

# Lecture 23, 19 November 2024

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Programming and Data Structures with Python

Lecture 23, 19 Nov 2024

- Factorial

- $fact(0) = 1$

- $fact(n) = n \times fact(n - 1)$

## ■ Factorial

- $fact(0) = 1$  — Base Case
- $fact(n) = n \times fact(n-1)$  — Inductive step

```
def fact(n):  
    if n <= 0:  
        return(1) — Base Case  
    else:  
        return(n * fact(n-1)) — recursive call
```

## ■ Factorial

- $fact(0) = 1$
- $fact(n) = n \times fact(n - 1)$

```
def fact(n):  
    if n <= 0:  
        return(1)  
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```

## ■ Insertion sort

- $isort([]) = []$  ← Base
- $isort([x_0, x_1, \dots, x_n]) =$   
 $insert(isort([x_0, x_1, \dots, x_{n-1}]), x_n)$

Inductive

# Inductive definitions, recursive programs, subproblems

## ■ Factorial

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- $fact(n) = n \times fact(n - 1)$

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## ■ Insertion sort

- $isort([]) = []$
- $isort([x_0, x_1, \dots, x_n]) = insert(isort([x_0, x_1, \dots, x_{n-1}]), x_n)$

## ■ $fact(n-1)$ is a subproblem of $fact(n)$

- So are  $fact(n-2)$ ,  $fact(n-3)$ ,  $\dots$ ,  $fact(0)$

## ■ $isort([x_0, x_1, \dots, x_{n-1}])$ is a subproblem of $isort([x_0, x_1, \dots, x_n])$

- So is  $isort([x_0, \dots, x_j])$  for any  $0 < j < n$

## ■ Solution to original problem can be derived by combining solutions to subproblems

# Evaluating subproblems

## ■ Fibonacci numbers

0 1 1 2 3 5 8 13

- $fib(0) = 0$  || Base cases
- $fib(1) = 1$  || Base cases
- $fib(n) = fib(n-1) + fib(n-2)$  Inductive

```
def fib(n):  
    if n <= 1: ||  
        value = n  
    else:  
        value = fib(n-1) + fib(n-2) Recursive  
    return(value)
```



Doesn't work, in practice  
Why?

# Evaluating subproblems

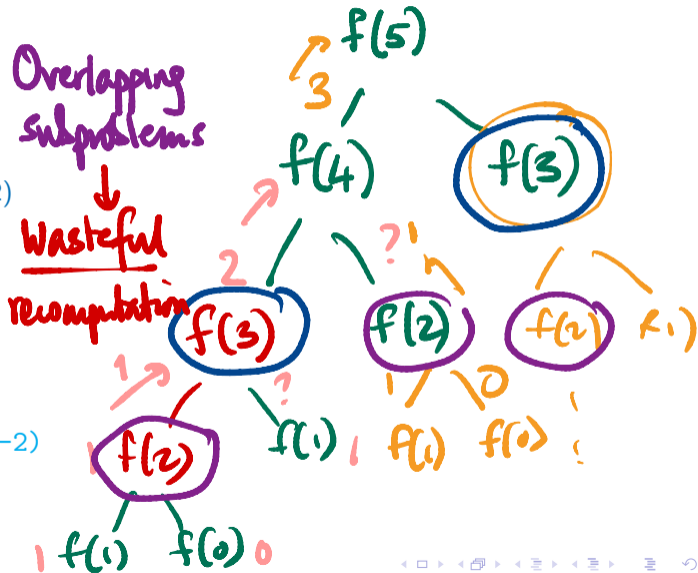
## ■ Fibonacci numbers

■  $fib(0) = 0$

■  $fib(1) = 1$

■  $fib(n) = fib(n-1) + fib(n-2)$

