

# Dynamic Programming

## part 2

# Week 7 Objectives

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- More dynamic programming examples
  - Matrix Multiplication Parenthesis
  - Longest Common Subsequence
- Subproblem Optimal structure
- Defining the dynamic recurrence
- Bottom up computation
- Tracing the solution

# Subproblem Optimal Structure

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- Divide and conquer – optimal subproblems
- divide PROBLEM into SUBPROBLEMS, solve SUBPROBLEMS
- combine results (conquer)
- **critical/optimal structure**: solution to the PROBLEM must include solutions to subproblems (or subproblem solutions must be combinable into the overall solution)
- PROBLEM = {DECISION/MERGING + SUBPROBLEMS}

# Optimal Structure – NON GREEDY

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- Cannot make a choice decision/CHOICE without solving subproblems first
- Might have to solve many subproblems before deciding which results to merge.

# Matrix Multiplication (Parenthesis)

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- Task: multiply matrices  $A_1 * A_2 * \dots * A_n$
- $A_i$  matrix has  $p_{i-1}$  rows and  $p_i$  columns (size  $p_{i-1} \times p_i$ )
  - #rows of matrix  $A_{i+1}$  has to be the same as #columns of  $A_i$
- Minimize the number of scalar multiplications
- Note that matrices can be multiplied in any order:
  - $A_1 * (A_2 * A_3) * A_4$  ;  $(A_1 * A_2) * (A_3 * A_4)$  ;  $A_1 * (A_2 * A_3 * A_4)$
  - $A_1(\text{size } p_0 \times p_1) * A_2(\text{size } p_1 \times p_2)$  takes  $p_0 * p_1 * p_2$  scalar multiplications
  - order matters, example:  $A_1(10 \times 100)$ ,  $A_2(100 \times 5)$ ;  $A_3(5 \times 50)$  ( $p_0 = 10$ ;  $p_1 = 100$ ;  $p_2 = 5$ ;  $p_3 = 50$ )
    - then  $A_1 * (A_2 * A_3)$  takes 75000 scalar multiplications
    - while  $(A_1 * A_2) * A_3$  takes 7500 scalar multip., 10 times less.

# Matrix Multiplication (Parenthesis)

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- NAIVE SOLUTION: try all ways to put parenthesis to see which one is best/minimum

- $A_1 * ((A_2 * A_3) * A_4)$  ;  $(A_1 * A_2) * (A_3 * A_4)$  ;  $A_1 * (A_2 * (A_3 * A_4))$

- $((A_1 * A_2) * A_3) * A_4$  ;  $(A_1 * (A_2 * A_3)) * A_4$

- $P(n)$  = number of ways to parenthesize  $n$  matrices

- recursion on  $n$

$$P(n) = \begin{cases} 1 & \text{if } n = 1 \\ \sum_{k=1}^{n-1} P(k)P(n-k) & \text{if } n \geq 2 \end{cases}$$

- why? proof this recursion

- show that this  $P(n)$  is exponential in  $n$

# Matrix Multiplication (Parenthesis)

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- 1) characterize optimal solution structure
- optimal solution SOL parenthesis has a "main split", or "last product" - that is the last matrix multiplication

- say it is between matrices  $A_k$  and  $A_{k+1}$

$$\underbrace{\left( (A_i A_{i+1} \dots A_k) \right)}_{\text{prefix subchain}} \underbrace{\left( A_{k+1} A_{k+2} \dots A_j \right)}_{\text{suffix subchain}}$$

- then SOL parenthesis on the left side  $(A_i^* \dots^* A_k)$  must be optimal
- same for right side: parenthesis on  $(A_{k+1}^* \dots^* A_j)$  must be optimal
  - why? use an exchange argument

# Matrix Multiplication (Parenthesis)

- 2) dynamic programming recursion
- $C[i,j]$  = min scalar multip. to multiply  $A_i * A_{i+1} * \dots * A_j$ 
  - $C[i,i]=0$ ;  $C[i,i+1] = p_{i-1} * p_i * p_{i+1}$
- $A_i * A_{i+1} * \dots * A_j$  can be computed by first deciding the main split at some  $k$ ,  $1 < k < j$ 
  - for that split  $C[i,j] = C[i,k] + C[k+1,j] + p_{i-1} * p_k * p_j$

$$\underbrace{\boxed{C[i,k]} \quad \boxed{p_{i-1} * p_k * p_j} \quad \boxed{C[k+1,j]}}_C$$

$$((A_i A_{i+1} \dots A_k) (A_{k+1} A_{k+2} \dots A_j))$$

- but we don't know what  $k$  is best, so we have to try all of them

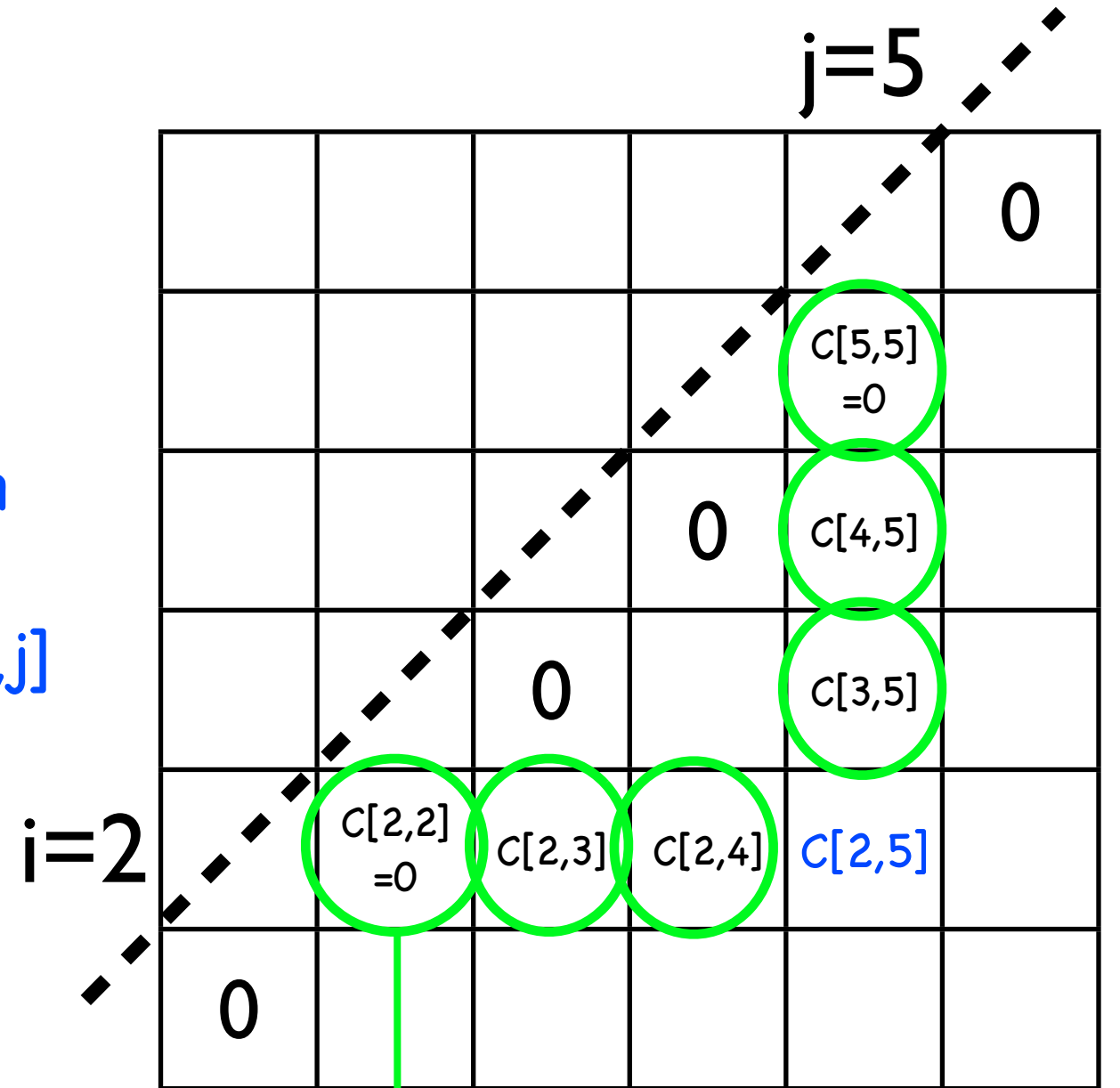
$$C[i,j] = \begin{cases} 0 & \text{if } i = j, \\ \min_{i \leq k < j} \{ C[i,k] + C[k+1,j] + p_{i-1} p_k p_j \} & \text{if } i < j. \end{cases}$$



