

# Lecture 24, 21 November 2024

Madhavan Mukund

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

Programming and Data Structures with Python

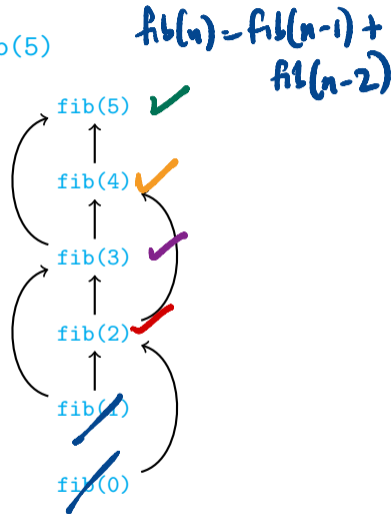
Lecture 24, 21 Nov 2024

# 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  $\text{fib}(5)$

$i$	$\text{fib}(i)$
0	0
1	1
2	1
3	2
4	3
5	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", "trisect" —  
"isect", length 5
  - "bisect", "secret" —  
"sect", length 4
  - "director", "secretary" —  
"ectr", "retr", length 4

# 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
- 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”

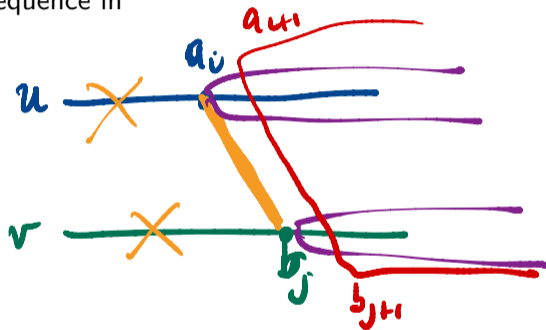
		0	1	2	3	4	5	6
		s	e	c	r	e	t	•
0	b	0	0	0	0	0	0	0
1	i	0	0	0	0	0	0	0
2	s	3	0	0	0	0	0	0
3	e	0	2	0	0	1	0	0
4	c	0	0	1	0	0	0	0
5	t	0	0	0	0	0	1	0
6	•	0	0	0	0	0	0	0

# Inductive structure

- $u = a_0a_1 \dots a_{m-1}$ ,  $v = b_0b_1 \dots b_{n-1}$
- $LCS(i, j)$  — length of longest common subsequence in  $a_ia_{i+1} \dots a_{m-1}$ ,  $b_jb_{j+1} \dots b_{n-1}$

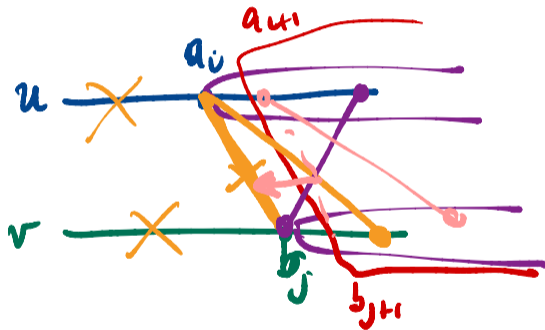
# Inductive structure

- $u = a_0a_1 \dots a_{m-1}, v = b_0b_1 \dots b_{n-1}$
- $LCS(i, j)$  — length of longest common subsequence in  $a_ia_{i+1} \dots a_{m-1}, b_jb_{j+1} \dots b_{n-1}$
- If  $a_i = b_j$ 
  - Can assume  $(a_i, b_j)$  is part of  $LCS$
  - $LCS(i, j) = 1 + LCS(i+1, j+1)$



# Inductive structure

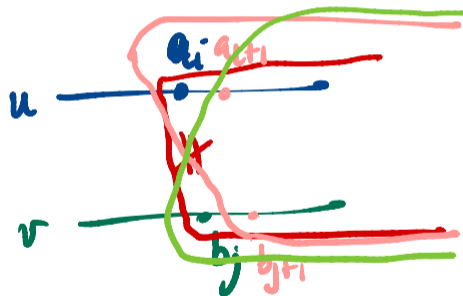
- $u = a_0a_1 \dots a_{m-1}, v = b_0b_1 \dots b_{n-1}$
- $LCS(i, j)$  — length of longest common subsequence in  $a_ia_{i+1} \dots a_{m-1}, b_jb_{j+1} \dots b_{n-1}$
- If  $a_i = b_j$ 
  - Can assume  $(a_i, b_j)$  is part of  $LCS$
  - $LCS(i, j) = 1 + LCS(i+1, j+1)$  ✓





# Inductive structure

- $u = a_0a_1 \dots a_{m-1}$ ,  $v = b_0b_1 \dots b_{n-1}$
- $LCS(i, j)$  — length of longest common subsequence in  $a_ia_{i+1} \dots a_{m-1}$ ,  $b_jb_{j+1} \dots b_{n-1}$
- If  $a_i = b_j$ 
  - Can assume  $(a_i, b_j)$  is part of  $LCS$
  - $LCS(i, j) = 1 + LCS(i+1, j+1)$
- If  $a_i \neq b_j$ ,  $a_i$  and  $b_j$  cannot both belong to  $LCS$ 
  - Which one should we drop?



