

Lecture 26, 20 November 2025

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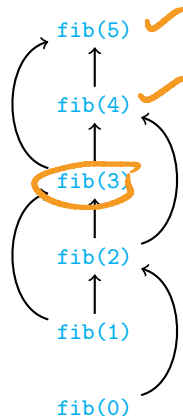
Programming and Data Structures with Python

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Dynamic programming

- Anticipate the structure of subproblems
 - Derive from inductive definition
 - Dependencies are acyclic
- Solve subproblems in appropriate order
 - Start with base cases — no dependencies
 - Evaluate a value after all its dependencies are available
 - Fill table iteratively
 - Never need to make a recursive call

Evaluating `fib(5)`



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", "trisection" —
"isect", length 5
 - "bisect", "secret" —
"sect", length 4
 - "director", "secretary" —
"ectr", "retr", length 4

Longest common subsequence

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- Given two strings, find the (length of the) longest common subsequence
 - "secret", "secretary" — "secret", length 6
 - "bisect", "trisection" — "isect", length 5
 - "bisect", "secret" — "sect", length 4
 - "director", "secretary" — "ectr", "retr", length 4
- LCS is the longest path connecting non-zero LCW entries, moving right/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 similar if their DNA has long common subsequences

- `diff` command in Unix/Linux

- Compares text files
- Find the longest matching subsequence of lines
- Each line of text is a “character”

		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

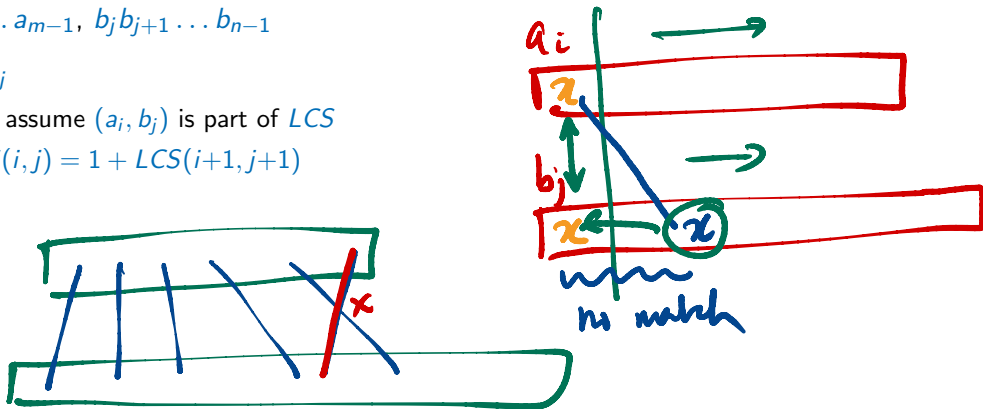
Inductive structure

- $u = a_0 a_1 \dots a_{m-1}$, $v = b_0 b_1 \dots b_{n-1}$

- $LCS(i, j)$ — length of longest common subsequence in
 $a_i a_{i+1} \dots a_{m-1}$, $b_j b_{j+1} \dots b_{n-1}$

Inductive structure

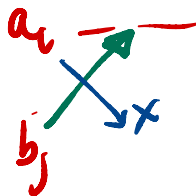
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- If $a_i = b_j$
 - Can assume (a_i, b_j) is part of LCS
 - $LCS(i, j) = 1 + LCS(i+1, j+1)$



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- If $a_i \neq b_j$, a_i and b_j cannot both belong to LCS
 - Which one should we drop?

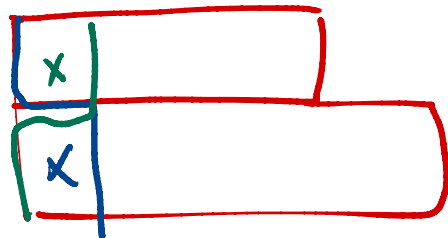
Handwritten diagram illustrating the inductive structure of the LCS problem. It shows two strings: $abc\ d$ (top) and $b\ c\ d$ (middle). A red circle highlights the 'b' in the first string and the 'b c d' in the second string. Below the second string, the string $a\ c\ d$ is written, with the 'a' and 'c' crossed out, leaving 'd'.