# Matrix Multiplication (Parenthesis)

## 3) bottom up computation of table $C[]$

- what is the right order to fill the table?
- guarantee that values needed for recursion are already computed when we compute  $C[i,j]$
- might need any value  $C[i,k]$  and  $C[k+1,j]$



need these values for  $C[2,5]$



# Matrix Multiplication (Parenthesis)

- 3) bottom up computation of table  $C[]$

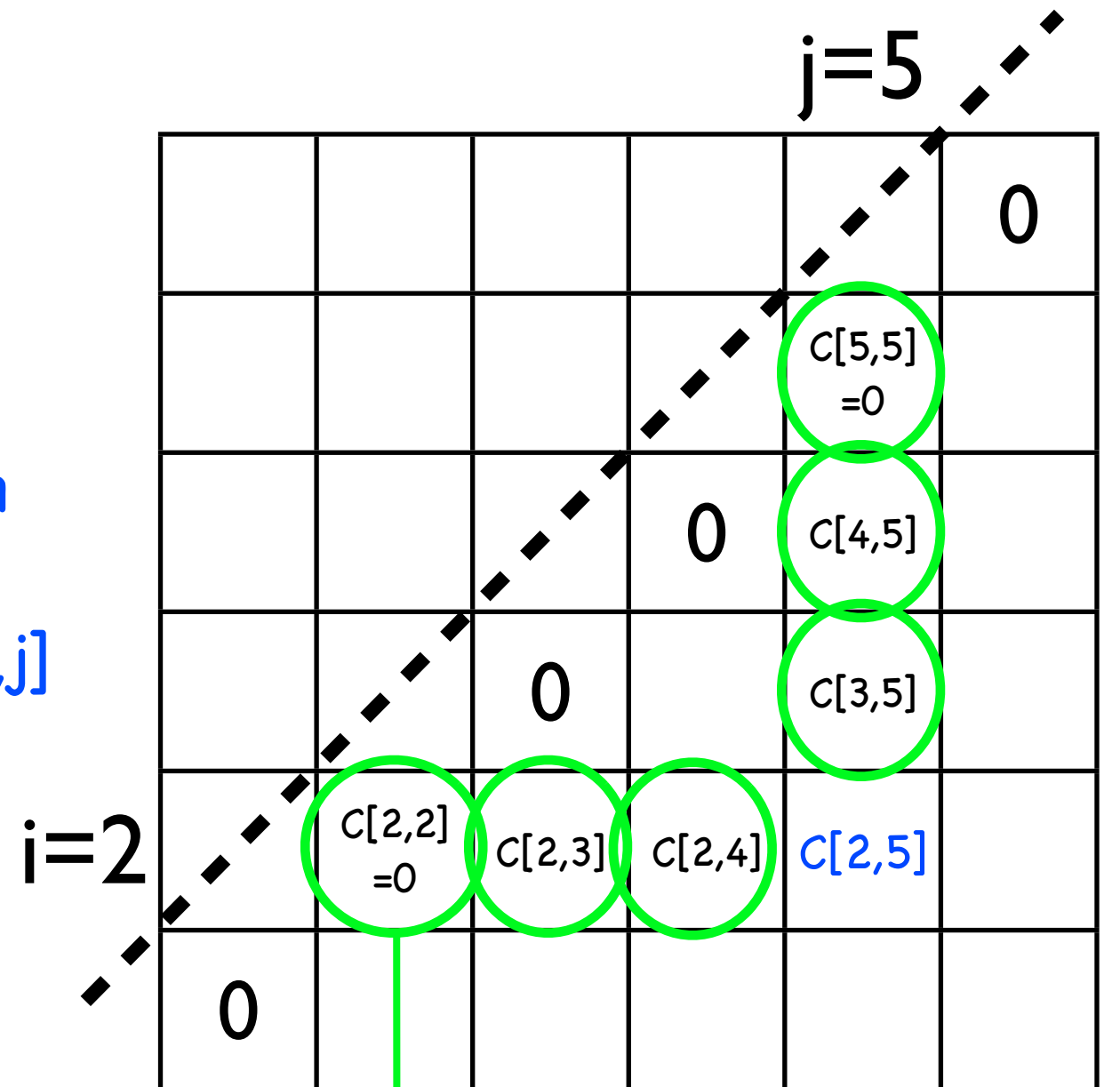
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- when computing  $C[i,j]$ ,  $\text{length}=j-i$
- values needed  $C[i,k]$  and  $C[k+1,j]$  have smaller lengths for any  $k$

- fill table  $C[]$  by length

- from cells with small length (main diagonal) to cells of high lengths (corners)



