\end{aligned}
$$

$$
\begin{aligned}
& c[i-2, j-2] \quad c[i-2, j-1] \quad c[i-2, j] \\
& c[i-1, j-2] \longrightarrow c[i-i, j-1] \longrightarrow c[i-1, j] \\
& c[i, j-2] \longrightarrow c[i, j-1] \longrightarrow c[i, j]
\end{aligned}
$$

## Proof of recursion formula

$c[i, j]= \begin{cases}c[i-1, j-1]+1 & \text { if } x[i-1]=y[j-1] \\ \max (c[i, j-1], c[i-1, j]) & \text { otherwise }\end{cases}$

$$
x[i-1]=y[j-1]=\alpha
$$

If a common subsequence does not use $\alpha$ as its last element, it can be made longer.

## Proof of recursion formula

$$
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$$

$$
x[i-1] \neq y[j-1]
$$

- LCS does not use the "last" element of $x$, or
- LCS does not use the "last" element of $y$


## The trouble with recursion

- Although recursion is a useful step to a dynamic programming algorithm, naive recursion is often expensive because of repeated subproblems


## Recursive algorithm for LCS

$$
\begin{aligned}
& \operatorname{LCS}(x, y, i, j) \\
& \text { if } x[i]=y[j] \\
& \text { then } c[i, j] \leftarrow \operatorname{LCS}(x, y, i-1, j-1)+1 \\
& \text { else } c[i, j] \leftarrow \max \{\operatorname{LCS}(x, y, i-1, j), \\
& \operatorname{LCS}(x, y, i, j-1)\}
\end{aligned}
$$

## Recursive algorithm for LCS

$\operatorname{LCS}(x, y, i, j)$

$$
\text { if } x[i]=y[j]
$$

$$
\text { then } c[i, j] \leftarrow \operatorname{LCS}(x, y, i-1, j-1)+1
$$ else $c[i, j] \leftarrow \max \{\operatorname{LCS}(x, y, i-1, j)$, $\operatorname{LCS}(x, y, i, j-1)\}$

Worst-case: $x[i] \neq y[j]$, in which case the algorithm evaluates two subproblems, each with only one parameter decremented.
$m=3, n=4$ :


## Recursion tree



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

## Recursion tree



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

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

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> "small" number of distinct subproblems repeated many times.

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

## Memoization

## Recursive Version

function $\operatorname{RecuR}\left(p_{1}, \ldots p_{k}\right)$
:
return val
end function

## Memoization

Memoized version


## Recursive Version

function $\operatorname{RECUR}\left(p_{1}, \ldots p_{k}\right)$ :
return val
end function

## Memoized LCS

```
def lcs(c,x,y,i,j):
if (i < 1) or (j<1):
    return 0
    if c[i][j] == None:
    if x[i-1] == y[j-1]:
        c[i][j]=lcs(c,x,y,i-1,j-1)+1
    else:
\[
\begin{array}{r}
c[i][j]=\max (\operatorname{lcs}(c, x, y, i-1, j), \\
\\
\operatorname{lcs}(c, x, y, i, j-1))
\end{array}
\]
```

return c[i][j]

## Memoized LCS

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\begin{aligned}
& c[i][j]=\max (\operatorname{lcs}(c, x, y, i-1, j), \\
&\operatorname{lcs}(c, x, y, i, j-1))
\end{aligned}
\]
```

- $c[i, j]$ written at most once.
returned value written immediately
return c[i][j]


## Memoized LCS

```
def lcs(c,x,y,i,j):
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    return 0
if c[i][j] == None:
    if x[i-1] == y[j-1]:
        c[i][j]=lcs(c,x,y,i-1,j-1)+1
    else:
        c[i][j] = max(lcs(c,x,y,i-1,j),
```

    return c[i][j]
    
## Eliminating Recursion completely

$$
\begin{aligned}
& \text { def } \operatorname{lcs}(x, y): \\
& n=\operatorname{len}(x) ; m=l e n(y) \\
& c=[\quad[0 \text { for } j \text { in range }(m+1)] \\
& \text { for i in range }(n+1)] \\
& \text { for in range }(1, n+1): \\
& \text { for } j \text { in range }(1, m+1): \\
& \text { if } x[i-1]==y[j-1]: \\
& c[i][j]=c[i-1][j-1]+1 \\
& \text { else: } \\
& c[i][j]=\max (c[i-1][j], \\
& c[i][j-1])
\end{aligned}
$$

return c

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- Both versions add extra memory use to pure recursion.


## Comparing Memoized to Iterative LCS

$\Rightarrow$ Asymptotic time is the same

- Iterative version is typically faster/more robust in practice
- memoized version is easier to derive (even automatically) from the recursive version.
- Iterative version is easier to analyze
- Both versions add extra memory use to pure recursion.
- Memoization never solves unneeded subproblems.


## Reading back the sequence

```
def backtrace(c,x,y,i,j):
    if (i<1) or (j<1):
        return ""
    elif x[i-1] == y[j-1]:
        return backtrace(c,x,y,i-1,j-1)
        +x[i-1]
    elif (c[i][j-1] > c[i-1][j]):
        return backtrace(c,x,y,i,j-1)
    else:
        return backtrace(c,x,y,i-1,j)
```

$>$ What is the running time?

