

Dynamic Programming

Madhavan Mukund

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

Programming and Data Structures with Python

Lecture 22, 03 Nov 2022

Memoizing recursive implementations

```
def fib(n):  
    if n in fibtable.keys():  
        return(fibtable[n])  
    if n <= 1:  
        value = n  
    else:  
        value = fib(n-1) + fib(n-2)  
    fibtable[n] = value  
    return(value)
```

In general

```
def f(x,y,z):  
    if (x,y,z) in ftable.keys():  
        return(ftable[(x,y,z)])  
    recursively compute value  
    from subproblems  
    ftable[(x,y,z)] = value  
    return(value)
```

Dynamic programming

- Anticipate the structure of subproblems
 - Derive from inductive definition
 - Dependencies are acyclic

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Evaluating `fib(5)`

`fib(5)`

`fib(4)`

`fib(3)`

`fib(2)`

`fib(1)`

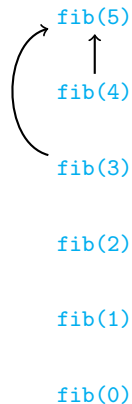
`fib(0)`

Dynamic programming

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Evaluating `fib(5)`

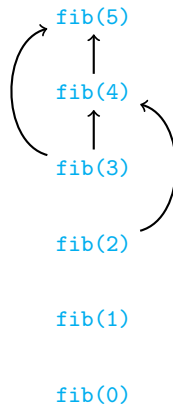


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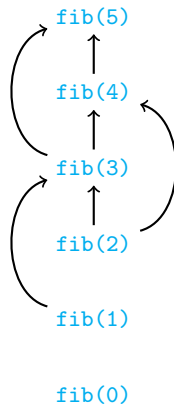


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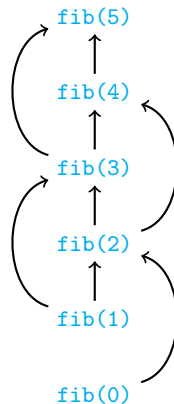


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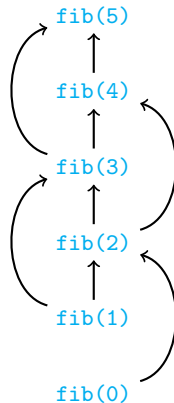
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Dynamic programming

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- Solve subproblems in appropriate order

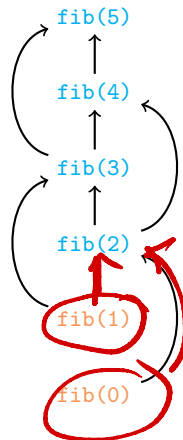
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Dynamic programming

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- Solve subproblems in appropriate order
 - Start with base cases — no dependencies

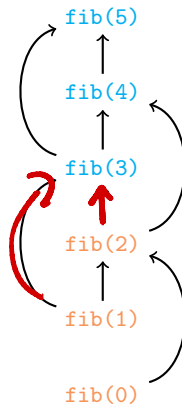
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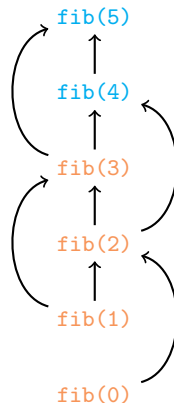
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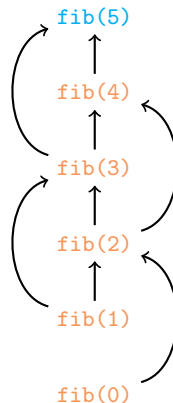
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Evaluating `fib(5)`



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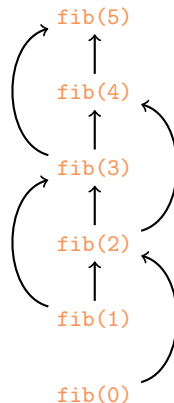
- Solve subproblems in appropriate order

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fib(8)

0 1 2 3 4 5 6 7 8
0 1 1 2 3 5 8 13 21

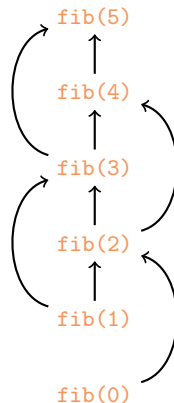
Evaluating *fib(5)*



Dynamic programming

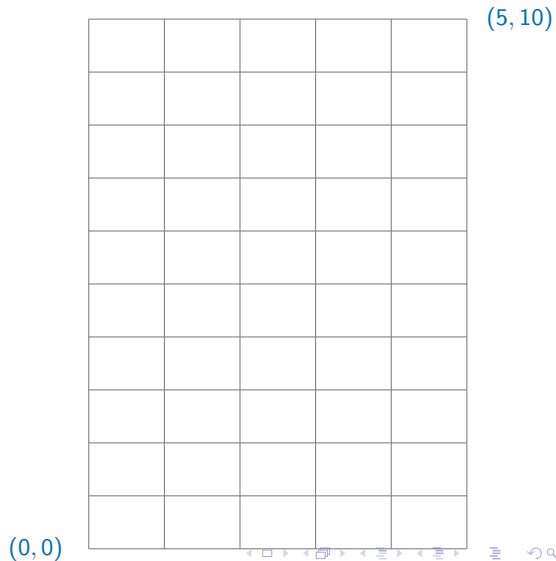
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 - Start with base cases — no dependencies
 - Evaluate a value after all its dependencies are available
 - Fill table iteratively
 - Never need to make a recursive call

Evaluating `fib(5)`



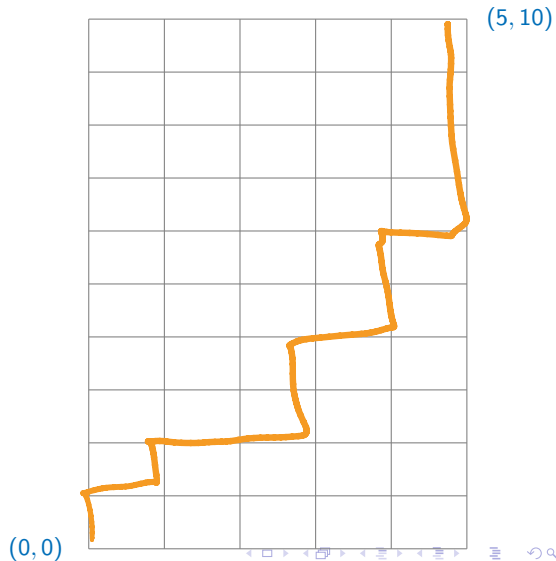
Grid paths

- Rectangular grid of one-way roads



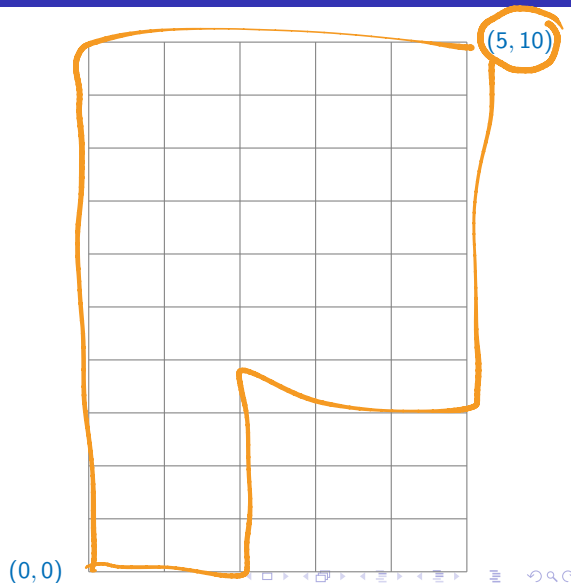
Grid paths

- Rectangular grid of one-way roads
- Can only go up and right



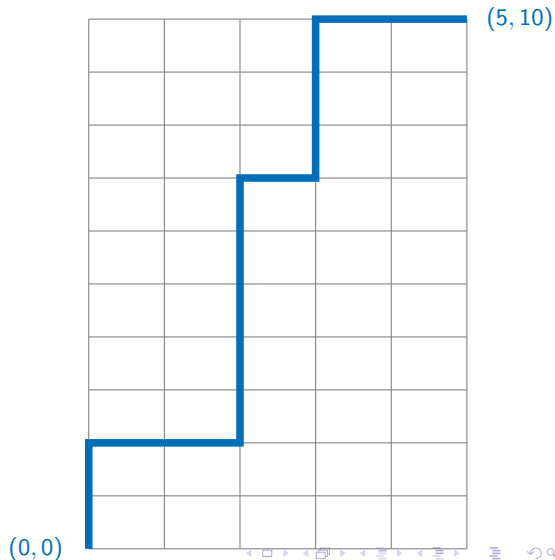
Grid paths

- Rectangular grid of one-way roads
- Can only go up and right
- How many paths from $(0, 0)$ to (m, n) ?