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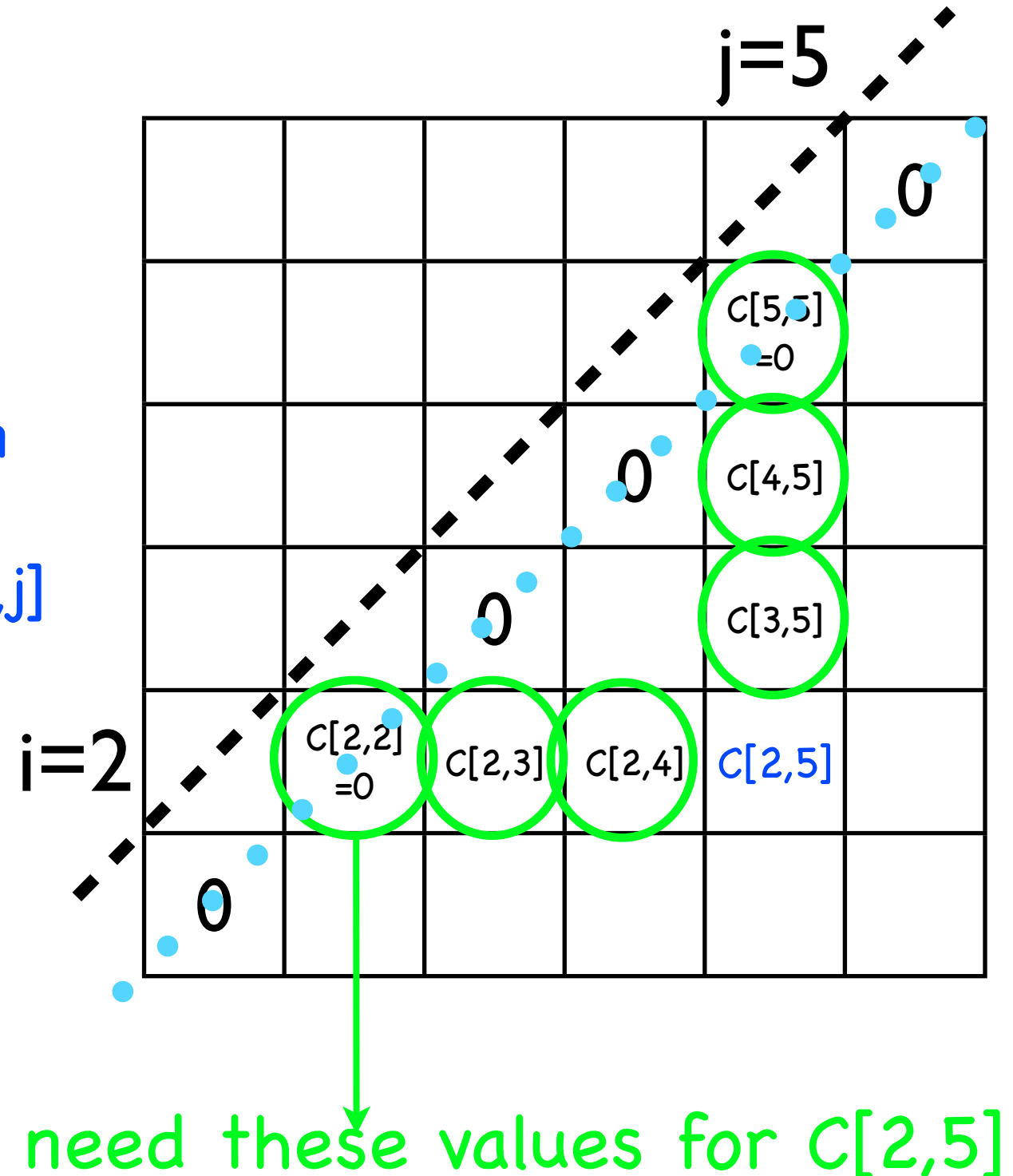
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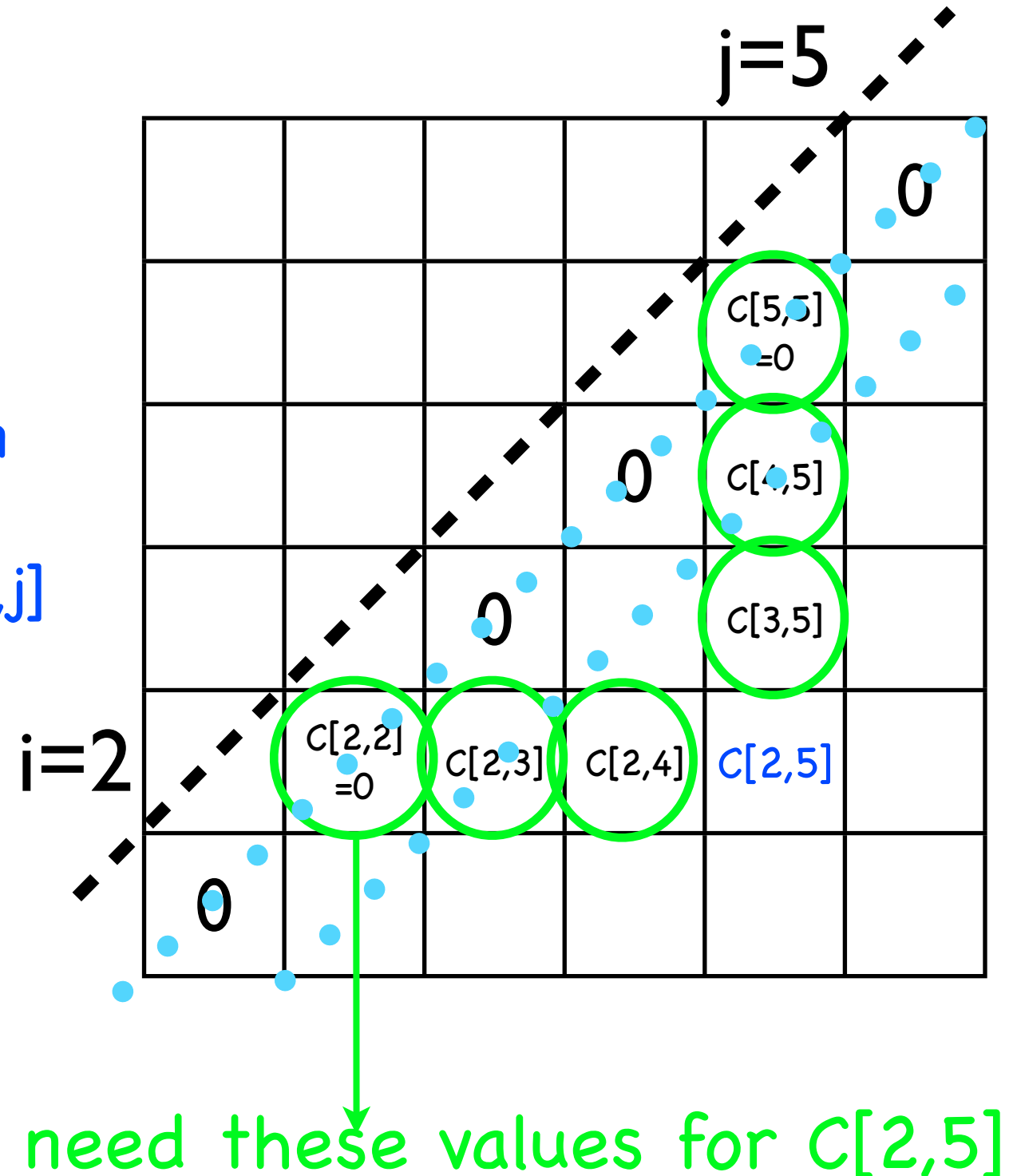