```
def fib(n):  
    if n <= 1:  
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    return(value)
```



# Evaluating subproblems

- Build a table of values already computed
  - Memory table

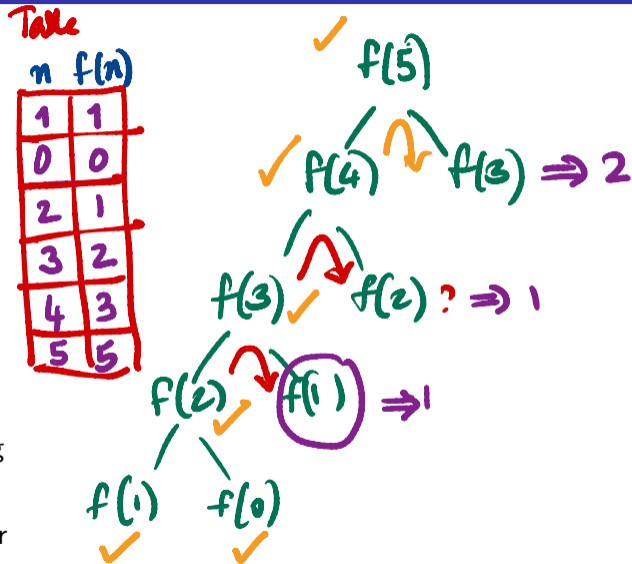


# Evaluating subproblems

- Build a table of values already computed
  - Memory table
- Memoization
  - Check if the value to be computed was already seen before

# Evaluating subproblems

- Build a table of values already computed
  - Memory table
- Memoization
  - Check if the value to be computed was already seen before
- Store each newly computed value in a table
- Look up the table before making a recursive call
- Computation tree becomes linear



# Memoizing recursive implementations

```
def fib(n):  
    if n <= 1:  
        value = n  
    else:  
        value = fib(n-1) + fib(n-2)  
    return(value)
```

# 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)
```

*- Check table*

*- Updating table*

# Memoizing recursive implementations

```
def fib(n):  
    if n in fibtable.keys():  
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    if n <= 1:  
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```

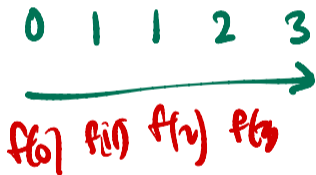
In general