# Inductive structure

- $u = a_0a_1 \dots a_{m-1}$ ,  $v = b_0b_1 \dots b_{n-1}$
- $LCS(i, j)$  — length of longest common subsequence in  $a_ia_{i+1} \dots a_{m-1}$ ,  $b_jb_{j+1} \dots b_{n-1}$
- If  $a_i = b_j$ 
  - Can assume  $(a_i, b_j)$  is part of  $LCS$
  - $LCS(i, j) = 1 + LCS(i+1, j+1)$
- If  $a_i \neq b_j$ ,  $a_i$  and  $b_j$  cannot both belong to  $LCS$ 
  - Which one should we drop?
  - $LCS(i, j) = \max(LCS(i, j+1), LCS(i+1, j))$

# Inductive structure

- $u = a_0a_1 \dots a_{m-1}$ ,  $v = b_0b_1 \dots b_{n-1}$
- $LCS(i, j)$  — length of longest common subsequence in  $a_i a_{i+1} \dots a_{m-1}$ ,  $b_j b_{j+1} \dots b_{n-1}$
- If  $a_i = b_j$ 
  - Can assume  $(a_i, b_j)$  is part of  $LCS$
  - $LCS(i, j) = 1 + LCS(i+1, j+1)$
- If  $a_i \neq b_j$ ,  $a_i$  and  $b_j$  cannot both belong to  $LCS$ 
  - 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  $0 \leq i \leq m, 0 \leq j \leq n$

# Subproblem dependency

- Subproblems are  $LCS(i, j)$ , 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	•							

# Subproblem dependency

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

		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

- Subproblems are  $LCS(i, j)$ , for  $0 \leq i \leq m, 0 \leq j \leq n$
- Table of  $(m + 1) \cdot (n + 1)$  values
- $LCS(i, j)$  depends on  $LCS(i+1, j+1)$ ,  $LCS(i, j+1)$ ,  $LCS(i+1, j)$ ,
- No dependency for  $LCS(m, n)$  — start at bottom right 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

# Subproblem dependency

- Subproblems are  $LCS(i, j)$ , for  $0 \leq i \leq m, 0 \leq j \leq n$
- Table of  $(m + 1) \cdot (n + 1)$  values
- $LCS(i, j)$  depends on  $LCS(i+1, j+1)$ ,  $LCS(i, j+1)$ ,  $LCS(i+1, j)$ ,
- No dependency for  $LCS(m, n)$  — start at bottom right and fill by row, column or diagonal

		0	1	2	3	4	5	6
		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



# Subproblem dependency

- Subproblems are  $LCS(i, j)$ , for  $0 \leq i \leq m, 0 \leq j \leq n$
- Table of  $(m + 1) \cdot (n + 1)$  values
- $LCS(i, j)$  depends on  $LCS(i+1, j+1)$ ,  $LCS(i, j+1)$ ,  $LCS(i+1, j)$ ,
- No dependency for  $LCS(m, n)$  — start at bottom right and fill by row, column or diagonal

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

# Subproblem dependency

- Subproblems are  $LCS(i, j)$ , for  $0 \leq i \leq m, 0 \leq j \leq n$
- Table of  $(m + 1) \cdot (n + 1)$  values
- $LCS(i, j)$  depends on  $LCS(i+1, j+1)$ ,  $LCS(i, j+1), LCS(i+1, j)$ ,
- No dependency for  $LCS(m, n)$  — start at bottom right and fill by row, column or diagonal

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

# Subproblem dependency

- Subproblems are  $LCS(i, j)$ , for  $0 \leq i \leq m, 0 \leq j \leq n$
- Table of  $(m + 1) \cdot (n + 1)$  values
- $LCS(i, j)$  depends on  $LCS(i+1, j+1)$ ,  $LCS(i, j+1), LCS(i+1, j)$ ,
- No dependency for  $LCS(m, n)$  — start at bottom right and fill by row, column or diagonal