Inductive structure

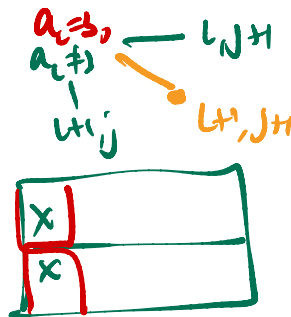
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 - $LCS(i, j) = \max(LCS(i, j+1), LCS(i+1, j))$

skip b_j skip a_i



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 - Which one should we drop?
 - $LCS(i, j) = \max(LCS(i, j+1), LCS(i+1, j))$
- Base cases as with LCW
 - $LCS(i, n) = 0$ for all $0 \leq i \leq m$
 - $LCS(m, j) = 0$ for all $0 \leq j \leq n$



Subproblem dependency

- Subproblems are $LCS(i, j)$, for $0 \leq i \leq m, 0 \leq j \leq n$

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- Table of $(m + 1) \cdot (n + 1)$ values

		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	•							

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- Subproblems are $LCS(i, j)$, for $0 \leq i \leq m, 0 \leq j \leq n$
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- $LCS(i, j)$ depends on $LCS(i+1, j+1)$, $LCS(i, j+1)$, $LCS(i+1, j)$,

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

Handwritten annotations on the table:

- A green box around the 't' in row 5, column 7.
- An orange box around the '1' in row 4, column 7.
- A green box around the '1' in row 5, column 7.
- A red oval around the '1' in row 4, column 7 and the '1' in row 5, column 7.
- A red arrow pointing to the '0' in row 6, column 8.
- Orange text "c ≠ t" next to row 4, column 3.
- Red text "max" next to row 5, column 8.
- Green text "+" next to row 6, column 8.

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		s	e	c	r	e	t	•
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1	i					2	1	0
2	s					2	1	0
3	e					2	1	0
4	c					1	1	0
5	t					1	1	0
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Reading off the solution

- Trace back the path by which each entry was filled

		0	1	2	3	4	5	6
		s	e	c	r	e	t	•
0	b	4	3	2	2	2	1	0
1	i	4	3	2	2	2	1	0
2	s	4	3	2	2	2	1	0
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Reading off the solution