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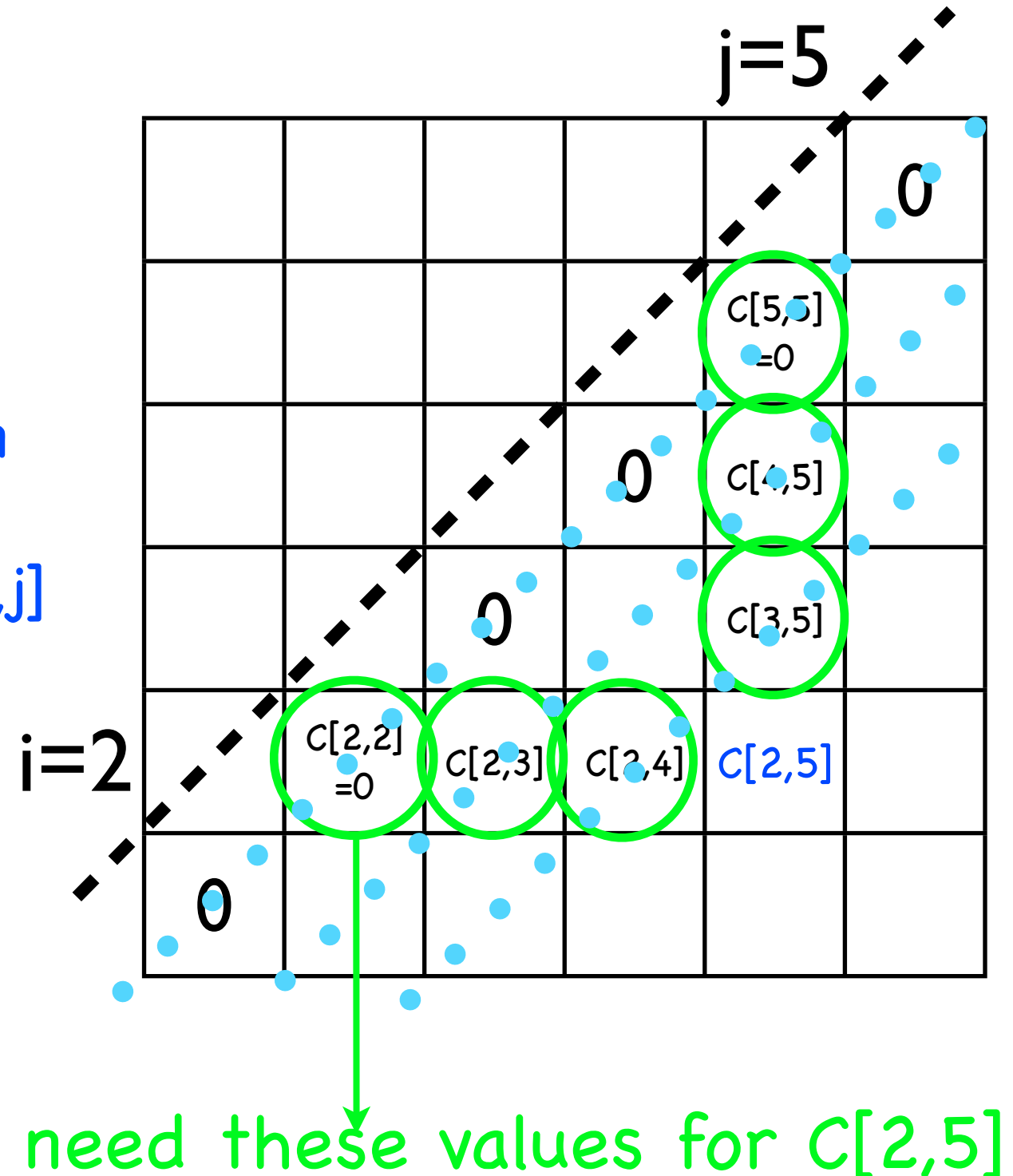
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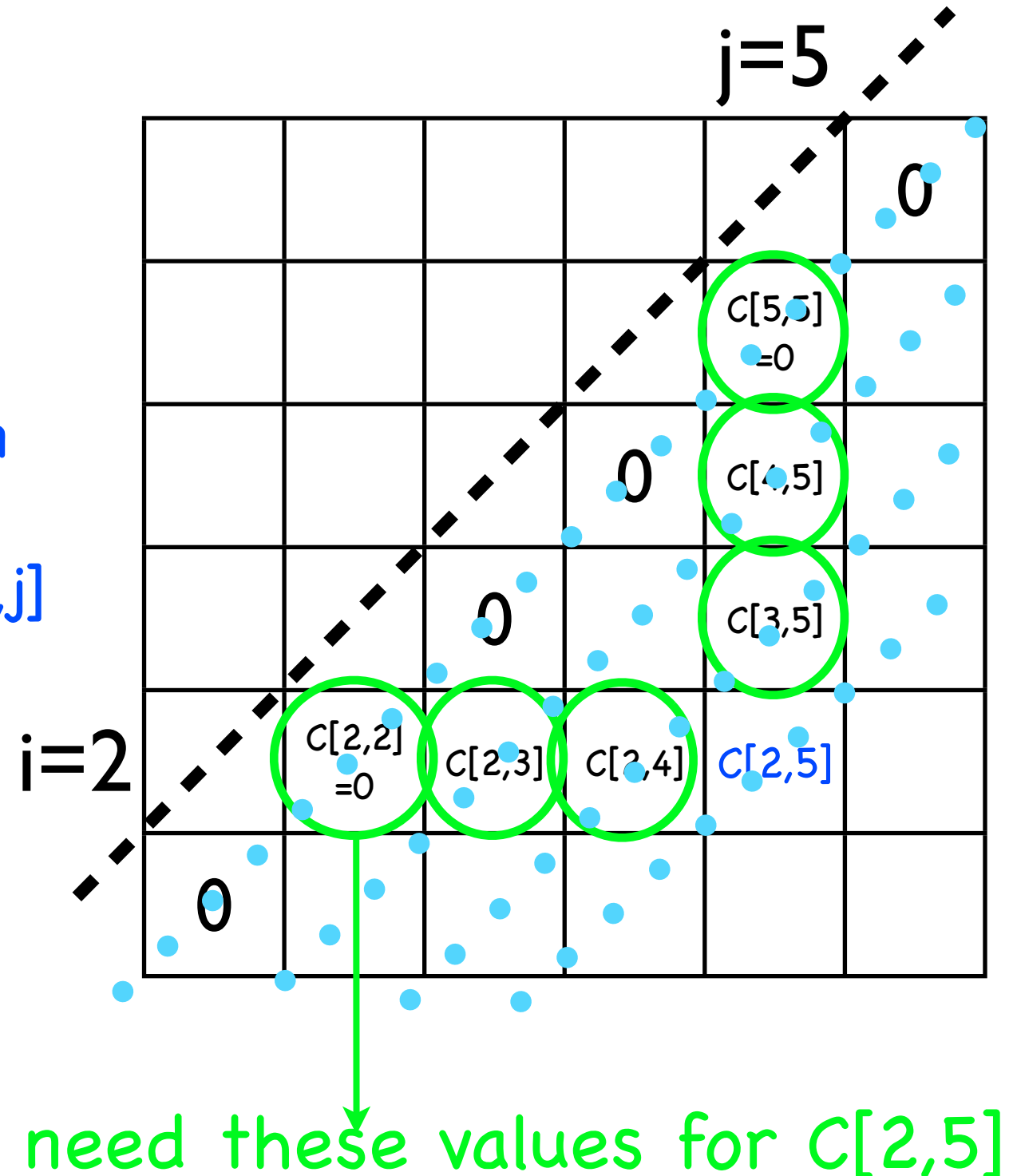
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