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

# Subproblem dependency

- Subproblems are  $LCS(i, j)$ , for  $0 \leq i \leq m, 0 \leq j \leq n$
- Table of  $(m + 1) \cdot (n + 1)$  values
- $LCS(i, j)$  depends on  $LCS(i+1, j+1)$ ,  $LCS(i, j+1), LCS(i+1, j)$ ,
- No dependency for  $LCS(m, n)$  — start at bottom right and fill by row, column or diagonal

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

# Subproblem dependency

- Subproblems are  $LCS(i, j)$ , for  $0 \leq i \leq m, 0 \leq j \leq n$
- Table of  $(m + 1) \cdot (n + 1)$  values
- $LCS(i, j)$  depends on  $LCS(i+1, j+1)$ ,  $LCS(i, j+1)$ ,  $LCS(i+1, j)$ ,
- No dependency for  $LCS(m, n)$  — start at bottom right and fill by row, column or diagonal

		0	1	2	3	4	5	6
			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
5	t	1	1	1	1	1	1	0
6	•	0	0	0	0	0	0	0

# Subproblem dependency

- Subproblems are  $LCS(i, j)$ , for  $0 \leq i \leq m, 0 \leq j \leq n$
- Table of  $(m + 1) \cdot (n + 1)$  values
- $LCS(i, j)$  depends on  $LCS(i+1, j+1)$ ,  $LCS(i, j+1)$ ,  $LCS(i+1, j)$ ,
- No dependency for  $LCS(m, n)$  — start at bottom right and fill by row, column or diagonal

## 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
3	e	3	3	2	2	2	1	0
4	c	2	2	2	1	1	1	0
5	t	1	1	1	1	1	1	0
6	•	0	0	0	0	0	0	0

# Subproblem dependency

- Subproblems are  $LCS(i, j)$ , for  $0 \leq i \leq m, 0 \leq j \leq n$
- Table of  $(m + 1) \cdot (n + 1)$  values
- $LCS(i, j)$  depends on  $LCS(i+1, j+1)$ ,  $LCS(i, j+1)$ ,  $LCS(i+1, j)$ ,
- No dependency for  $LCS(m, n)$  — start at bottom right and fill by row, column or diagonal

## 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 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
5	t	1	1	1	1	1	1	0
6	•	0	0	0	0	0	0	0

# 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],  
                               lcs[i,j+1])  
  
    return(lcs[0,0])
```



```
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],
                              lcs[i,j+1])

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

## Complexity

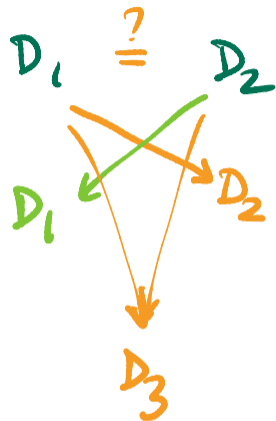
- Again  $O(mn)$ , using dynamic programming or memoization
  - Fill a table of size  $O(mn)$
  - Each table entry takes constant time to compute

# 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”
- “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
  - Delete a character
  - Substitute one character by another



# 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
    - Delete a character
    - Substitute one character by another
- “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

# 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
  - Delete a character
  - Substitute one character by another

- “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

## 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

- 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

## 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  $v$

# 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

## 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  $v$ 
  - `bisect`, `secret` — LCS is `sect`



# 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

## 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, ~~se~~cret — LCS is sect
  - Delete **b**, **i** in **bisect** and **r**, **e** in **secret**

# 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

## 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  $v$ 
  - `bisect`, `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

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

- Recall LCS
- $LCS(i, j)$  — length of longest common subsequence in  $a_i a_{i+1} \dots a_{m-1}, b_j b_{j+1} \dots b_{n-1}$
- If  $a_i = b_j$ ,  
 $LCS(i, j) = 1 + LCS(i+1, j+1)$
- If  $a_i \neq b_j$ ,  
 $LCS(i, j) = \max[ LCS(i, j+1), LCS(i+1, j) ]$

# Inductive structure for edit distance

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

- Recall LCS

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

- If  $a_i = b_j$ ,  
 $LCS(i, j) = 1 + LCS(i+1, j+1)$

- If  $a_i \neq b_j$ ,  
 $LCS(i, j) = \max[ LCS(i, j+1), LCS(i+1, j) ]$

- Edit distance — aim is to transform  $u$  to  $v$

# Inductive structure for edit distance

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

ED( $i, j$ )