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

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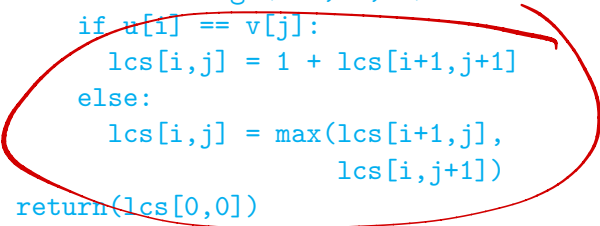
Implementation

```
def LCS(u,v):  
    import numpy as np  
    (m,n) = (len(u),len(v))  
    lcs = np.zeros((m+1,n+1))  
  
    for j in range(n-1,-1,-1):  
        for i in range(m-1,-1,-1):  
            if u[i] == v[j]:  
                lcs[i,j] = 1 + lcs[i+1,j+1]  
            else:  
                lcs[i,j] = max(lcs[i+1,j],  
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    return(lcs[0,0])
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```



Complexity

- Again $O(mn)$, using dynamic programming or memoization
 - Fill a table of size $O(mn)$
 - Each table entry takes constant time to compute

Document similarity

- “The students were able to appreciate the concept optimal substructure property and its use in designing algorithms”
- “The lecture taught the students to appreciate how the concept of optimal substructures can be used in designing algorithms”

Document similarity

- ~~“The students were able to appreciate the concept optimal substructure property and its use in designing algorithms”~~ Delete

- “The lecture taught the students to appreciate how the concept of optimal substructures can be used in designing algorithms” Insert

- Edit operations to transform documents

- Insert a character
- Delete a character
- Substitute one character by another Delete + Insert

Document similarity

- “The students were able to appreciate the concept optimal substructure property and its use in designing algorithms”
 - “The lecture taught the students to appreciate how the concept of optimal substructures can be used in designing algorithms”
 - Edit operations to transform documents
 - Insert a character
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- “The lecture taught the students ~~were able~~ to appreciate how the concept of optimal substructures ~~property~~ and ~~it~~ be used in designing algorithms”
 - insert, ~~delete~~, substitute

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- “The lecture taught the students ~~were able~~ to appreciate how the concept of optimal substructures ~~property~~ ~~and it~~ ~~base~~ used in designing algorithms”
- insert, ~~delete~~, ~~substitute~~

Edit distance

- Minimum number of edit operations needed
- In our example, 24 characters inserted, 18 ~~deleted~~, 2 ~~substituted~~
- Edit distance is at most 44

Edit distance

- Minimum number of editing operations needed to transform one document to the other
 - Insert a character
 - Delete a character
 - Substitute one character by another
- Also called Levenshtein distance
 - Vladimir Levenshtein, 1965
- Applications
 - Suggestions for spelling correction
 - Genetic similarity of species

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Edit distance and LCS

- Longest common subsequence of u , v
 - Minimum number of deletes needed to make them equal
- Deleting a letter from u is equivalent to inserting it in v

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 - Delete **b**, **i** in **bisect** and **r**, **e** in **secret**

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Edit distance and LCS

- Longest common subsequence of u , v
 - Minimum number of deletes needed to make them equal
- Deleting a letter from u is equivalent to inserting it in v
 - ~~b~~isect, secret — LCS is sect
 - Delete b , i in $bisect$ and r , e in $secret$
 - Delete b , i and then insert r , e in $bisect$
- From LCS, we can compute edit distance without substitution

Inductive structure for edit distance

■ $u = a_0a_1 \dots a_{m-1}, v = b_0b_1 \dots b_{n-1}$

Inductive structure for edit distance

- $u = a_0a_1 \dots a_{m-1}, v = b_0b_1 \dots b_{n-1}$

- Recall LCS

Inductive structure for edit distance

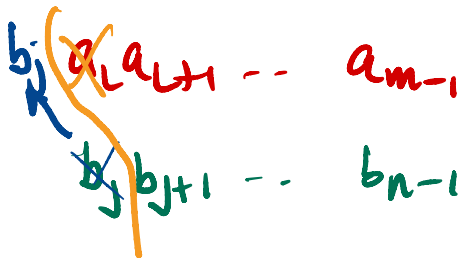
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- Edit distance — aim is to transform u to v



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- If $a_i = b_j$, nothing to be done

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- Edit distance — aim is to transform u to v
- If $a_i = b_j$, nothing to be done
- If $a_i \neq b_j$, best among