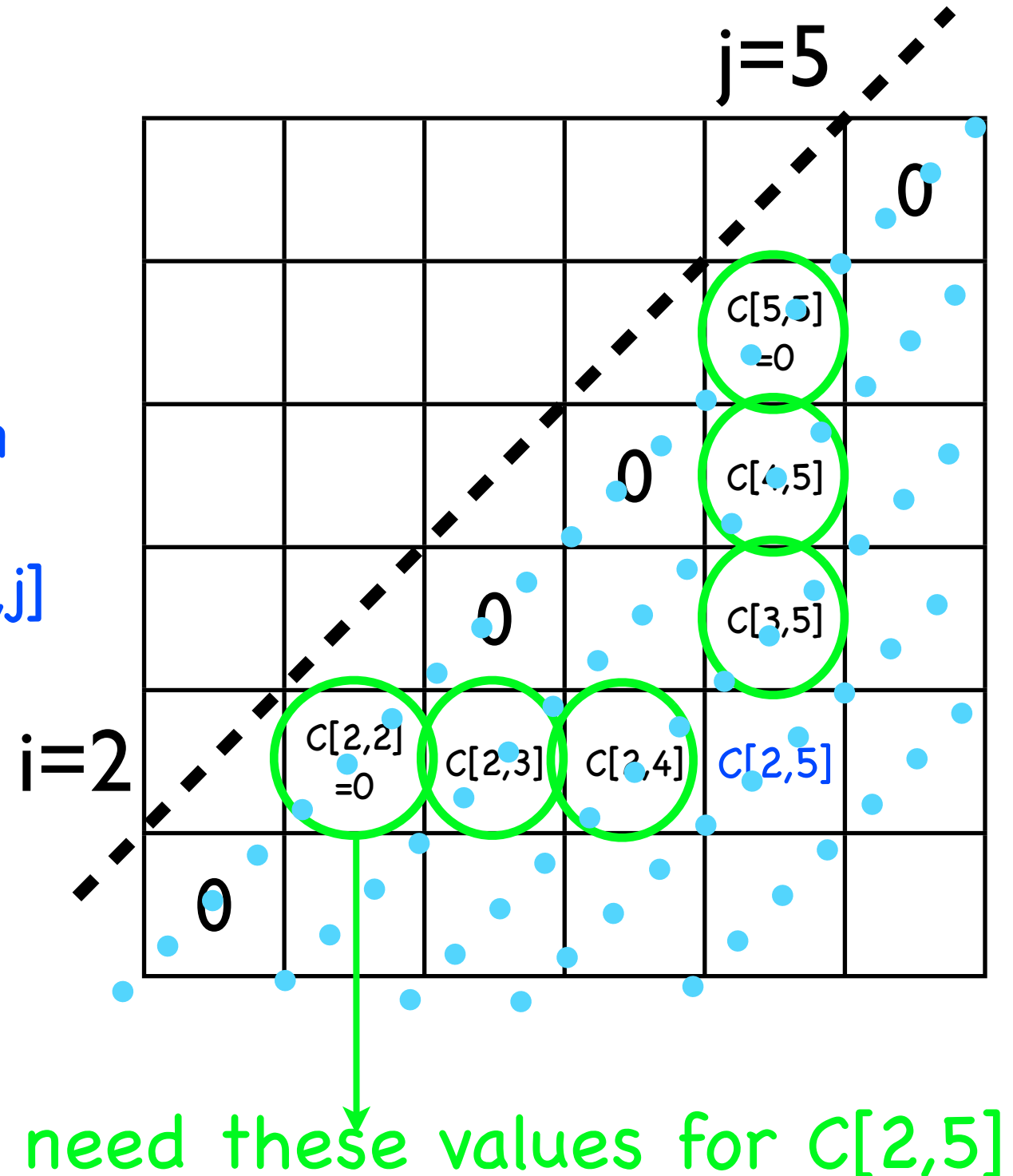
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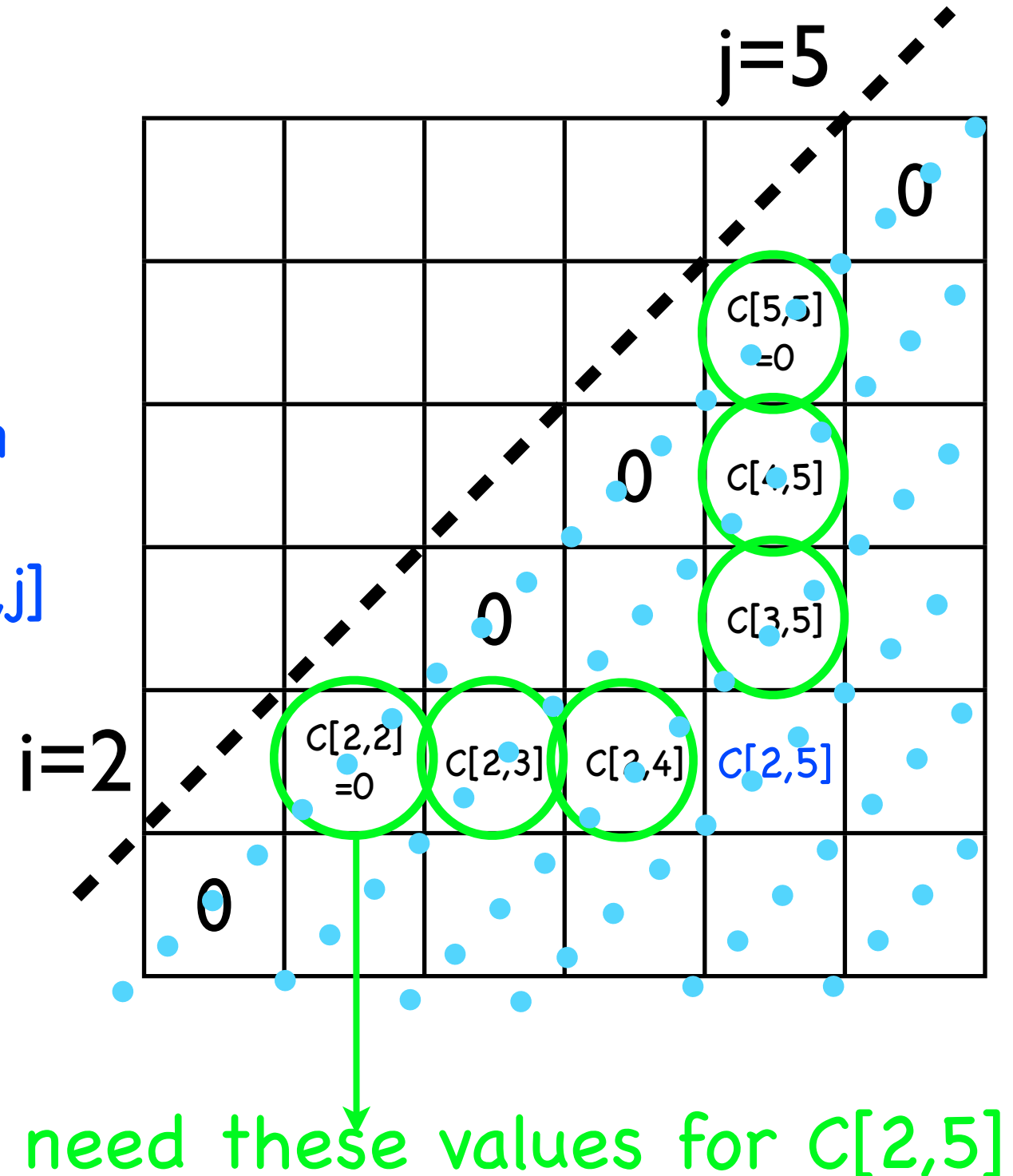
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## fill table $C[]$ by length