- Recall LCS
- $LCS(i, j)$  — length of longest common subsequence in  $a_i a_{i+1} \dots a_{m-1}, b_j b_{j+1} \dots b_{n-1}$
- If  $a_i = b_j$ ,  
 $LCS(i, j) = 1 + LCS(i+1, j+1)$
- If  $a_i \neq b_j$ ,  
 $LCS(i, j) = \max[ LCS(i, j+1), LCS(i+1, j) ]$
- Edit distance — aim is to transform  $u$  to  $v$
- If  $a_i = b_j$ , nothing to be done

# Inductive structure for edit distance

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

- Recall LCS

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

- If  $a_i = b_j$ ,

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

- If  $a_i \neq b_j$ ,

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

- Edit distance — aim is to transform  $u$  to  $v$

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

$i+1, j+1$

- If  $a_i \neq b_j$ , best among



# 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  $a_i a_{i+1} \dots a_{m-1}, b_j b_{j+1} \dots b_{n-1}$
- If  $a_i = b_j$ ,  
 $LCS(i, j) = 1 + LCS(i+1, j+1)$
- If  $a_i \neq b_j$ ,  
 $LCS(i, j) = \max[ LCS(i, j+1), LCS(i+1, j) ]$
- 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  $a_i a_{i+1} \dots a_{m-1}, b_j b_{j+1} \dots b_{n-1}$

- If  $a_i = b_j$ ,  
 $LCS(i, j) = 1 + LCS(i+1, j+1)$

- If  $a_i \neq b_j$ ,  
 $LCS(i, j) = \max[ LCS(i, j+1), LCS(i+1, j) ]$

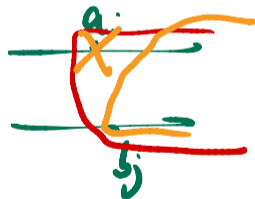
- Edit distance — aim is to transform  $u$  to  $v$

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

- If  $a_i \neq b_j$ , best among

- Substitute  $a_i$  by  $b_j$

- Delete  $a_i$



# 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  $a_i a_{i+1} \dots a_{m-1}, b_j b_{j+1} \dots b_{n-1}$

- If  $a_i = b_j$ ,

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

- If  $a_i \neq b_j$ ,

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

- 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  $b_j$
- Delete  $a_i$
- Insert  $b_j$  before  $a_i$



# 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  $a_i a_{i+1} \dots a_{m-1}$ ,  $b_j b_{j+1} \dots b_{n-1}$
- If  $a_i = b_j$ , nothing to be done
- If  $a_i \neq b_j$ , best among
  - Substitute  $a_i$  by  $b_j$
  - Delete  $a_i$
  - Insert  $b_j$  before  $a_i$

# 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  $b_j$

■ Delete  $a_i$

■ Insert  $b_j$  before  $a_i$

■ If  $a_i = b_j$ ,

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

■ If  $a_i \neq b_j$ ,

$$ED(i, j) = 1 + \min \left[ \begin{array}{l} ED(i+1, j+1), \\ ED(i+1, j), \\ ED(i, j+1) \end{array} \right]$$

delete  $a_i$

insert  $b_j$  before  $a_i$

substitute

# 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  $b_j$
  - Delete  $a_i$
  - Insert  $b_j$  before  $a_i$
- If  $a_i = b_j$ ,  
 $ED(i, j) = ED(i+1, j+1)$
- If  $a_i \neq b_j$ ,  
 $ED(i, j) = 1 + \min[ ED(i+1, j+1), ED(i+1, j), ED(i, j+1) ]$
- Base cases
  - $ED(m, n) = 0$
  - $ED(i, n) = m - i$  for all  $0 \leq i \leq m$   
Delete  $a_ia_{i+1} \dots a_{m-1}$  from  $u$
  - $ED(m, j) = n - j$  for all  $0 \leq j \leq n$   
Insert  $b_jb_{j+1} \dots b_{n-1}$  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	•							



# 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
- Like LCS,  $ED(i, j)$  depends on  $ED(i+1, j+1)$ ,  $ED(i, j+1)$ ,  $ED(i+1, j)$

		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

- Subproblems are  $ED(i, j)$ , for  $0 \leq i \leq m, 0 \leq j \leq n$
- Table of  $(m + 1) \cdot (n + 1)$  values
- Like LCS,  $ED(i, j)$  depends on  $ED(i+1, j+1)$ ,  $ED(i, j+1)$ ,  $ED(i+1, j)$
- No dependency for  $ED(m, n)$  — start at bottom right and fill by row, column or diagonal

		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		6	5	4	3	2	1	0

# 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
- Like LCS,  $ED(i, j)$  depends on  $ED(i+1, j+1)$ ,  $ED(i, j+1)$ ,  $ED(i+1, j)$
- No dependency for  $ED(m, n)$  — start at bottom right and fill by row, column or diagonal

		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

Handwritten annotations on the table:

- A green circle around the cell (2, 5) containing 't'.
- A green circle around the cell (5, 2) containing 's'.
- A red circle around the cell (5, 0) containing 't'.
- A red circle around the cell (6, 6) containing '0'.
- A red arrow pointing from the cell (5, 0) to the cell (6, 6).
- A green bracket around the cells (2, 5), (3, 5), (4, 5), (5, 5), (6, 5) with the label "i+3".
- The word "Min" is written in green next to the cell (3, 5).