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- Edit distance — aim is to transform u to v
- If $a_i = b_j$, nothing to be done
- If $a_i \neq b_j$, best among
 - Substitute a_i by b_j

Inductive structure for edit distance

$$\blacksquare u = a_0a_1 \dots a_{m-1}, v = b_0b_1 \dots b_{n-1}$$

- Recall LCS
- $LCS(i,j)$ — length of longest common subsequence in $a_ia_{i+1} \dots a_{m-1}, b_jb_{j+1} \dots b_{n-1}$
- If $a_i = b_j$,
 $LCS(i,j) = 1 + LCS(i+1,j+1)$
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- If $a_i = b_j$, nothing to be done
- If $a_i \neq b_j$, best among
 - Substitute a_i by b_j
 - Delete a_i
 - Insert b_j before a_i

} all changes only on u

Inductive structure for edit distance

- $u = a_0a_1 \dots a_{m-1}$, $v = b_0b_1 \dots b_{n-1}$
- $ED(i, j)$ — edit distance for $a_ia_{i+1} \dots a_{m-1}$, $b_jb_{j+1} \dots b_{n-1}$
- If $a_i = b_j$, nothing to be done
- If $a_i \neq b_j$, best among
 - Substitute a_i by b_j
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- If $a_i \neq b_j$, best among

- Substitute a_i by b_j

- Delete a_i

- Insert b_j before a_i

- If $a_i = b_j$,

$$ED(i, j) = ED(i+1, j+1)$$

- If $a_i \neq b_j$,

$$ED(i, j) = 1 + \min \begin{bmatrix} ED(i+1, j+1), \\ ED(i+1, j), \\ ED(i, j+1) \end{bmatrix}$$

Subst
del
insert

Inductive structure for edit distance

- $u = a_0 a_1 \dots a_{m-1}$, $v = b_0 b_1 \dots b_{n-1}$

- $ED(i, j)$ — edit distance for $a_i a_{i+1} \dots a_{m-1}$, $b_j b_{j+1} \dots b_{n-1}$

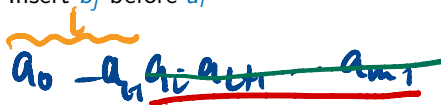
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- If $a_i \neq b_j$, best among

- Substitute a_i by b_j

- Delete a_i

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- If $a_i = b_j$,

$$ED(i, j) = ED(i+1, j+1)$$

- If $a_i \neq b_j$, $ED(i, j) = 1 + \min \begin{matrix} ED(i+1, j+1), \\ ED(i+1, j), \\ ED(i, j+1) \end{matrix}$

- Base cases

- $ED(m, n) = 0$

- $ED(i, n) = m - i$ for all $0 \leq i \leq m$
Delete $a_i a_{i+1} \dots a_{m-1}$ from u

- $ED(m, j) = n - j$ for all $0 \leq j \leq n$
Insert $b_j b_{j+1} \dots b_{n-1}$ into u

Subproblem dependency

- Subproblems are $ED(i, j)$, for
 $0 \leq i \leq m, 0 \leq j \leq n$

Subproblem dependency

- Subproblems are $ED(i, j)$, for $0 \leq i \leq m, 0 \leq j \leq n$
- Table of $(m + 1) \cdot (n + 1)$ values

		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	•							

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		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	•							

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

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

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

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

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

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

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		0	1	2	3	4	5	6
		s	e	c	r	e	t	•
0	b	4	4	4	4	4	5	6
1	i	3	4	3	3	3	4	5
2	s	2	3	3	2	2	3	4
3	e	3	2	3	2	1	2	3
4	c	4	3	2	2	1	1	2
5	t	5	4	3	2	1	0	1
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Reading off the solution

- Transform **bisect** to **secret**

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

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Reading off the solution

- Transform **bisect** to **secret**
- Delete **b**

		0	1	2	3	4	5	6
		s	e	c	r	e	t	•
0	b	4	4	4	4	4	5	6
1	i	3	4	3	3	3	4	5
2	s	2	3	3	2	2	3	4
3	e	3	2	3	2	1	2	3
4	c	4	3	2	2	1	1	2
5	t	5	4	3	2	1	0	1
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Reading off the solution

- Transform **bisect** to **secret**
- Delete **b**, Delete **i**

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

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Reading off the solution

- Transform **bisect** to **secret**
- Delete **b** , Delete **i** , Insert **r**

		0	1	2	3	4	5	6
		s	e	c	r	e	t	•
0	b	4	4	4	4	4	5	6
1	i	3	4	3	3	3	4	5
2	s	2	3	3	2	2	3	4
3	e	3	2	3	2	1	2	3
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5	t	5	4	3	2	1	0	1
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Reading off the solution

- Transform **bisect** to **secret**
- Delete **b** , Delete **i** , Insert **r** , Insert **e**

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

Implementation