```
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)
```

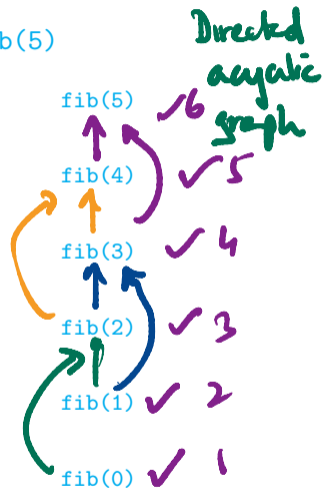
- Anticipate the structure of subproblems
  - Derive from inductive definition
  - Dependencies are acyclic

# Dynamic programming

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



Evaluating  $\text{fib}(5)$



# 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)`

Topological  
Sort

`fib(5)`

`fib(4)`

`fib(3)`

`fib(2)`

`fib(1)`

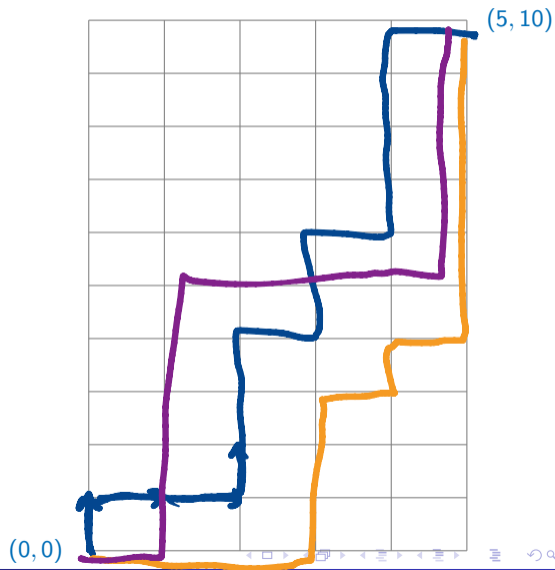
`fib(0)`

$f = \{3\}$   
 $f[0] = 0$   
 $f[1] = 1$   
for  $j$  in  
range(2, n+1)  
 $f[j] =$   
 $f[j-1]$   
 $+ f[j-2]$



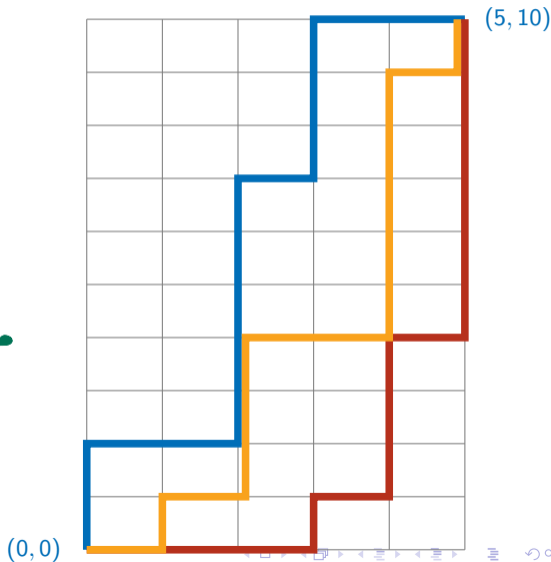
# Grid paths

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



# Combinatorial solution

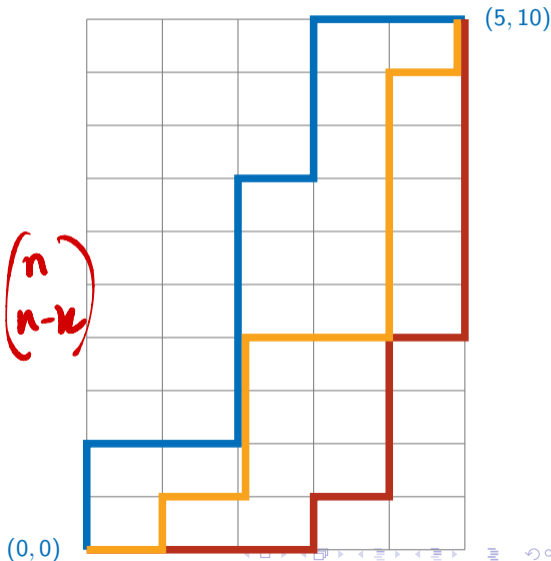
- Every path from  $(0, 0)$  to  $(5, 10)$  has 15 segments