# 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
- Like LCS,  $ED(i, j)$  depends on  $ED(i+1, j+1)$ ,  $ED(i, j+1)$ ,  $ED(i+1, j)$
- No dependency for  $ED(m, n)$  — start at bottom right and fill by row, column or diagonal

		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

# 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
- Like LCS,  $ED(i, j)$  depends on  $ED(i+1, j+1)$ ,  $ED(i, j+1)$ ,  $ED(i+1, j)$
- No dependency for  $ED(m, n)$  — start at bottom right and fill by row, column or diagonal

		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

# 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
- Like LCS,  $ED(i, j)$  depends on  $ED(i+1, j+1)$ ,  $ED(i, j+1)$ ,  $ED(i+1, j)$
- No dependency for  $ED(m, n)$  — start at bottom right and fill by row, column or diagonal

		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

# 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
- Like LCS,  $ED(i, j)$  depends on  $ED(i+1, j+1)$ ,  $ED(i, j+1)$ ,  $ED(i+1, j)$
- No dependency for  $ED(m, n)$  — start at bottom right and fill by row, column or diagonal

		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

# 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
- Like LCS,  $ED(i, j)$  depends on  $ED(i+1, j+1)$ ,  $ED(i, j+1)$ ,  $ED(i+1, j)$
- No dependency for  $ED(m, n)$  — start at bottom right and fill by row, column or diagonal

		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



# 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
- Like LCS,  $ED(i, j)$  depends on  $ED(i+1, j+1)$ ,  $ED(i, j+1)$ ,  $ED(i+1, j)$
- No dependency for  $ED(m, n)$  — start at bottom right and fill by row, column or diagonal

## 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

# 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
- Like LCS,  $ED(i, j)$  depends on  $ED(i+1, j+1)$ ,  $ED(i, j+1)$ ,  $ED(i+1, j)$
- No dependency for  $ED(m, n)$  — start at bottom right and fill by row, column or diagonal

## 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
6	•	6	5	4	3	2	1	0



# 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
- Like LCS,  $ED(i, j)$  depends on  $ED(i+1, j+1)$ ,  $ED(i, j+1)$ ,  $ED(i+1, j)$
- No dependency for  $ED(m, n)$  — start at bottom right and fill by row, column or diagonal

## 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
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

# 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
- Like LCS,  $ED(i, j)$  depends on  $ED(i+1, j+1)$ ,  $ED(i, j+1)$ ,  $ED(i+1, j)$
- No dependency for  $ED(m, n)$  — start at bottom right and fill by row, column or diagonal

## 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])
```

Initialization

# 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])
```

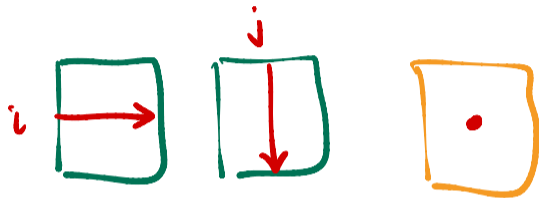
## Complexity

- 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  $A$ ,  $B$

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





# Multiplying matrices

- Multiply matrices  $A$ ,  $B$

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

- Dimensions must be compatible

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

- $AB : m \times p$

# 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  $O(mnp)$

$$O\left(\begin{matrix} n \\ n \end{matrix} \omega\right)$$

— Square matrices  $m=n=p$   
 $O(n^3)$

# 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

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

# 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!

# 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  $O(mnp)$

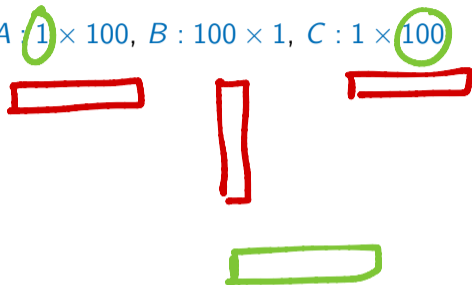
- Matrix multiplication is associative

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

- Bracketing does not change answer

- ... but can affect the complexity!