```
def ED(u,v):
    import numpy as np
    (m,n) = (len(u),len(v))
    ed = np.zeros((m+1,n+1))

    for i in range(m-1,-1,-1):
        ed[i,n] = m-i
    for j in range(n-1,-1,-1):
        ed[m,j] = n-j

    for j in range(n-1,-1,-1):
        for i in range(m-1,-1,-1):
            if u[i] == v[j]:
                ed[i,j] = ed[i+1,j+1]
            else:
                ed[i,j] = 1 + min(ed[i+1,j+1],
                                   ed[i,j+1],
                                   ed[i+1,j])

    return(ed[0,0])
```

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            if u[i] == v[j]:
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                ed[i,j] = 1 + min(ed[i+1,j+1],
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```

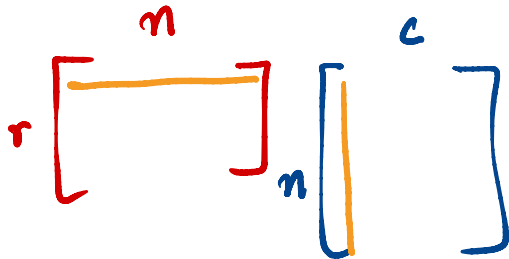
Complexity

- Again $O(mn)$, using dynamic programming or memoization
 - Fill a table of size $O(mn)$
 - Each table entry takes constant time to compute

Multiplying matrices

- Multiply matrices A, B

- $AB[i, j] = \sum_{k=0}^{n-1} A[i, k]B[k, j]$



$$(r_1 \times r_2) \times r_3$$

$r \cdot c$ entries
 k time to
compute

Multiplying matrices

- Multiply matrices A , B

- $AB[i,j] = \sum_{k=0}^{n-1} A[i,k]B[k,j]$

- Dimensions must be compatible

- $A : m \times n$, $B : n \times p$

- $AB : m \times p$

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- $A : m \times n$, $B : n \times p$

- $AB : m \times p$

- Computing each entry in AB is $O(n)$

- Overall, computing AB is $O(mnp)$

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- $ABC = (AB)C = A(BC)$

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- Bracketing does not change answer

- ... but can affect the complexity!

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- ... but can affect the complexity!

- Let $A : 1 \times 100$, $B : 100 \times 1$, $C : 1 \times 100$

Multiplying matrices

- Multiply matrices A , B

- $AB[i,j] = \sum_{k=0}^{n-1} A[i,k]B[k,j]$

- Dimensions must be compatible

- $A : m \times n$, $B : n \times p$

- $AB : m \times p$

- Computing each entry in AB is $O(n)$

- Overall, computing AB is $O(mnp)$

- Matrix multiplication is associative

- $ABC = (AB)C = A(BC)$

- Bracketing does not change answer

- ... but can affect the complexity!

- Let $A : 1 \times 100$, $B : 100 \times 1$, $C : 1 \times 100$

- Computing $A(BC)$

- $BC : 100 \times 100$, takes

- $100 \cdot 1 \cdot 100 = 10000$ steps to compute

- $A(BC) : 1 \times 100$, takes

- $1 \cdot 100 \cdot 100 = 10000$ steps to compute

Multiplying matrices

- Multiply matrices A , B

- $$AB[i,j] = \sum_{k=0}^{n-1} A[i,k]B[k,j]$$

- Dimensions must be compatible

- $A : m \times n$, $B : n \times p$

- $AB : m \times p$

- Computing each entry in AB is $O(n)$

- Overall, computing AB is $O(mnp)$

- Matrix multiplication is associative

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- Let $A : 1 \times 100$, $B : 100 \times 1$, $C : 1 \times 100$

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- $A(BC) : 1 \times 100$, takes

- $1 \cdot 100 \cdot 100 = 10000$ steps to compute

- Computing $(AB)C$

- $AB : 1 \times 1$, takes

- $1 \cdot 100 \cdot 1 = 100$ steps to compute