  - Out of 15, exactly 5 are right moves, 10 are up moves
  - Fix the positions of the 5 right moves among the 15 positions overall



# Combinatorial solution

- Every path from  $(0, 0)$  to  $(5, 10)$  has 15 segments
  - 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

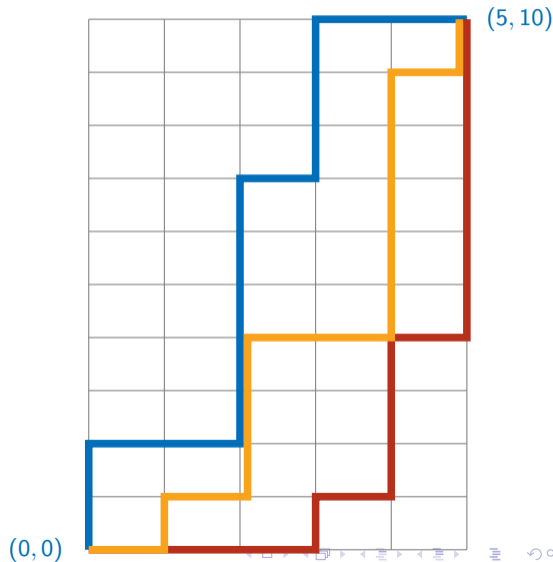
$$\binom{n}{k} = \binom{n}{n-k}$$



# Combinatorial solution

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

$$\binom{m+n}{m} \binom{m+n}{n}$$



- What if an intersection is blocked?

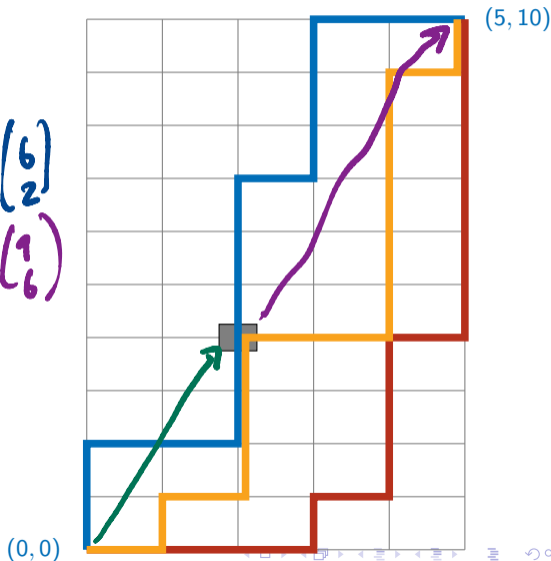
- For instance, (2, 4)

$$P_1 (0,0) \rightarrow (2,4) \quad \begin{pmatrix} 6 \\ 4 \end{pmatrix} \approx \begin{pmatrix} 6 \\ 2 \end{pmatrix}$$

$$P_2 (2,4) \rightarrow (5,10) \quad \begin{pmatrix} 9 \\ 3 \end{pmatrix} \approx \begin{pmatrix} 1 \\ 6 \end{pmatrix}$$