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



# 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

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

- 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

- 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  $A$ ,  $B$

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

- 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

- 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

- 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

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

- $AB : m \times p$

- 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!

# 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!

- 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

# Multiplying matrices

- Multiply matrices  $A$ ,  $B$

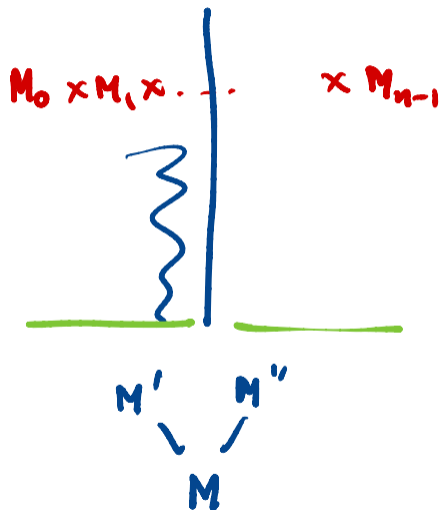
- $$AB[i,j] = \sum_{k=0}^{n-1} A[i,k]B[k,j]$$

- 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!

- 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  $0 < k < n$



# 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  $r_k = c_{k-1}$

# 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  $r_k = c_{k-1}$
- Let  $C(0, n-1)$  denote the overall cost

# 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  $r_k = c_{k-1}$
- Let  $C(0, n-1)$  denote the overall cost
- Final multiplication is  $O(r_0 r_k c_{n-1})$

# Inductive structure

- Final step combines two subproducts  
 $(M_0 \cdot M_1 \cdots M_{k-1}) \cdot (M_k \cdot M_{k+1} \cdots M_{n-1})$   
for some  $0 < k < n$
- First factor is  $r_0 \times c_{k-1}$ , second is  
 $r_k \times c_{n-1}$ , where  $r_k = c_{k-1}$
- Let  $C(0, n-1)$  denote the overall cost
- Final multiplication is  $O(r_0 r_k c_{n-1})$
- Inductively, costs of factors are  $C(0, k-1)$   
and  $C(k, n-1)$



# 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  $r_k = c_{k-1}$
- Let  $C(0, n-1)$  denote the overall cost
- Final multiplication is  $O(r_0 r_k c_{n-1})$
- Inductively, costs of factors are  $C(0, k-1)$   
and  $C(k, n-1)$
- $C(0, n-1) =$   
 $C(0, k-1) + C(k, n-1) + r_0 r_k c_{n-1}$

# Inductive structure

- Final step combines two subproducts  
 $(M_0 \cdot M_1 \cdots M_{k-1}) \cdot (M_k \cdot M_{k+1} \cdots M_{n-1})$   
for some  $0 < k < n$
- First factor is  $r_0 \times c_{k-1}$ , second is  
 $r_k \times c_{n-1}$ , where  $r_k = c_{k-1}$
- Let  $C(0, n-1)$  denote the overall cost
- Final multiplication is  $O(r_0 r_k c_{n-1})$
- Inductively, costs of factors are  $C(0, k-1)$   
and  $C(k, n-1)$
- $C(0, n-1) =$   
 $C(0, k-1) + C(k, n-1) + r_0 r_k c_{n-1}$
- Which  $k$  should we choose?

# 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  $r_k = c_{k-1}$
- Let  $C(0, n-1)$  denote the overall cost
- Final multiplication is  $O(r_0 r_k c_{n-1})$
- Inductively, costs of factors are  $C(0, k-1)$   
and  $C(k, n-1)$
- $C(0, n-1) =$   
 $C(0, k-1) + C(k, n-1) + r_0 r_k c_{n-1}$
- Which  $k$  should we choose?
  - Try all and choose the minimum!

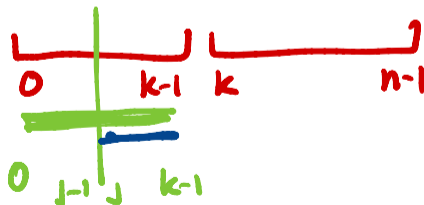
# Inductive structure

- 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  $r_k = c_{k-1}$
- Let  $C(0, n-1)$  denote the overall cost
- Final multiplication is  $O(r_0 r_k c_{n-1})$
- Inductively, costs of factors are  $C(0, k-1)$   
and  $C(k, n-1)$
- $C(0, n-1) =$   
 $C(0, k-1) + C(k, n-1) + r_0 r_k c_{n-1}$
- Which  $k$  should we choose?
  - Try all and choose the minimum!
- Subproblems?