- $(AB)C : 1 \times 100$, takes

- $1 \cdot 1 \cdot 100 = 100$ steps to compute

Multiplying matrices

- Multiply matrices A , B

- $AB[i,j] = \sum_{k=0}^{n-1} A[i,k]B[k,j]$

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- $A : m \times n$, $B : n \times p$

- $AB : m \times p$

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- Let $A : 1 \times 100$, $B : 100 \times 1$, $C : 1 \times 100$

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- $AB : 1 \times 1$, takes

- $1 \cdot 100 \cdot 1 = 100$ steps to compute

- $(AB)C : 1 \times 100$, takes

- $1 \cdot 1 \cdot 100 = 100$ steps to compute

- 20000 steps vs 200 steps!

Multiplying matrices

- Multiply matrices A , B

- $AB[i,j] = \sum_{k=0}^{n-1} A[i,k]B[k,j]$

- Dimensions must be compatible

- $A : m \times n$, $B : n \times p$

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- Overall, computing AB is $O(mnp)$

- Matrix multiplication is associative

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- ... but can affect the complexity!

- Given n matrices $M_0 : r_0 \times c_0$,

- $M_1 : r_1 \times c_1, \dots, M_{n-1} : r_{n-1} \times c_{n-1}$

- Dimensions match: $r_j = c_{j-1}$, $0 < j < n$

- Product $M_0 \cdot M_1 \cdots M_{n-1}$ can be computed

$(M_0 M_1) M_2 (M_3 M_4)$

Multiplying matrices

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- $AB[i,j] = \sum_{k=0}^{n-1} A[i,k]B[k,j]$

- Dimensions must be compatible

- $A : m \times n$, $B : n \times p$

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- Computing each entry in AB is $O(n)$

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- Bracketing does not change answer

- ... but can affect the complexity!

- Given n matrices $M_0 : r_0 \times c_0$,

- $M_1 : r_1 \times c_1, \dots, M_{n-1} : r_{n-1} \times c_{n-1}$

- Dimensions match: $r_j = c_{j-1}$, $0 < j < n$

- Product $M_0 \cdot M_1 \cdots M_{n-1}$ can be computed

- Find an optimal order to compute the product

- Multiply two matrices at a time

- Bracket the expression optimally

Inductive structure

- Final step combines two subproducts
 $(M_0 \cdot M_1 \cdots M_{k-1}) \cdot (M_k \cdot M_{k+1} \cdots M_{n-1})$
for some $0 < k < n$

$$M_0 | M_1 | M_2 \cdots M_{n-2} | M_{n-1}$$

Inductive structure

- Final step combines two subproducts
 $(M_0 \cdot M_1 \cdots M_{k-1}) \cdot (M_k \cdot M_{k+1} \cdots M_{n-1})$
for some $0 < k < n$
- First factor is $r_0 \times c_{k-1}$, second is
 $r_k \times c_{n-1}$, where $r_k = c_{k-1}$

$$r_0 \times c_{k-1} = r_k \times c_{n-1}$$

Inductive structure

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- $C(0, n-1) =$
 $C(0, k-1) + C(k, n-1) + r_0 r_k c_{n-1}$

Inductive structure

- Final step combines two subproducts
 $(M_0 \cdot M_1 \cdots M_{k-1}) \cdot (M_k \cdot M_{k+1} \cdots M_{n-1})$
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- Which k should we choose?
- First factor is $r_0 \times c_{k-1}$, second is
 $r_k \times c_{n-1}$, where $r_k = c_{k-1}$
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- Which k should we choose?
 - Try all and choose the minimum!

- Subproblems?

- $M_0 \cdot M_1 \cdots M_{k-1}$ would decompose