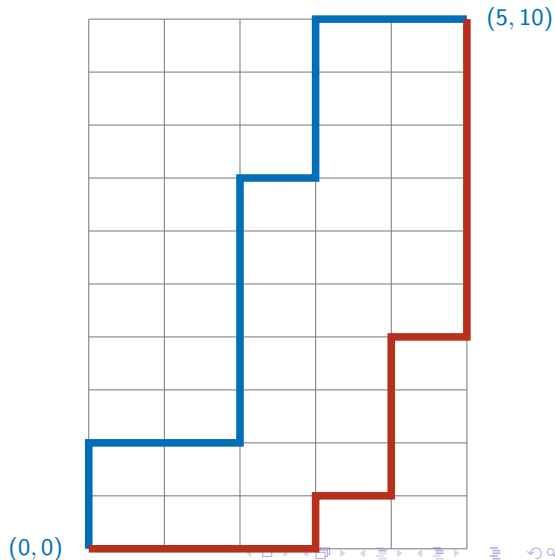
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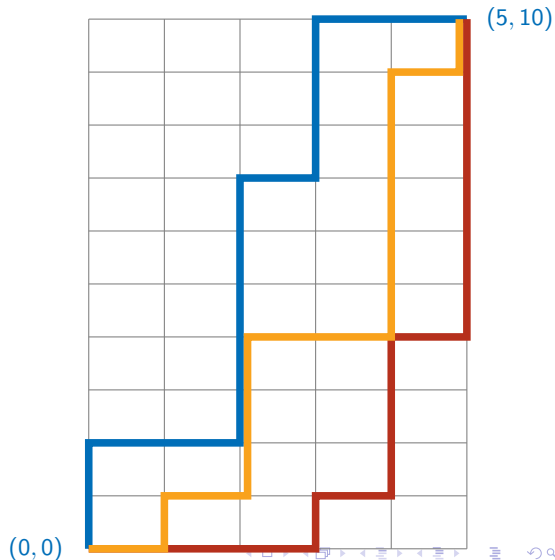
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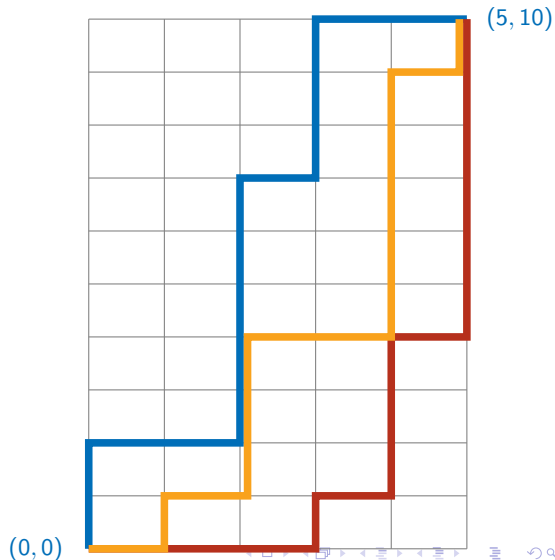
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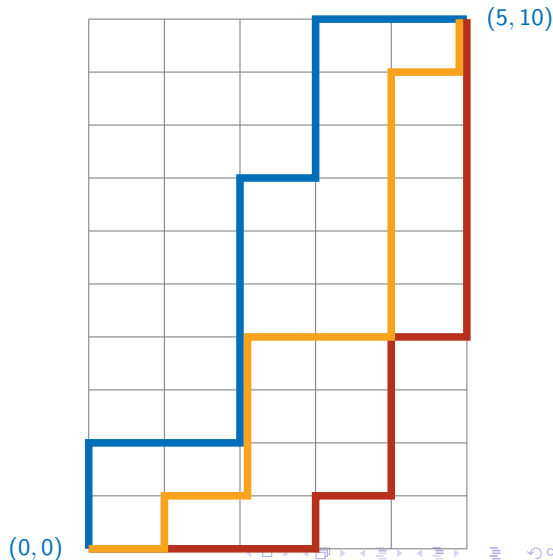
Combinatorial solution

- Every path from $(0,0)$ to $(5,10)$ has 15 segments
- In general $m+n$ segments from $(0,0)$ to (m,n)



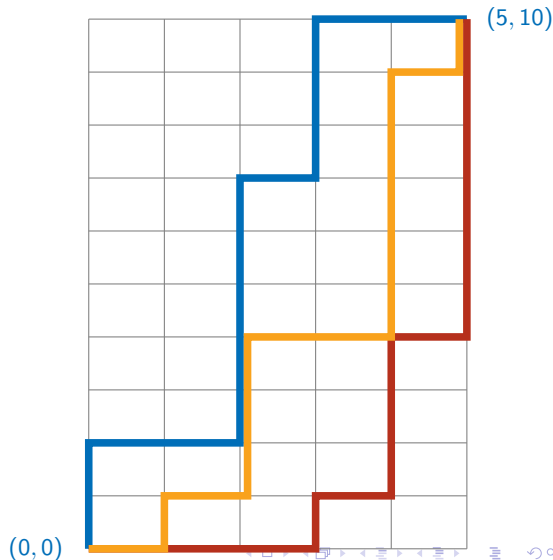
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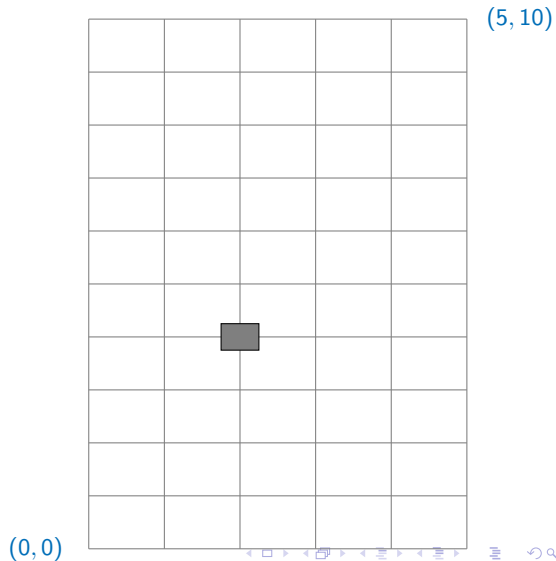
Combinatorial solution

- Every path from $(0, 0)$ to $(5, 10)$ has 15 segments
 - In general $m+n$ segments from $(0, 0)$ to (m, n)
- Out of 15, exactly 5 are right moves, 10 are up moves
- Fix the positions of the 5 right moves among the 15 positions overall
 - $\binom{15}{5} = \frac{15!}{10! \cdot 5!} = 3003$
 - Same as $\binom{15}{10}$ — fix the 10 up moves