- from cells with small length (main diagonal) to cells of high lengths (corners)



# Matrix Multiplication (Parenthesis)

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- 3) Bottom-up computation of  $C[]$ 
  - by diagonal from short length, to long length
- keep track of split at  $k$ , for sequence  $[i..j]$ :  $S[i,j]=k$ 
  - $A_i * A_2 * \dots * A_j$  multiplied best as  $(A_i * A_{i+1} * \dots * A_k)(A_{k+1} * \dots * A_j)$

MATRIX-CHAIN-ORDER( $p$ )

```
1   $n = p.length - 1$ 
2  let  $C[1..n, 1..n]$  and  $S[1..n - 1, 2..n]$  be new tables
3  for  $i = 1$  to  $n$ 
4       $C[i, i] = 0$ 
5  for  $l = 2$  to  $n$  //  $l$  is the chain length
6      for  $i = 1$  to  $n - l + 1$ 
7           $j = i + l - 1$ 
8           $C[i, j] = 0$ 
9          for  $k = i$  to  $j - 1$ 
10              $q = C[i, k] + C[k + 1, j] + p_{i-1}p_kp_j$ 
11             if  $q < C[i, j]$ 
12                  $C[i, j] = q$ 
13                  $S[i, j] = k$ 
14 return  $C$  and  $S$ 
```

# Matrix Multiplication (Parenthesis)

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- 4) Trace the solution - Exercise
  - use  $S[i,j]$  to determine the main split
  - run recursion on both sides of the split
- also calculate the running time of the trace

# Matrix Multiplication (Parenthesis)

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- Running time
  - $C[]$  table fills about  $1/2 * n * n$  cells –  $\Theta(n^2)$  cells
  - each cell  $C[i,j]$  tries all  $k$  ;  $1 \leq k < j$  –  $\Theta(n)$  steps
- Total  $\Theta(n^3)$  time for bottom up computation
- Trace solution: certainly lower than  $\Theta(n^3)$ , so it doesn't add to the running time asymptote.

# Top-down computation instead of bottom up

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- Suppose we want to do the computation top down
- Recursively follow the recursion

```
▶ Rec-Matrix-Chain(p, i, j) // bad running time
▶   if(i==j) return 0;
▶   m[i,j]=∞
▶   for k=i:j-1
▶     q=Rec-Matrix-Chain(p, i, k) + Rec-Matrix-Chain(p, k+1, j) + pi-1pkpj;
▶     if (q<m[i,j]) m[i,j]=q;
▶   return m[i,j]
```

- Exponential number of calls VS bottom up which is only  $\Theta(n^2)$  for this section of the code

# Top-down with memoization

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- memoization: “store, dont recompute” the computed results; each actual computation only happen once
- init all  $m[i,j]=\infty$ ; call MEMOIZATION-top-down( $p,1,n$ )
  - ▶ MEMOIZATION-top-down( $p, i, j$ )
    - ▶ if ( $m[i,j]<\infty$ ) return  $m[i,j]$  // look up previous computed values
    - ▶ if( $i==j$ )  $m[i,j] = 0$ ;
    - ▶ else for  $k=i:j-1$ 
      - ▶  $q=\text{Rec-Matrix-Chain}(p,i,k) + \text{Rec-Matrix-Chain}(p,k+1,j) + p_{i-1}p_kp_j$ ;
      - ▶ if ( $q<m[i,j]$ )  $m[i,j]=q$ ; //store value for future look up
    - ▶ return  $m[i,j]$

# Memoization

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- now same running time as bottom-up :  $\Theta(n^3)$  overall
- bottom-up (DP) VS top-down (Memoization):
  - DP advantage: no overhead (stack of calls, recursion), efficient when the whole table has to be computed anyway
  - DP requires a certain fill-order of the table
  - Memoization: better when not all values must be computed
  - Memoization follow literally the recursion; easier to implement

# Longest Common Subsequence (LCS)



# Longest Common Subsequence

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- Given two  $X=(x_1, x_2, \dots, x_m)$  and  $Y=(y_1, y_2, \dots, y_n)$  find the longest common subsequence
  - it doesn't have to be continuous in either  $X$  or  $Y$
  - not unique: possible that several common sequences have maximum length
- example
  - $X=(absscddtgt)$   $Y=(xasbsdcggg)$
  - $LCS=Z=(absdg)$