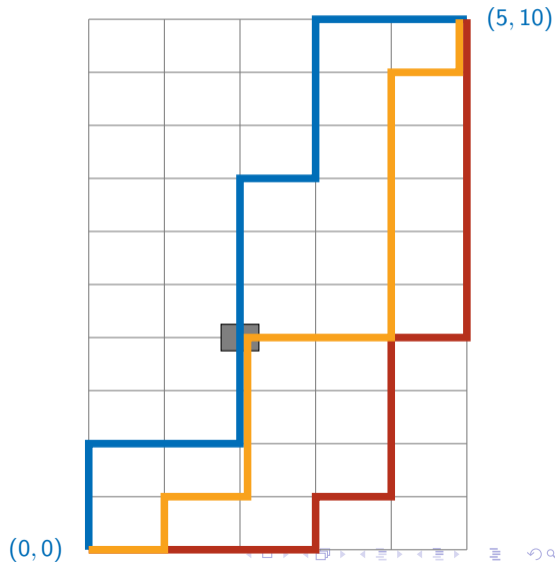
$P_1 \times P_2$  bad paths

$$\begin{pmatrix} 15 \\ 5 \end{pmatrix} - (P_1 \times P_2)$$



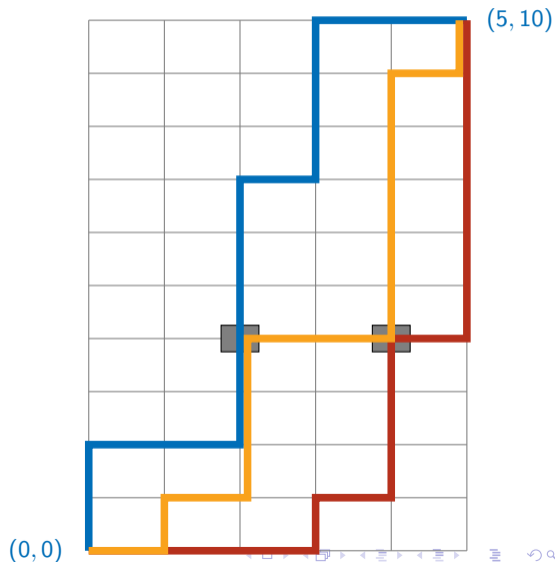
# Combinatorial solution for holes

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



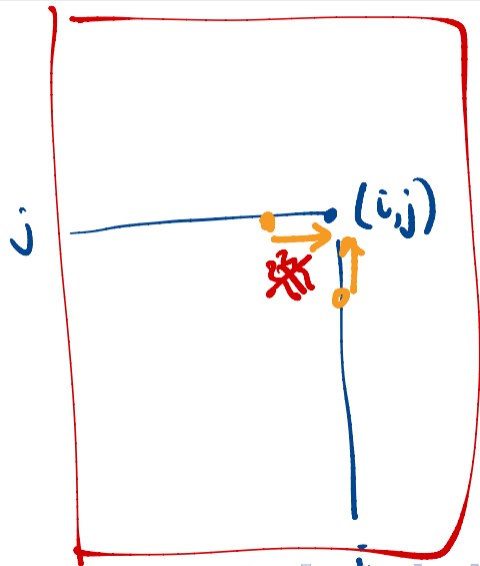
# More holes

- 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  $(i,j)$



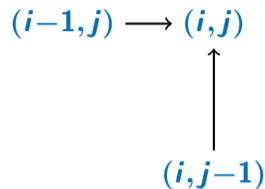


# Inductive formulation

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

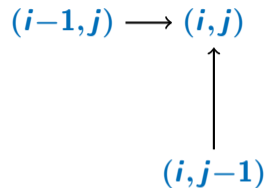
# Inductive formulation

- How can a path reach  $(i, j)$ 
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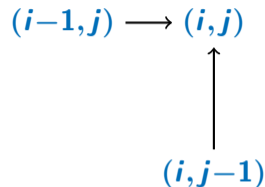
# Inductive formulation

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



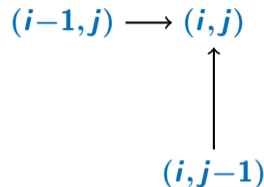