as $(M_0 \cdots M_{j-1}) \cdot (M_j \cdots M_{k-1})$
- Generic subproblem is
 $M_j \cdot M_{j+1} \cdots M_k$

Handwritten diagram illustrating the decomposition of matrix chain multiplication. A red cross splits the sequence $M_0 \cdots M_{k-1}$ and $M_k \cdots M_{n-1}$ into two subproblems: $M_0 \cdots M_{j-1}$ and $M_j \cdots M_{k-1}$ on the left, and $M_k \cdots M_{j+1}$ and $M_{j+1} \cdots M_{n-1}$ on the right.

Inductive structure

- Final step combines two subproducts
 $(M_0 \cdot M_1 \cdots M_{k-1}) \cdot (M_k \cdot M_{k+1} \cdots M_{n-1})$
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- Which k should we choose?
 - Try all and choose the minimum!
- Subproblems?
 - $M_0 \cdot M_1 \cdots M_{k-1}$ would decompose
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 - Generic subproblem is
 $M_j \cdot M_{j+1} \cdots M_k$
- $C(j, k) =$
 $\min_{j < \ell \leq k} [C(j, \ell-1) + C(\ell, k) + \underline{r_j r_\ell c_k}]$

last
step

Inductive structure

- Final step combines two subproducts
 $(M_0 \cdot M_1 \cdots M_{k-1}) \cdot (M_k \cdot M_{k+1} \cdots M_{n-1})$
for some $0 < k < n$
- First factor is $r_0 \times c_{k-1}$, second is
 $r_k \times c_{n-1}$, where $r_k = c_{k-1}$
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- $C(j, k) =$
 $\min_{j < \ell \leq k} [C(j, \ell-1) + C(\ell, k) + r_j r_\ell c_k]$
- Base case: $C(j, j) = 0$ for $0 \leq j < n$

$$M_0 \cdot [M_1 \dots M_{n-1}]$$

$$C(0,0) \quad \vee \quad C(1,n)$$

$$0$$

Subproblem dependency

- Compute $C(i,j)$, $0 \leq i,j < n$

	0	...	i	...	...	j	...	$n-1$
0								
...								
i								
...								
...								
j								
...								
$n-1$								

Subproblem dependency

- Compute $C(i,j)$, $0 \leq i,j < n$
 - Only for $i \leq j$
 - Entries above main diagonal

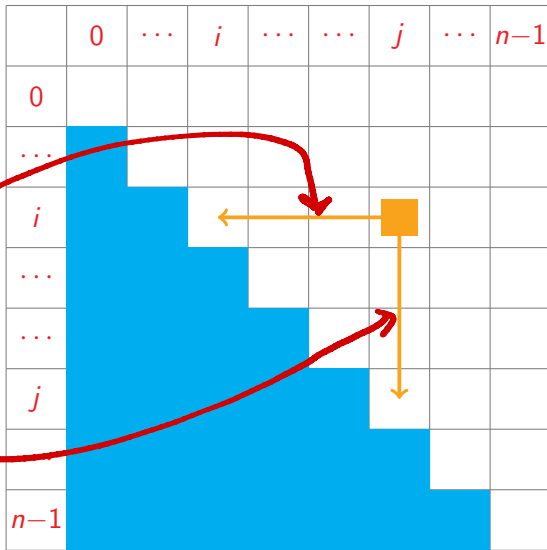
A grid representing subproblems $C(i,j)$ for $0 \leq i, j < n$. The columns are indexed by j (0, ..., i , ..., j , ..., $n-1$) and the rows by i (0, ..., i , ..., j , ..., $n-1$). The lower triangular part of the grid (where $i > j$) is filled with blue, indicating that these subproblems are already computed. The upper triangular part (where $i \leq j$) is white. An orange circle highlights the cell at row i , column i . An orange arrow points from this cell to the right, indicating the sequence of computations for a fixed i as j increases.

	0	...	i	...	...	j	...	$n-1$
0								
...								
i								
...								
...								
j								
...								
$n-1$								

Subproblem dependency

- Compute $C(i, j)$, $0 \leq i, j < n$
 - Only for $i \leq j$
 - Entries above main diagonal
- $C(i, j)$ depends on $C(i, k-1)$, $C(k, j)$ for every $i < k \leq j$

$$C(i, j) = C(i, k) + C(k+1, j)$$



Subproblem dependency

- Compute $C(i, j)$, $0 \leq i, j < n$
 - Only for $i \leq j$
 - Entries above main diagonal
- $C(i, j)$ depends on $C(i, k-1)$, $C(k, j)$ for every $i < k \leq j$

	0	...	i	...	...	j	...	$n-1$
0								
...								
i								
...								
...								
j								
...								
$n-1$								

Subproblem dependency

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	0	...	i	...	...	j	...	$n-1$
0								
...								
i								
...								
...								
j								
...								