# Longest Common Subsequence

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- 1) Characterize optimal solution structure - (add general army- needs more cannons story)
  - notation:  $X_{m-1} = (x_1, x_2, \dots, x_{m-1})$ ;  $Y_{n-1} = (y_1, y_2, \dots, y_{n-1})$  etc
- if  $X = (x_1, x_2, \dots, x_m)$  and  $Y = (y_1, y_2, \dots, y_n)$  have an LCS  $Z = (z_1, z_2, \dots, z_k)$  then
  - if  $x_m = y_n$ ; then  $z_k = x_m = y_n$  and  $Z_{k-1} = \text{LCS}(X_{m-1}, Y_{n-1})$
  - if  $x_m \neq y_n$  and  $z_k \neq x_m$  then  $Z = \text{LCS}(X_{m-1}, Y)$
  - if  $x_m \neq y_n$  and  $z_k \neq y_n$  then  $Z = \text{LCS}(X_m, Y_{n-1})$

# Longest Common Subsequence

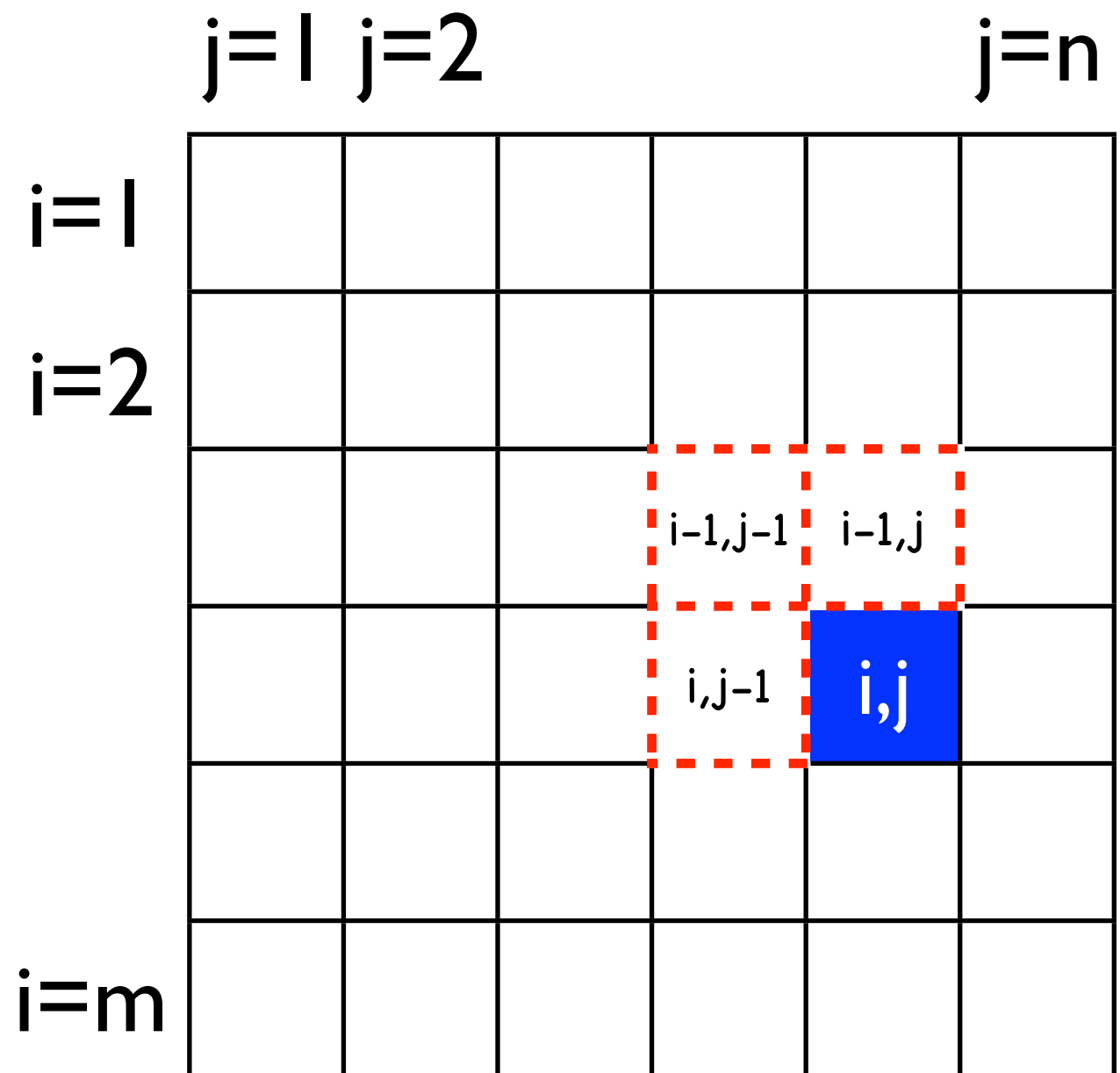
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- 2) dynamic recursion
- $C[i,j] = \text{LCS}(X_i, Y_j)$  where  $X_i = (x_1, x_2, \dots, x_i)$   $Y_j = (y_1, y_2, \dots, y_j)$
- $C[i,j]$  is
  - 0 ; for base case  $i=0$  or  $j=0$
  - $C[i-1, j-1] + 1$  ; for  $i, j > 0$  and  $x_i = y_j$
  - $\max \{C[i-1, j], C[i, j-1]\}$  ; for  $i, j > 0$  and  $x_i \neq y_j$