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- Recurrence for  $P(i, j)$ , number of paths from  $(0, 0)$  to  $(i, j)$ 
  - $P(i, j) = P(i - 1, j) + P(i, j - 1)$



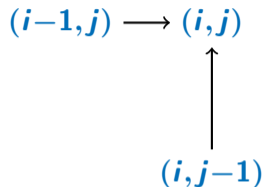
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  - $P(i, j) = P(i - 1, j) + P(i, j - 1)$
  - $P(0, 0) = 1$  — base case



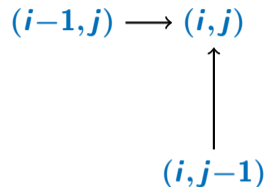
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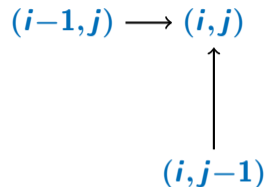
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# Inductive formulation

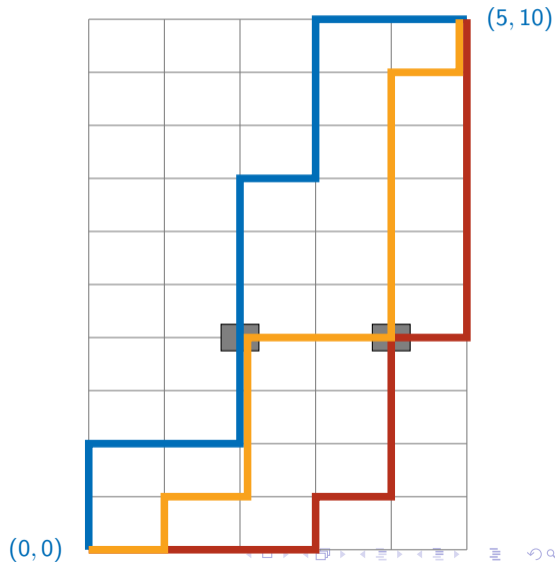
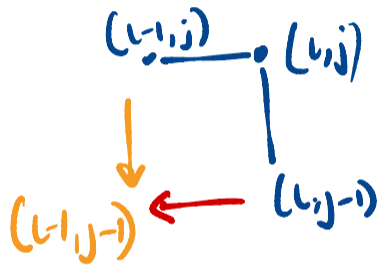
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  - $P(0, j) = P(0, j - 1)$  — left column
- $P(i, j) = 0$  if there is a hole at  $(i, j)$





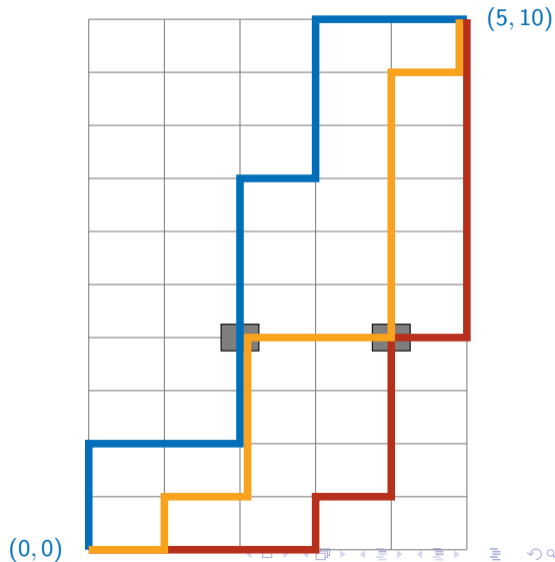