# 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  $r_k = c_{k-1}$
- Let  $C(0, n-1)$  denote the overall cost
- Final multiplication is  $O(r_0 r_k c_{n-1})$
- Inductively, costs of factors are  $C(0, k-1)$   
and  $C(k, n-1)$
- $C(0, n-1) =$   
 $C(0, k-1) + C(k, n-1) + r_0 r_k c_{n-1}$

- 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  
 $M_j \cdot M_{j+1} \cdots M_k$



# 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  $r_k = c_{k-1}$
- Let  $C(0, n-1)$  denote the overall cost
- Final multiplication is  $O(r_0 r_k c_{n-1})$
- Inductively, costs of factors are  $C(0, k-1)$   
and  $C(k, n-1)$
- $C(0, n-1) =$   
 $C(0, k-1) + C(k, n-1) + r_0 r_k c_{n-1}$

- 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  
 $M_j \cdot M_{j+1} \cdots M_k$

- $C(j, k) =$  inductive costs  
 $\min_{j < \ell \leq k} [C(j, \ell-1) + C(\ell, k) + \underbrace{r_j r_\ell c_k}_{\text{final mult}}]$



# 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  $r_k = c_{k-1}$
- Let  $C(0, n-1)$  denote the overall cost
- Final multiplication is  $O(r_0 r_k c_{n-1})$
- Inductively, costs of factors are  $C(0, k-1)$   
and  $C(k, n-1)$
- $C(0, n-1) =$   
 $C(0, k-1) + C(k, n-1) + r_0 r_k c_{n-1}$

- 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  
 $M_j \cdot M_{j+1} \cdots M_k$
- $C(j, k) =$    
 $\min_{j < \ell \leq k} [C(j, \ell-1) + C(\ell, k) + r_j r_\ell c_k]$
- Base case:  $C(j, j) = 0$  for  $0 \leq j < n$