# Longest Common Subsequence

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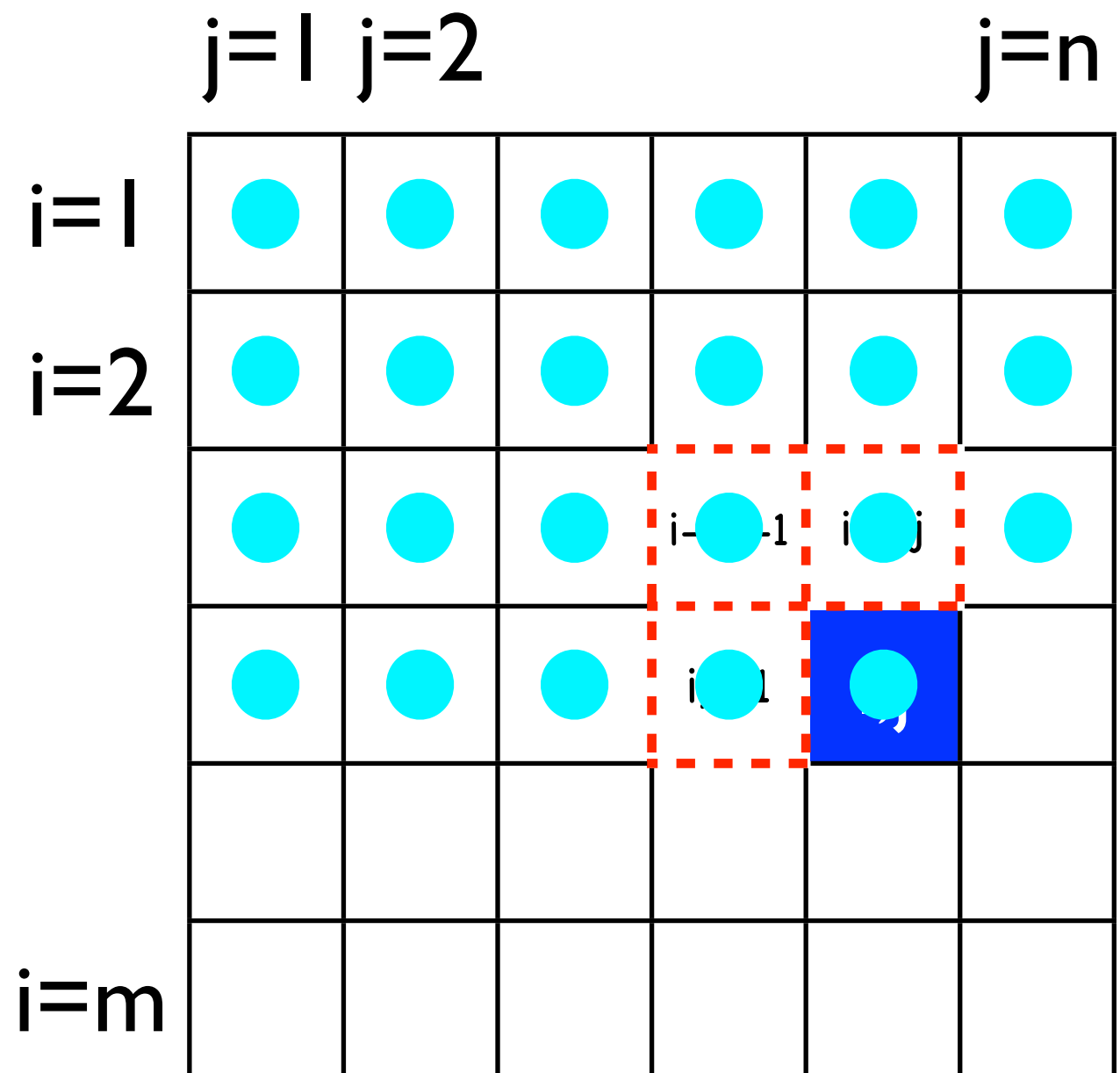
- 3) bottom up computation
- in order to compute  $C[i,j]$  we need to have already computed the following three values:
  - $C[i-1,j-1]$
  - $C[i,j-1]$
  - $C[i-1,j]$



# Longest Common Subsequence

---

- 3) bottom up computation
- in order to compute  $C[i,j]$  we need to have already computed the following three values:
  - $C[i-1,j-1]$
  - $C[i,j-1]$
  - $C[i-1,j]$
- fill row by row, each row from left to right



# Longest Common Subsequence

---

- 3) bottom up computation
- keep track of the solution:  $S[i,j]$  remembers which one of the three possibilities we used:

- $C[i-1,j-1] + 1$  ;  $S[i,j] = "\nwarrow"$
- $C[i,j-1]$  ;  $S[i,j] = "\uparrow"$  ;
- $C[i-1,j]$  ;  $S[i,j] = "\leftarrow"$

LCS-LENGTH( $X, Y$ )

1  $m = X.length$

2  $n = Y.length$

3 let  $S[1..m, 1..n]$  and  $C[0..m, 0..n]$  be

4 for  $i = 1$  to  $m$

5  $C[i, 0] = 0$

6 for  $j = 0$  to  $n$

7  $C[0, j] = 0$

8 for  $i = 1$  to  $m$

9 for  $j = 1$  to  $n$

10 if  $x_i == y_j$

11  $C[i, j] = C[i - 1, j - 1] + 1$

12  $S[i, j] = "\nwarrow"$

13 elseif  $C[i - 1, j] \geq C[i, j - 1]$

14  $C[i, j] = C[i - 1, j]$

15  $S[i, j] = "\uparrow"$

16 else  $C[i, j] = C[i, j - 1]$

17  $S[i, j] = "\leftarrow"$

18 return  $C$  and  $S$

# Longest Common Subsequence

- 3) bottom up computation

- illustrated are  $C[]$  and  $S[]$  tables on the same grid
- $C[i,j]$  is the size of  $LCS(X_i, Y_j)$

- $S[i,j]$  is the arrow pointing to the subproblem

- "↖" indicates a common item, part of LCS; subproblem decreases both  $i$  and  $j$
- "↑" indicates discarding last value of  $X_i$ ; decrease  $i$
- "←" indicates discarding last value of  $Y_j$ ; decrease  $j$

		$j$	0	1	2	3	4	5	6
$i$	$y_i$		$B$	$D$	$C$	$A$	$B$	$A$	
0	$x_i$		0	0	0	0	0	0	0
1	$A$		0	↑	↑	↑	↖	←	↖
2	$B$		0	↖	←	←	↑	↖	←
3	$C$		0	↑	↑	↖	←	↑	↑
4	$B$		0	↖	↑	↑	↑	↖	←
5	$D$		0	↑	↖	↑	↑	↑	↑
6	$A$		0	↑	↑	↑	↖	↑	↖
7	$B$		0	↖	↑	↑	↑	↖	↑



# Longest Common Subsequence

- 4) trace solution
- start at  $S[m,n]$ , follow arrows:
- every " $\nwarrow$ " means a common item is found by LCS

```

PRINT-LCS( $S, X, i, j$ )
1  if  $i == 0$  or  $j == 0$ 
2      return
3  if  $S[i, j] == \nwarrow$ 
4      PRINT-LCS( $S, X, i - 1, j - 1$ )
5      print  $x_i$ 
6  elseif  $S[i, j] == \uparrow$ 
7      PRINT-LCS( $S, X, i - 1, j$ )
8  else PRINT-LCS( $S, X, i, j - 1$ )
    
```

$j$	0	1	2	3	4	5	6
$i$	$y_i$	$B$	$D$	$C$	$A$	$B$	$A$
0	$x_i$						
1	$A$	0	0	0	0	1	1
2	$B$	0	1	1	1	2	2
3	$C$	0	1	1	2	2	2
4	$B$	0	1	1	2	2	3
5	$D$	0	1	2	2	2	3
6	$A$	0	1	2	2	3	3
7	$B$	0	1	2	2	3	4



# Longest Common Subsequence

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- Running time

- bottom up computation fills a table of  $m \times n$  cells
- each cell takes constant time

- overall  $\Theta(mn)$

- Trace solution  $O(m+n)$

- we “walk” on the table towards the  $[0,0]$  cell either vertical or horizontal or diagonal.