# Computing $P(i, j)$

- Naive recursion recomputes same subproblem repeatedly



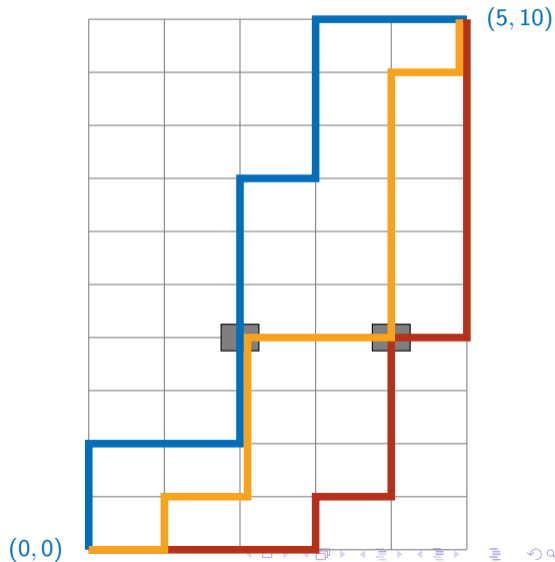
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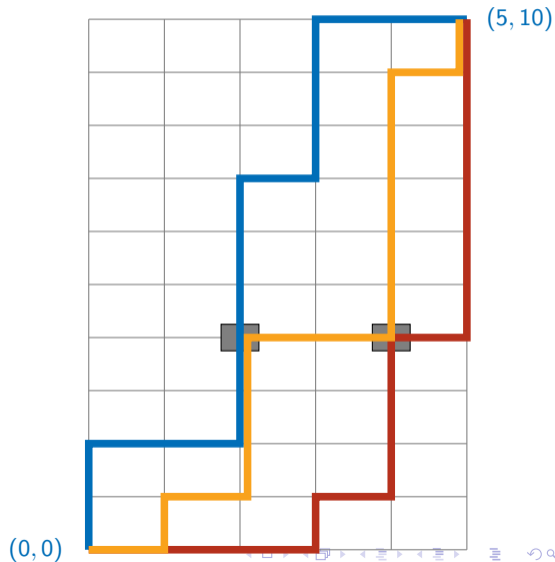
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  - Both  $P(4, 10)$ ,  $P(5, 9)$  require  $P(4, 9)$



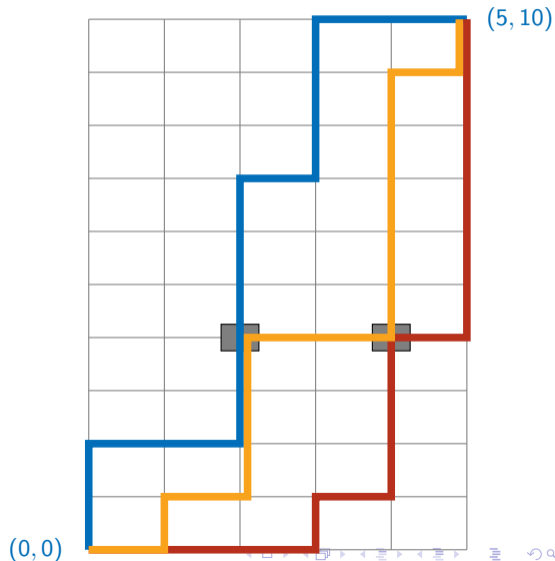
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- Use memoization ...



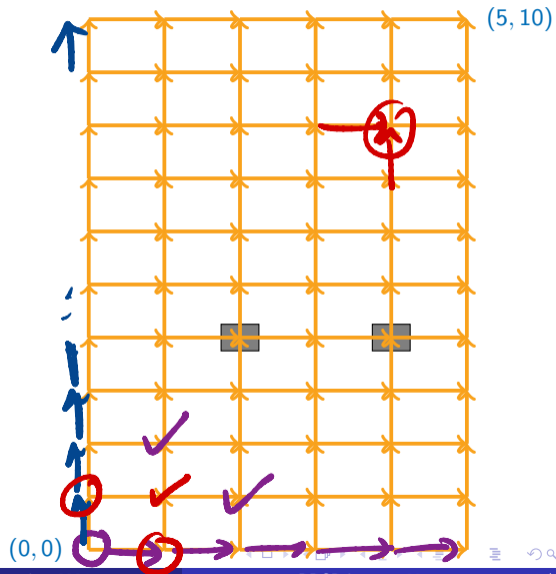
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- Naive recursion recomputes same subproblem repeatedly
  - $P(5, 10)$  requires  $P(4, 10)$ ,  $P(5, 9)$
  - Both  $P(4, 10)$ ,  $P(5, 9)$  require  $P(4, 9)$
- Use memoization ...
- ... or find a suitable order to compute the subproblems



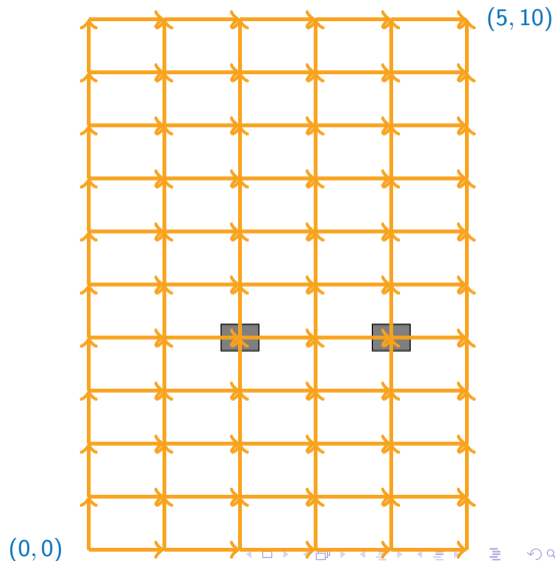