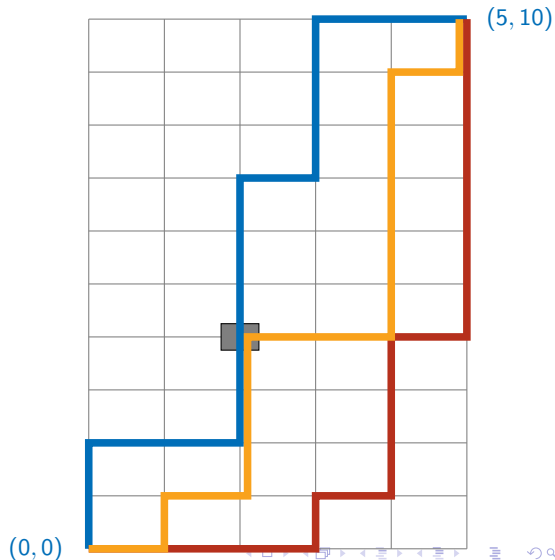
Holes

- What if an intersection is blocked?
 - For instance, $(2, 4)$



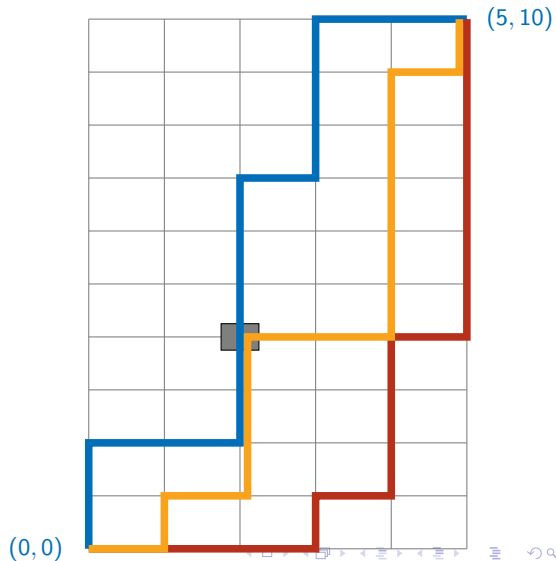
Holes

- What if an intersection is blocked?
 - For instance, $(2, 4)$
- Need to discard paths passing through $(2, 4)$
 - Two of our earlier examples are invalid paths



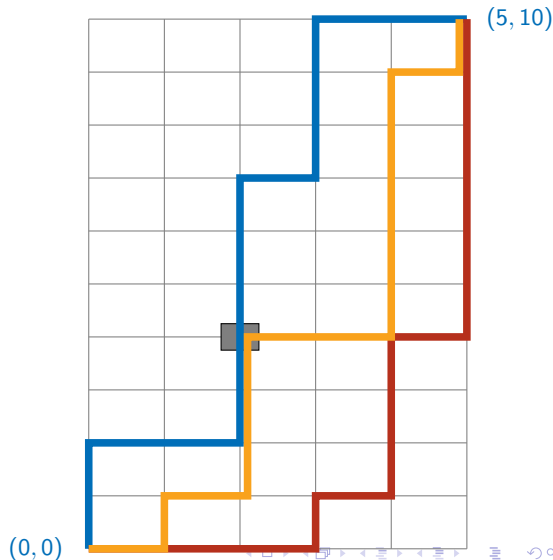
Combinatorial solution for holes

- Discard paths passing through $(2, 4)$



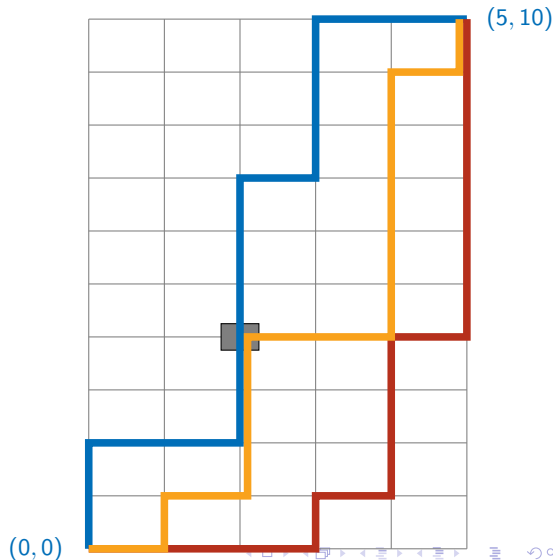
Combinatorial solution for holes

- Discard paths passing through $(2, 4)$
- Every path via $(2, 4)$ combines a path from $(0, 0)$ to $(2, 4)$ with a path from $(2, 4)$ to $(5, 10)$
 - Count these separately
 - $\binom{2+4}{2} = 15$ paths $(0, 0)$ to $(2, 4)$
 - $\binom{3+6}{3} = 84$ paths $(2, 4)$ to $(5, 10)$



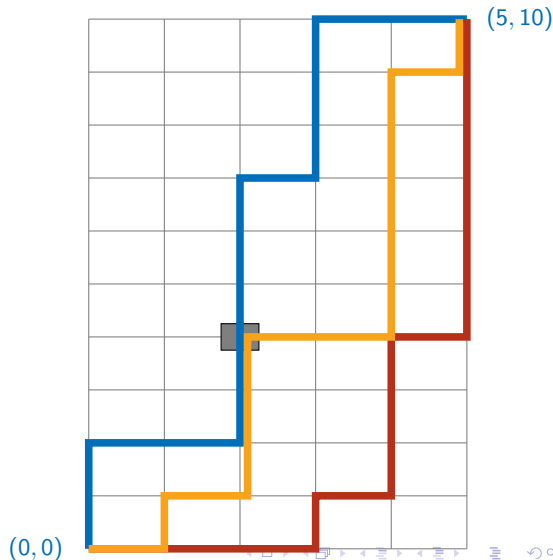
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- $15 \times 84 = 1260$ paths via $(2, 4)$



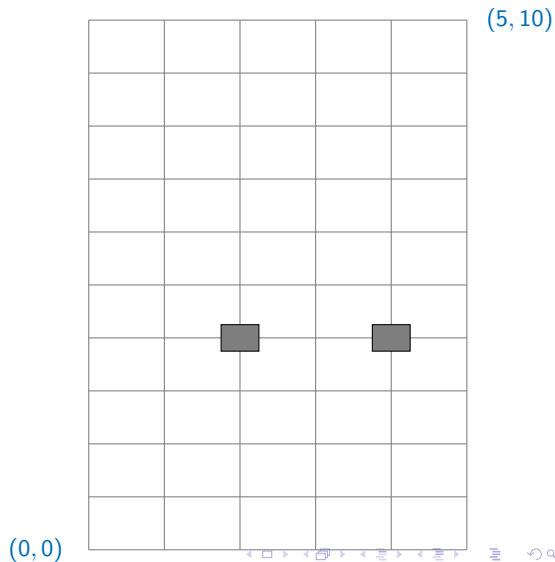
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- $15 \times 84 = 1260$ paths via $(2, 4)$
- $3003 - 1260 = 1743$ valid paths avoiding $(2, 4)$



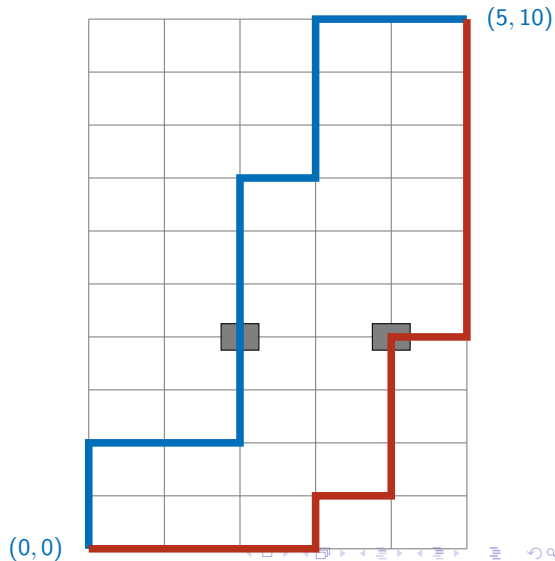
More holes

- What if two intersections are blocked?