$n-1$								

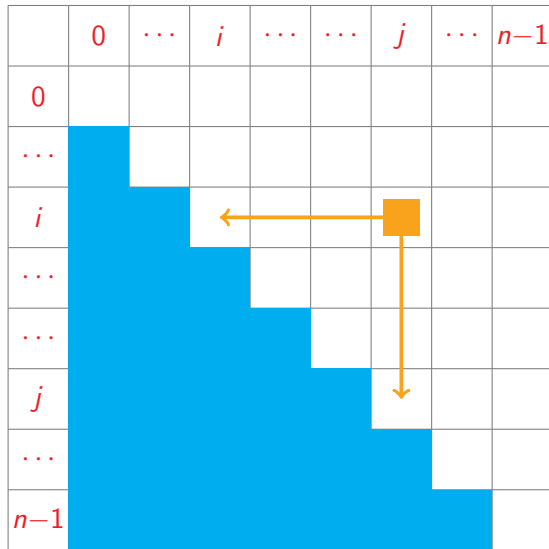
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	0	...	i	...	...	j	...	$n-1$
0								
...								
i			✓	✓	■	■		
...						✓		
...						✓		
j						■		
...								
$n-1$								

Subproblem dependency

- Compute $C(i, j)$, $0 \leq i, j < n$
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 - $O(n)$ dependencies per entry, unlike LCW, LCS and ED



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- Diagonal entries are base case

	0	...	i	...	...	j	...	$n-1$
0								
...								
i								
...								
...								
j								
...								
$n-1$								

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- Diagonal entries are base case
- Fill matrix by diagonal, from main diagonal

	0	...	i	...	...	j	...	$n-1$
0								
...								
i								
...								
...								
j								
...								
$n-1$								

Subproblem dependency

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	0	...	i	...	...	j	...	$n-1$
0	■	■	■					
...		■	■	■				
i			■	■	■			
...				■	■	■		
...						■	■	■
j						■	■	■
...							■	■
$n-1$								■

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	0	...	i	...	...	j	...	$n-1$
0	■	■	■	■				
...		■	■	■	■			
i			■	■	■	■		
...				■	■	■	■	
...					■	■	■	■
j						■	■	■
...							■	■
$n-1$								■

Subproblem dependency

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	0	...	i	...	...	j	...	$n-1$
0								
...								
i								
...								
...								
j								
...								
$n-1$								

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	0	...	i	...	...	j	...	$n-1$
0								
...								
i								
...								
...								
j								
...								
$n-1$								

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	0	...	i	...	...	j	...	$n-1$
0								
...								
i								
...								
...								
j								
...								
$n-1$								

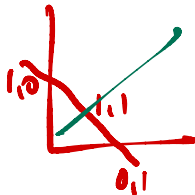
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	0	...	i	...	...	j	...	$n-1$
0								
...								
i								
...								
...								
j								
...								
$n-1$								

Implementation

```
def C(dim):  
    # dim: dimension matrix,  
    #     entries are pairs (r_i,c_i)  
    import numpy as np  
    n = dim.shape[0]  
    C = np.zeros((n,n))  
    for i in range(n):  
        C[i,i] = 0  
    for diff in range(1,n):  
        for i in range(0,n-diff):  
            j = i + diff  
            C[i,j] = C[i,i] +  
                    C[i+1,j] +  
                    dim[i][0]*dim[i+1][0]*dim[j][1]  
            for k in range(i+1,j+1):  
                C[i,j] = min(C[i,j],  
                             C[i,k-1] + C[k,j] +  
                             dim[i][0]*dim[k][0]*dim[j][1])  
    return(C[0,n-1])
```



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            C[i,j] = C[i,i] +
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            for k in range(i+1,j+1):
                C[i,j] = min(C[i,j],
                            C[i,k-1] + C[k,j] +
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```

Complexity

- We have to fill a table of size $O(n^2)$
- Filling each entry takes $O(n)$
- Overall, $O(n^3)$

Brute force is exponential