# 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

	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  $i < k \leq j$

	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  $i < k \leq j$

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

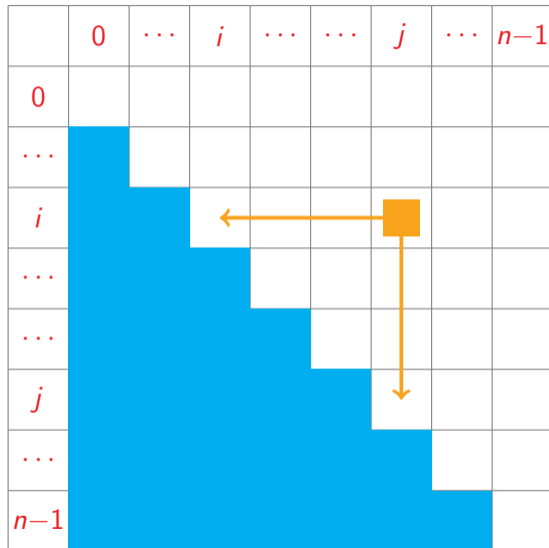
# Subproblem dependency

- 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  $i < k \leq j$

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

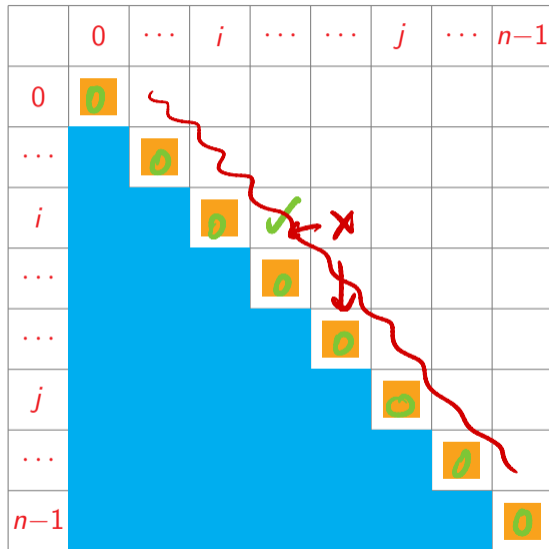
# Subproblem dependency

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



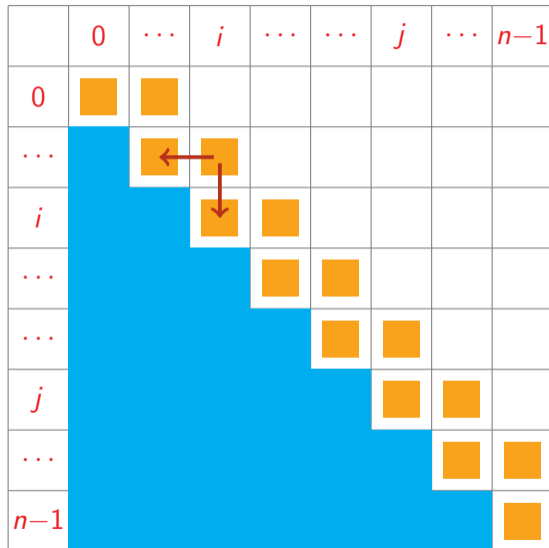
# Subproblem dependency

- 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  $i < k \leq j$ 
  - $O(n)$  dependencies per entry, unlike LCW, LCS and ED
- Diagonal entries are base case



# Subproblem dependency

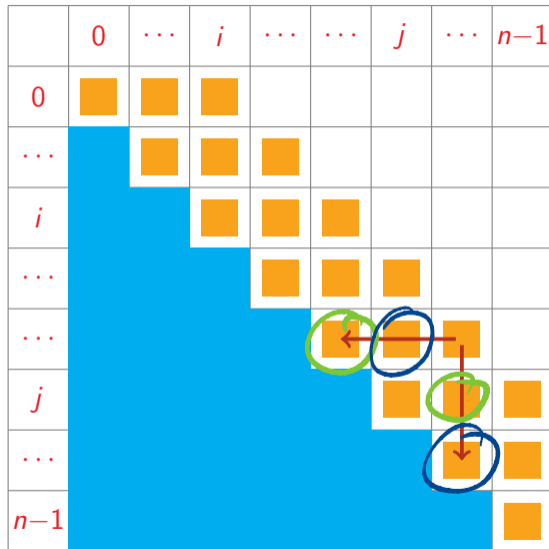
- Compute  $C(i,j)$ ,  $0 \leq i,j < n$ 
  - Only for  $i \leq j$
  - Entries above main diagonal
- $C(i,j)$  depends on  $C(i,k-1)$ ,  $C(k,j)$  for every  $i < k \leq j$ 
  - $O(n)$  dependencies per entry, unlike LCW, LCS and ED
- Diagonal entries are base case
- Fill matrix by diagonal, from main diagonal





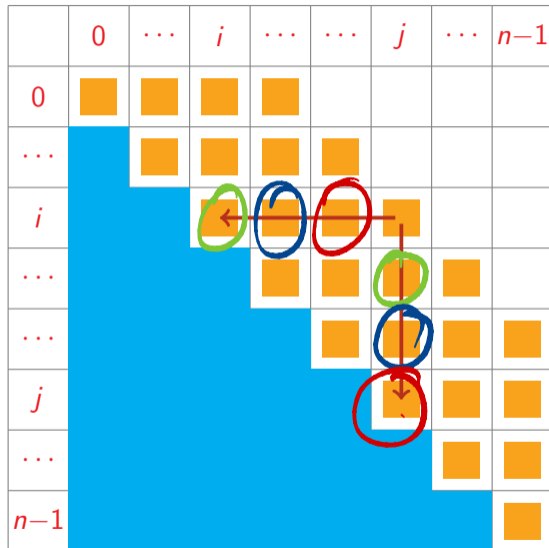
# Subproblem dependency

- 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  $i < k \leq j$ 
  - $O(n)$  dependencies per entry, unlike LCW, LCS and ED
- Diagonal entries are base case
- Fill matrix by diagonal, from main diagonal



# 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  $i < k \leq j$ 
  - $O(n)$  dependencies per entry, unlike LCW, LCS and ED
- Diagonal entries are base case
- Fill matrix by diagonal, from main diagonal



# 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  $i < k \leq j$ 
  - $O(n)$  dependencies per entry, unlike LCW, LCS and ED
- Diagonal entries are base case
- Fill matrix by diagonal, from main diagonal

	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  $i < k \leq j$ 
  - $O(n)$  dependencies per entry, unlike LCW, LCS and ED
- Diagonal entries are base case
- Fill matrix by diagonal, from main diagonal

	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  $i < k \leq j$ 
  - $O(n)$  dependencies per entry, unlike LCW, LCS and ED
- Diagonal entries are base case
- Fill matrix by diagonal, from main diagonal

	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  $i < k \leq j$ 
  - $O(n)$  dependencies per entry, unlike LCW, LCS and ED
- Diagonal entries are base case
- Fill matrix by diagonal, from main diagonal

$C(0, n-1)$

	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])
```

||

|| diagonal step

# 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])
```

## Complexity

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