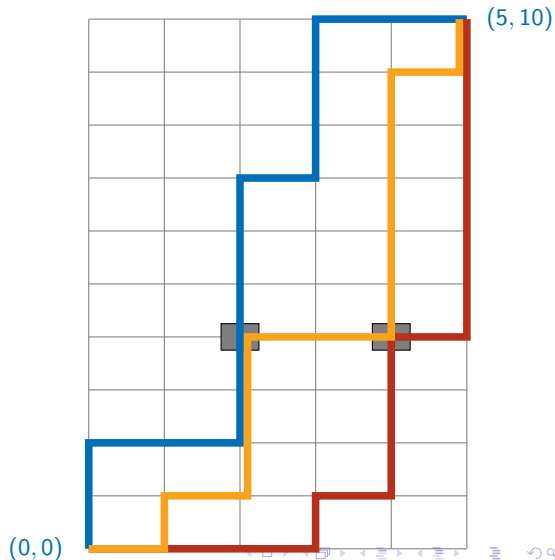
More holes

- What if two intersections are blocked?
- Discard paths via $(2, 4)$, $(4, 4)$



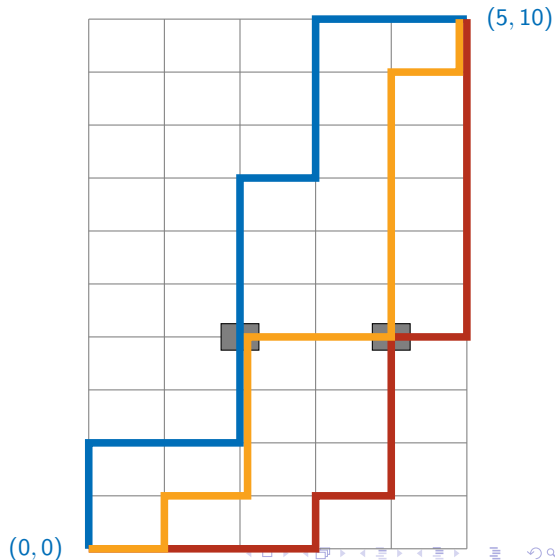
More holes

- What if two intersections are blocked?
- Discard paths via $(2, 4)$, $(4, 4)$
 - Some paths are counted twice



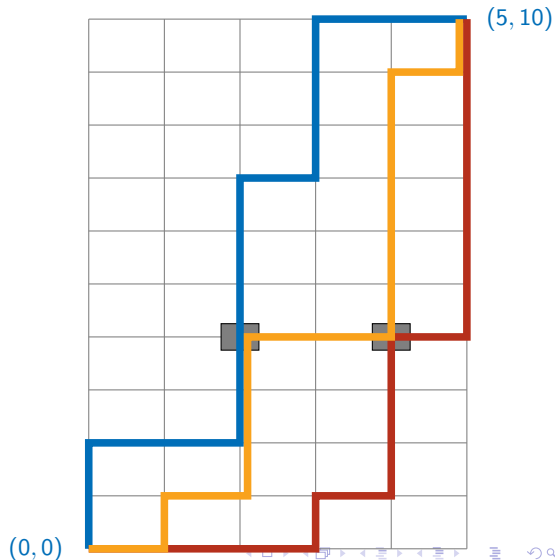
More holes

- What if two intersections are blocked?
- Discard paths via $(2, 4)$, $(4, 4)$
 - Some paths are counted twice
- Add back the paths that pass through both holes



More holes

- What if two intersections are blocked?
- Discard paths via $(2, 4)$, $(4, 4)$
 - Some paths are counted twice
- Add back the paths that pass through both holes
- **Inclusion-exclusion** — counting is messy



Inductive formulation

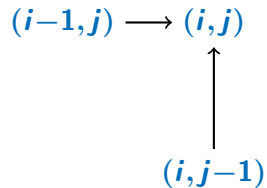
- How can a path reach (i, j)

Inductive formulation

- How can a path reach (i, j)
 - Move up from $(i, j - 1)$

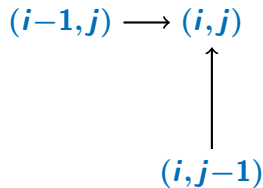
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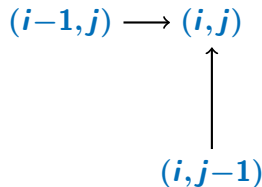
Inductive formulation

- How can a path reach (i, j)
 - Move up from $(i, j - 1)$
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- Each path to these neighbours extends to a unique path to (i, j)



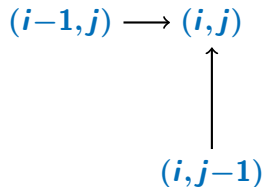
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- Recurrence for $P(i, j)$, number of paths from $(0, 0)$ to (i, j)
 - $P(i, j) = P(i - 1, j) + P(i, j - 1)$



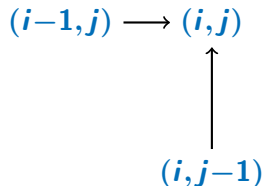
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 - $P(0, 0) = 1$ — base case



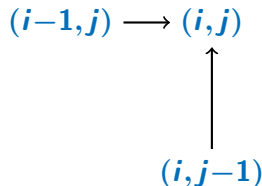
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 - $P(i, 0) = P(i - 1, 0)$ — bottom row



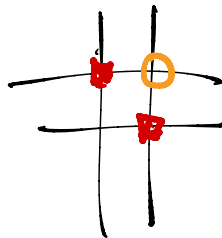
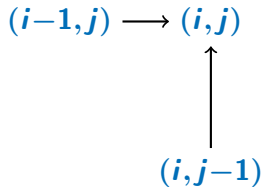
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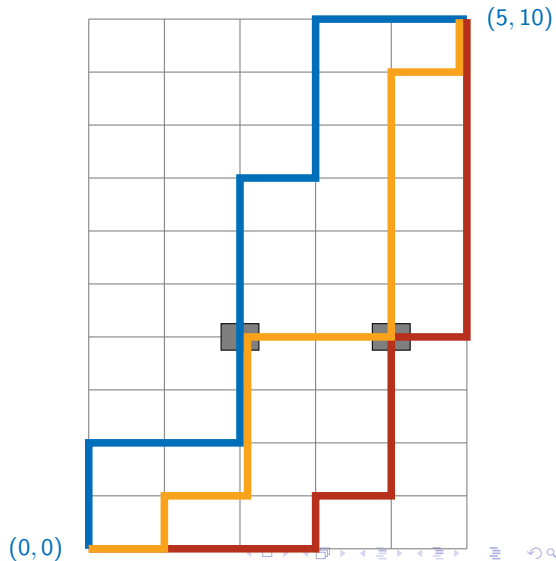
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 - $P(i, 0) = P(i - 1, 0)$ — bottom row
 - $P(0, j) = P(0, j - 1)$ — left column
- $P(i, j) = 0$ if there is a hole at (i, j)



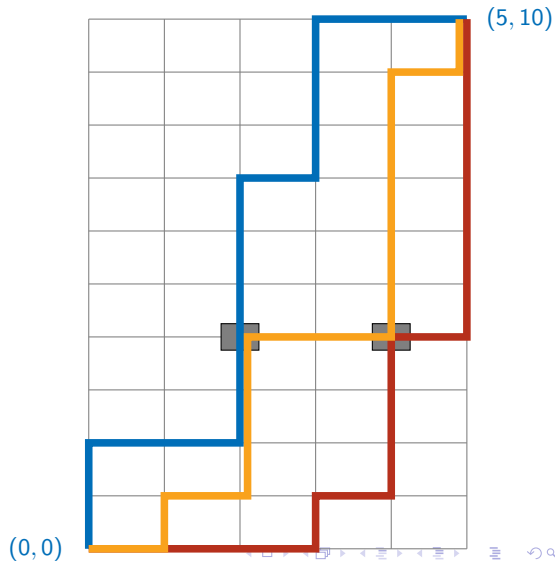
Computing $P(i,j)$

- Naive recursion recomputes same subproblem repeatedly



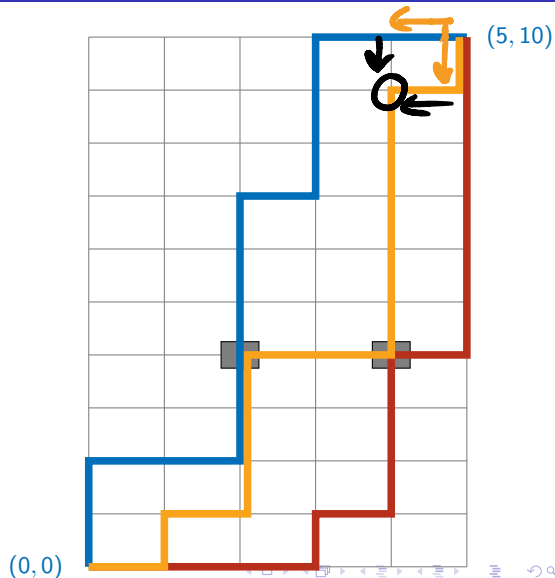
Computing $P(i,j)$

- Naive recursion recomputes same subproblem repeatedly
 - $P(5, 10)$ requires $P(4, 10)$, $P(5, 9)$



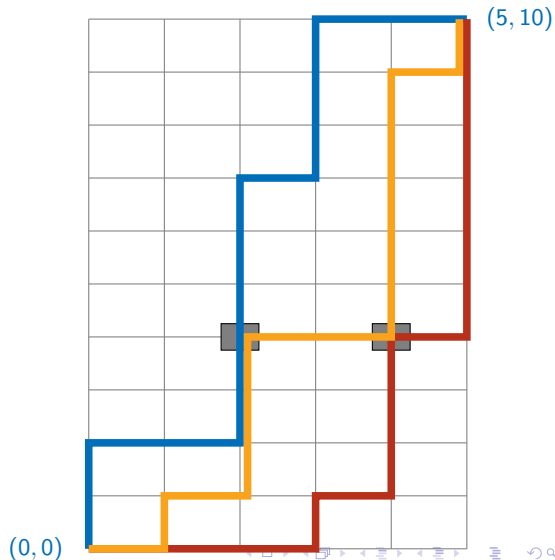
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 - Both $P(4, 10)$, $P(5, 9)$ require $P(4, 9)$



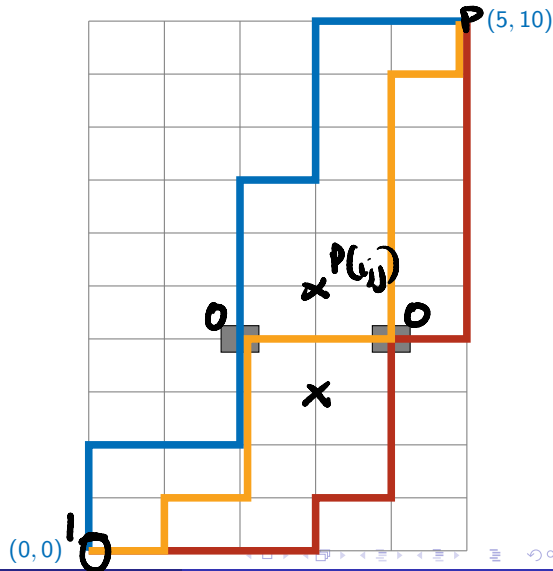
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- Use memoization ...



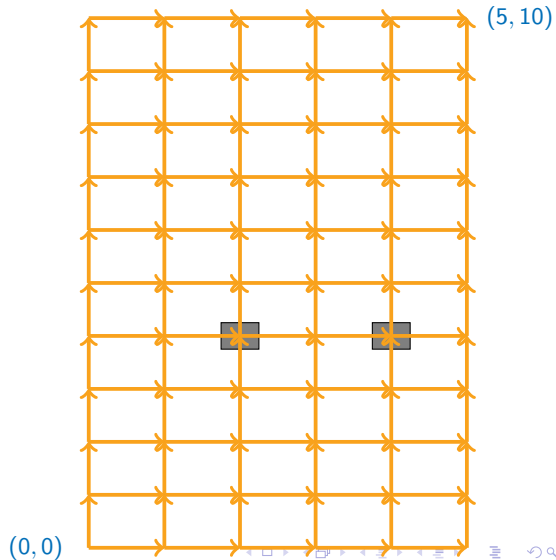
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- Naive recursion recomputes same subproblem repeatedly
 - $P(5, 10)$ requires $P(4, 10)$, $P(5, 9)$
 - Both $P(4, 10)$, $P(5, 9)$ require $P(4, 9)$
- Use memoization ...
- ...or find a suitable order to compute the subproblems



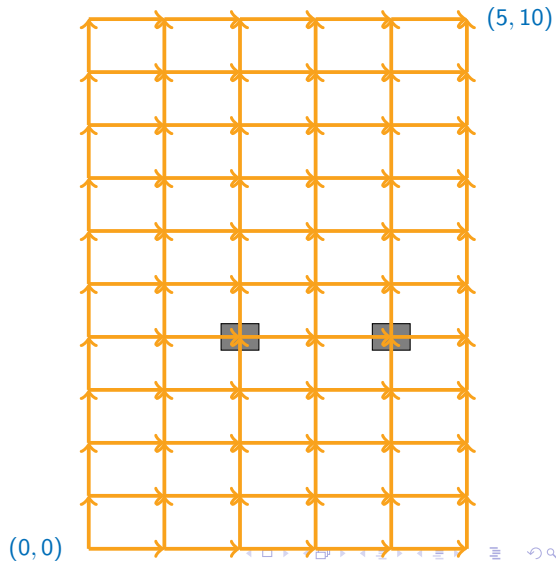
Dynamic programming

- Identify subproblem structure



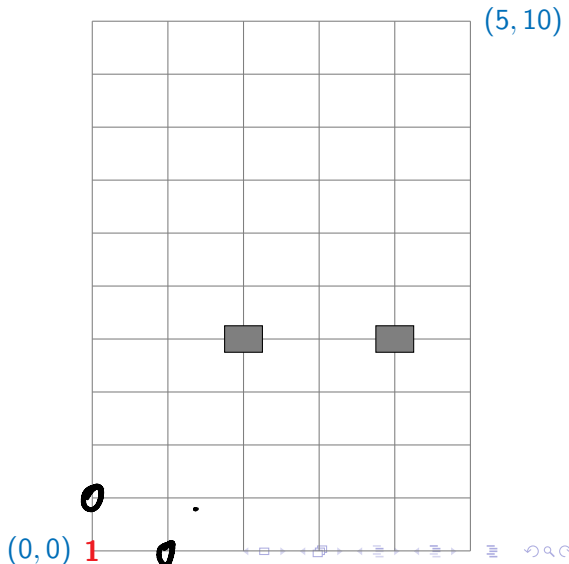
Dynamic programming

- Identify subproblem structure
- $P(0,0)$ has no dependencies



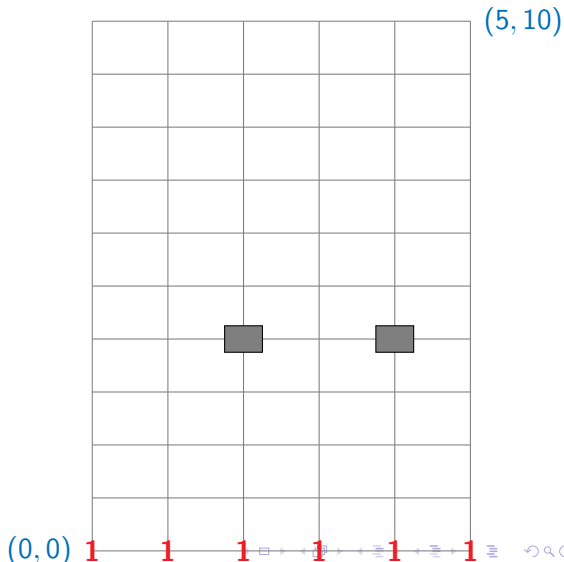
Dynamic programming

- Identify subproblem structure
- $P(0,0)$ has no dependencies
- Start at $(0,0)$



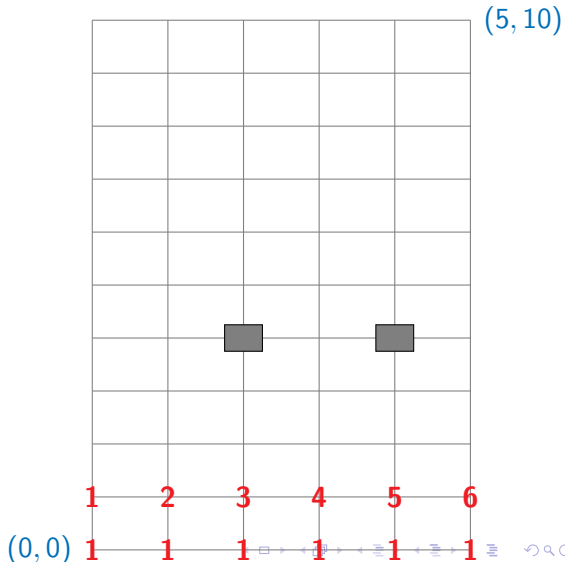
Dynamic programming

- Identify subproblem structure
- $P(0,0)$ has no dependencies
- Start at $(0,0)$
- Fill row by row



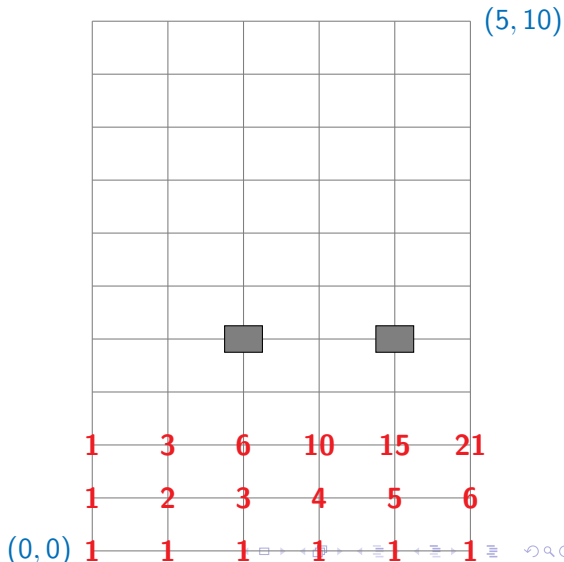
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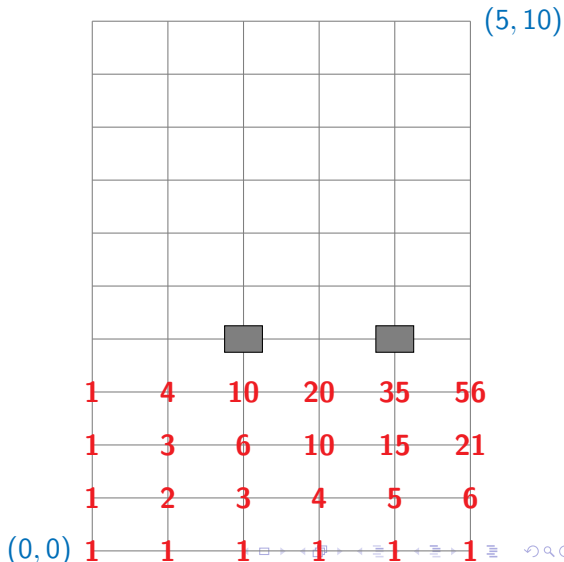
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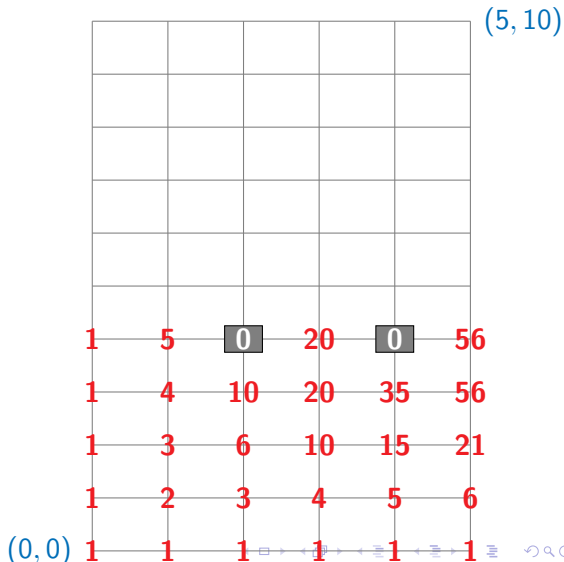
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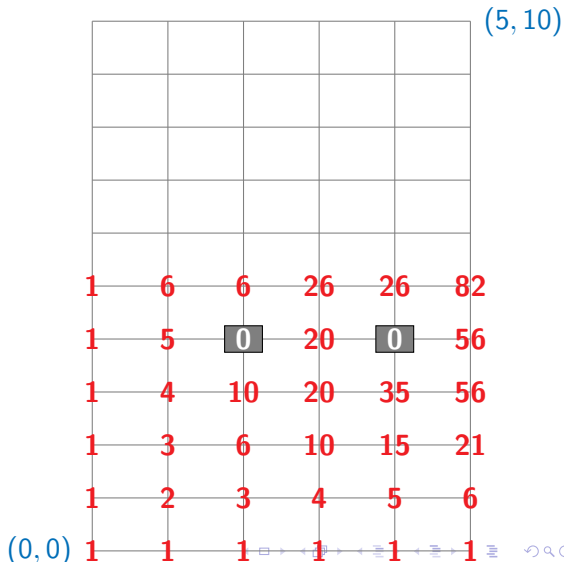
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Dynamic programming

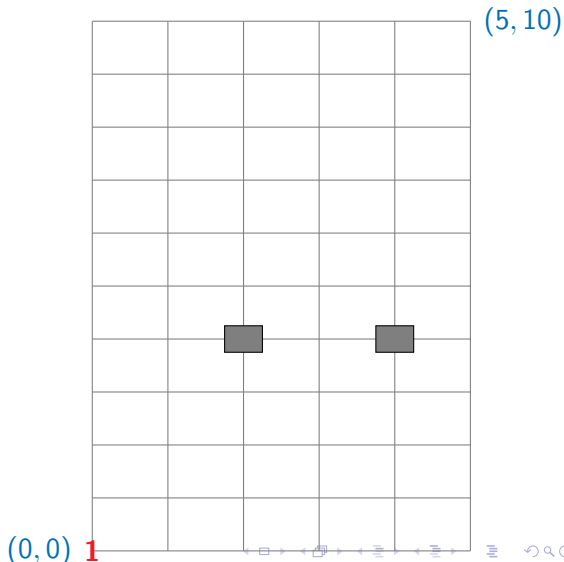
- Identify subproblem structure
- $P(0,0)$ has no dependencies
- Start at $(0,0)$
- Fill row by row

(5,10)

1	11	51	181	526	1358
1	10	40	130	345	832
1	9	30	90	215	487
1	8	21	60	125	272
1	7	13	39	65	147
1	6	6	26	26	82
1	5	0	20	0	56
1	4	10	20	35	56
1	3	6	10	15	21
1	2	3	4	5	6
(0,0)	1	1	1	1	1

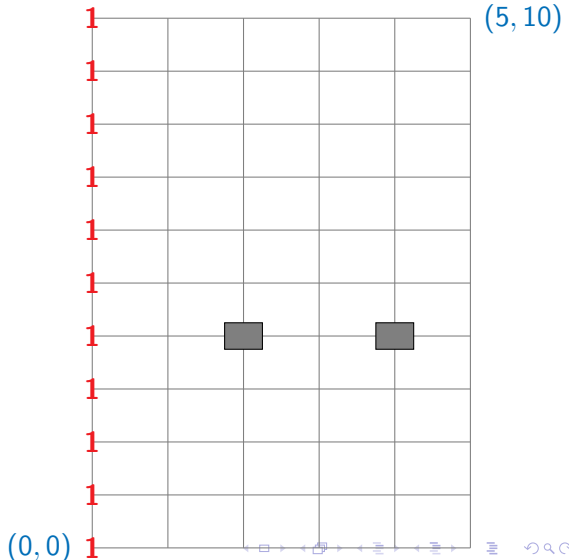
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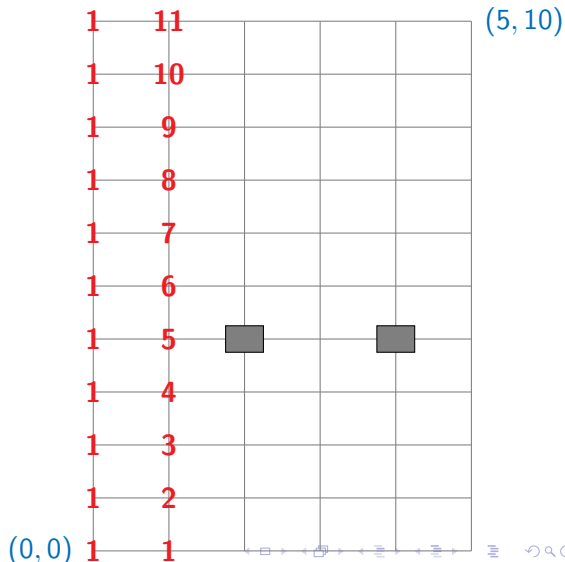
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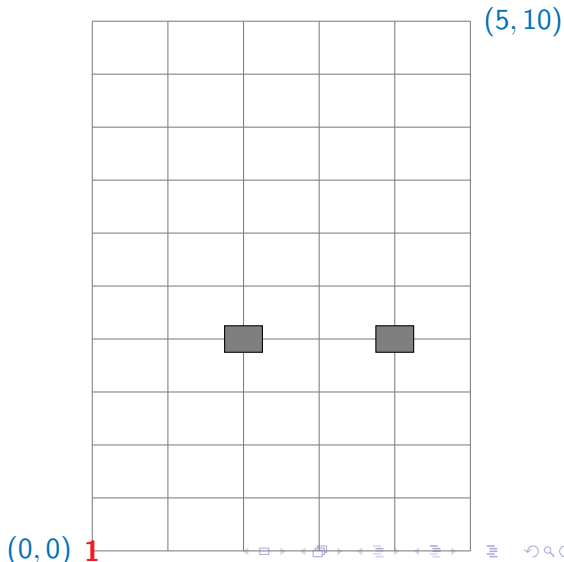
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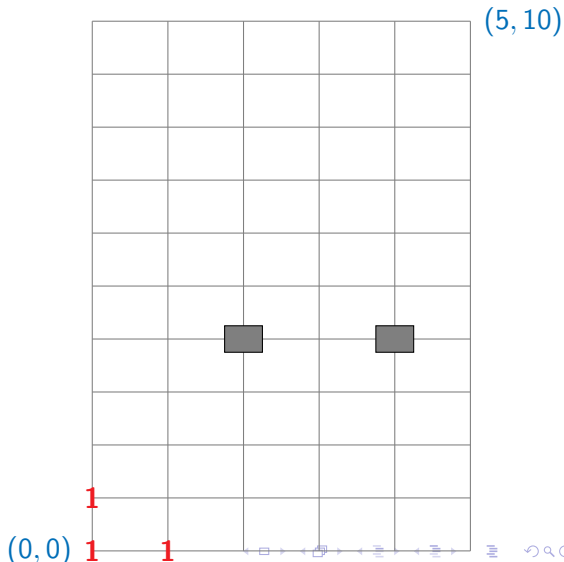
Dynamic programming

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- Fill column by column
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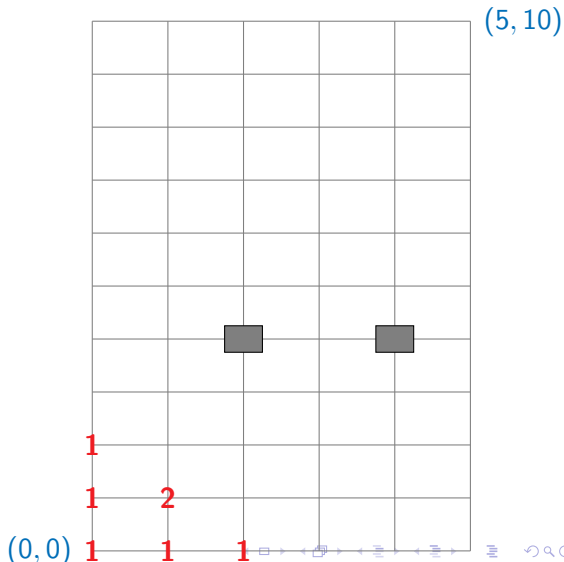
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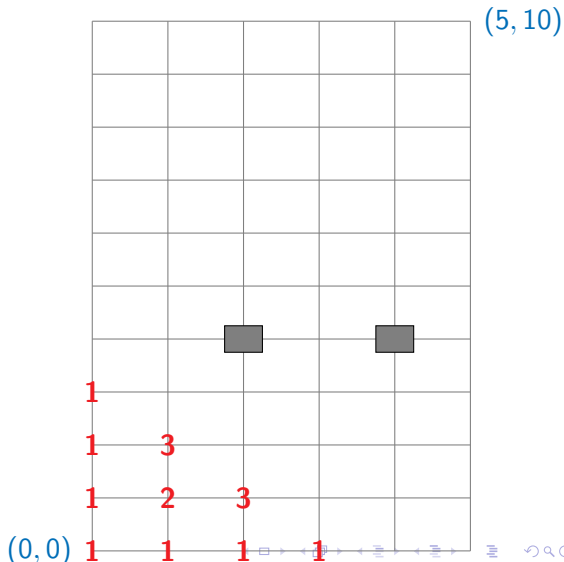
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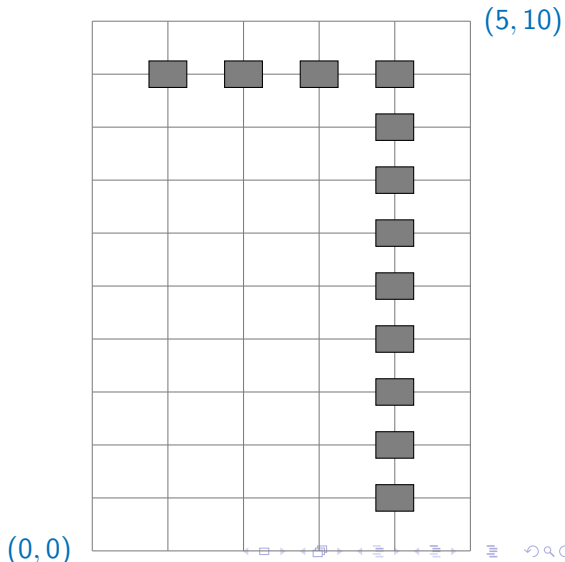
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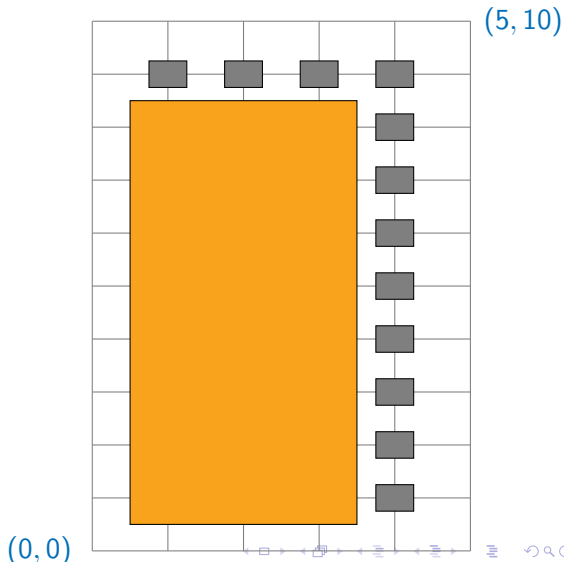
Memoization vs dynamic programming

- Barrier of holes just inside the border



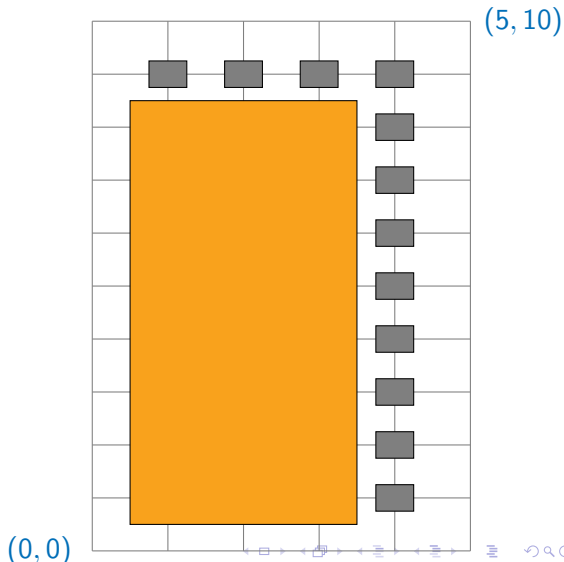
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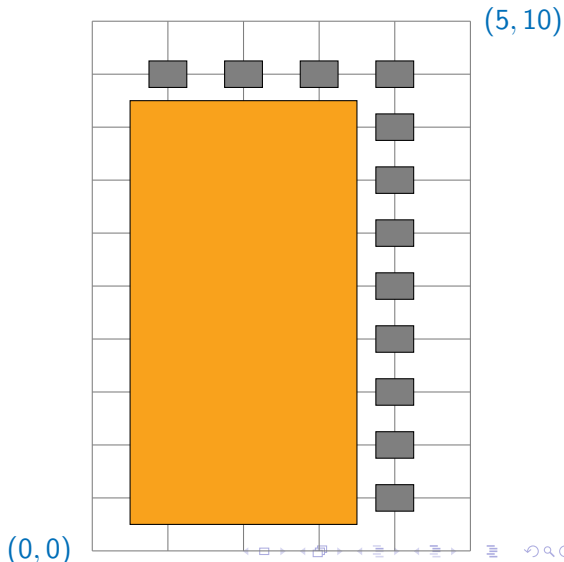
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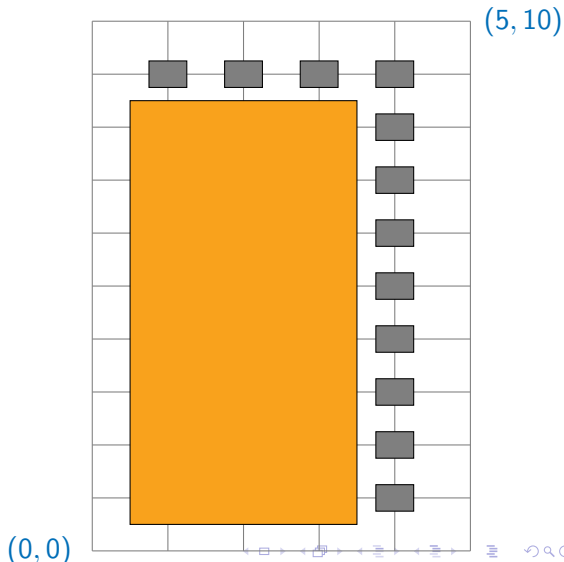
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- Barrier of holes just inside the border
- Memoization never explores the shaded region
- Memo table has $O(m + n)$ entries
- Dynamic programming blindly fills all mn cells of the table
- Tradeoff between recursion and iteration
 - “Wasteful” dynamic programming still better in general



Longest common subword

- Given two strings, find the (length of the) longest common subword
 - "secret", "secretary" — "secret", length 6
 - "bisect", "trisect" — "isect", length 5
 - "bisect", "secret" — "sec", length 3
 - "director", "secretary" — "ec", "re", length 2

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 - Find the largest such k — length of the longest common subword

Brute force

- $u = a_0 a_1 \dots a_{m-1}$
- $v = b_0 b_1 \dots b_{n-1}$
- Find the largest k such that for some positions i and j ,
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- Try every pair of starting positions i in u , j in v
 - Match $(a_i, b_j), (a_{i+1}, b_{j+1}), \dots$ as far as possible
 - Keep track of longest match

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 - Keep track of longest match
- Assuming $m > n$, this is $O(mn^2)$
 - mn pairs of starting positions
 - From each starting position, scan could be $O(n)$

Inductive structure

- $u = a_0 a_1 \dots a_{m-1}$
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 - Base case: $LCW(m, n) = 0$

Valid indices are $0 \leftrightarrow m-1$
 $0 \leftrightarrow n-1$

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 - In general, $LCW(m, j) = 0$ for all $0 \leq j \leq n$

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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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- Table of $(m + 1) \cdot (n + 1)$ values
- $LCW(i, j)$ depends on $LCW(i+1, j+1)$

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

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- Start at bottom right and fill row by row or column by column

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

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

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

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4	c				0	0	0	0
5	t				0	0	1	0
6	•				0	0	0	0

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2	s			0	0	0	0	0
3	e			0	0	1	0	0
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2	s		0	0	0	0	0	0
3	e		2	0	0	1	0	0
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Reading off the solution

- Find entry (i, j) with largest LCW value

		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	e	3	0	0	0	0	0	0
3	e	0	2	0	0	1	0	0
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Reading off the solution

- Find entry (i,j) with largest LCW value
- Read off the actual subword diagonally

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

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Implementation

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

    maxlcw = 0

    for j in range(n-1,-1,-1):
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Complexity

- Recall that brute force was $O(mn^2)$
- Inductive solution is $O(mn)$, using dynamic programming or memoization
 - Fill a table of size $O(mn)$
 - Each table entry takes constant time to compute

Longest common subsequence

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

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- 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
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6	•	0	0	0	0	0	0	0

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Applications

■ Analyzing genes

- DNA is a long string over A, T, G, C
- Two species are similar if their DNA has long common subsequences

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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

- $u = a_0 a_1 \dots a_{m-1}$

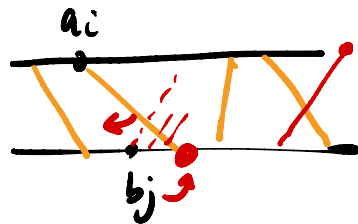
- $v = b_0 b_1 \dots b_{n-1}$

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 - Can assume (a_i, b_j) is part of LCS



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- Base cases as with LCW
 - $LCS(i, n) = 0$ for all $0 \leq i \leq m$
 - $LCS(m, j) = 0$ for all $0 \leq j \leq n$

$$LCS(i, j) \\ a_i \neq b_j \\ = \max(LCS(i+1, j), LCS(i, j+1))$$

Subproblem dependency

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

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

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

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2	s				2	2	0	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	1	1	0	0
1	i	4	3	2	1	1	0	0
2	s	4	3	2	1	1	0	0
3	e	3	3	2	1	1	0	0
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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	1	1	0	0
1	i	4	3	2	1	1	0	0
2	s	4	3	2	1	1	0	0
3	e	3	3	2	1	1	0	0
4	c	2	2	2	1	1	0	0
5	t	1	1	1	1	1	1	0
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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