# Dynamic programming

- Identify subproblem structure



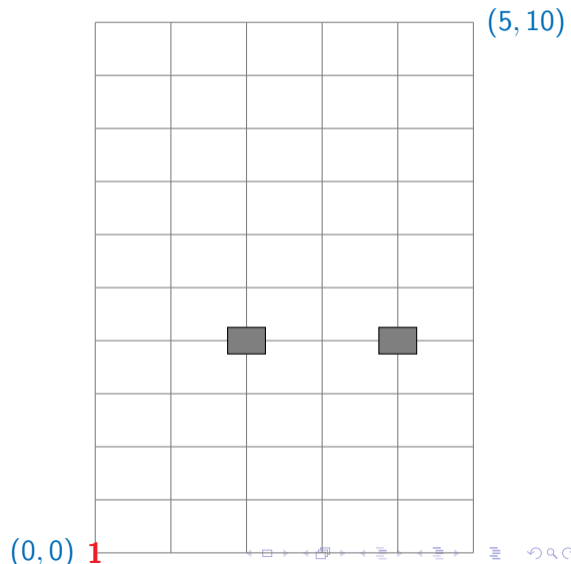
# Dynamic programming

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



# Dynamic programming

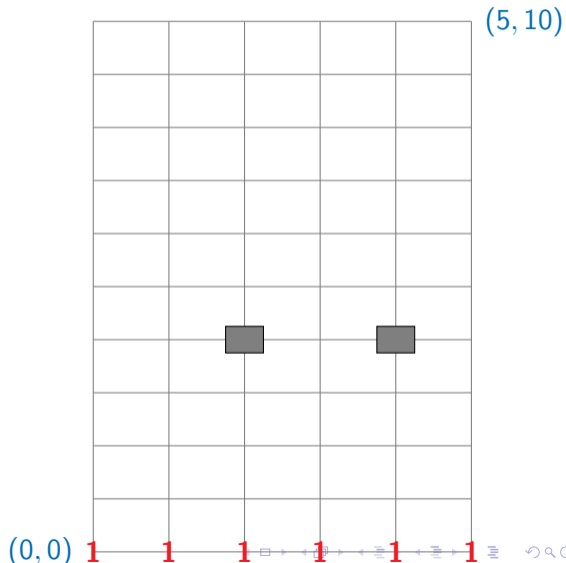
- Identify subproblem structure
- $P(0, 0)$  has no dependencies
- Start at  $(0, 0)$





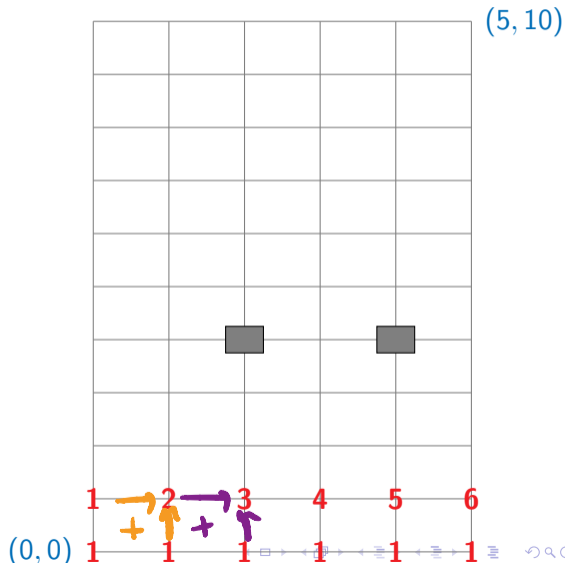
# Dynamic programming

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



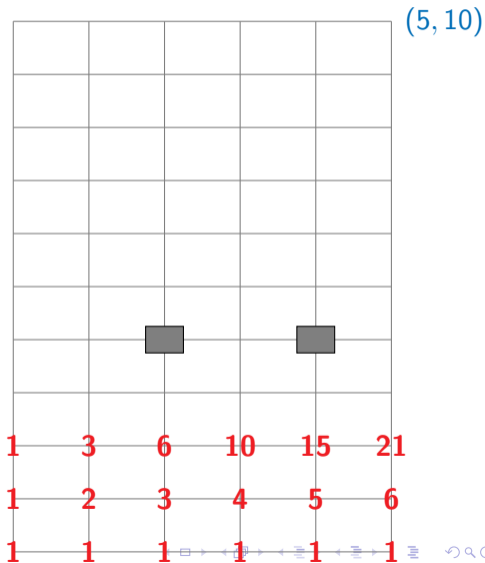
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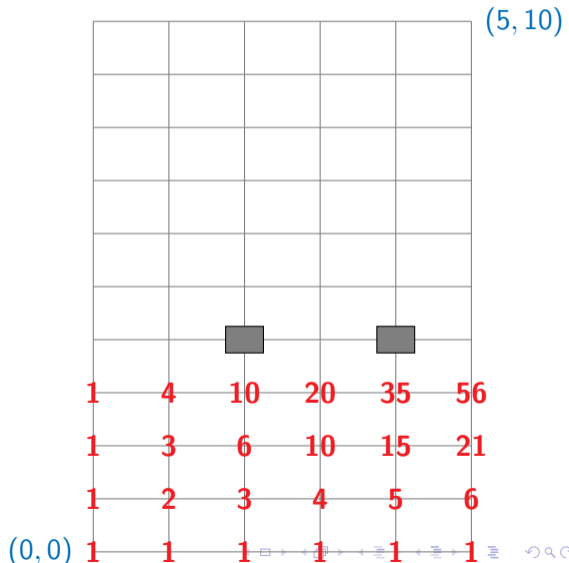
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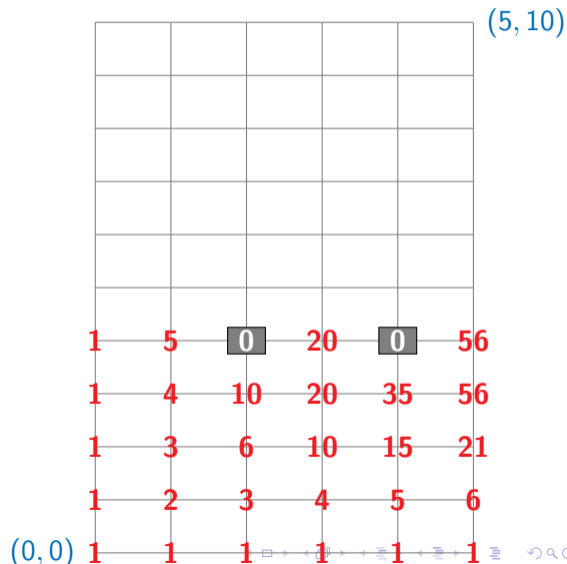
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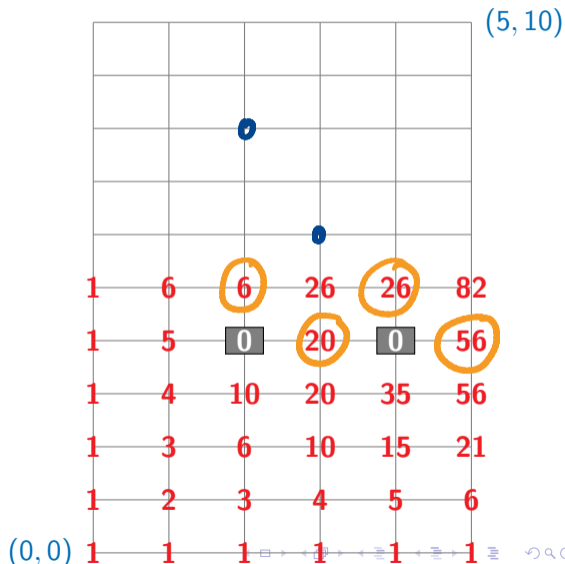
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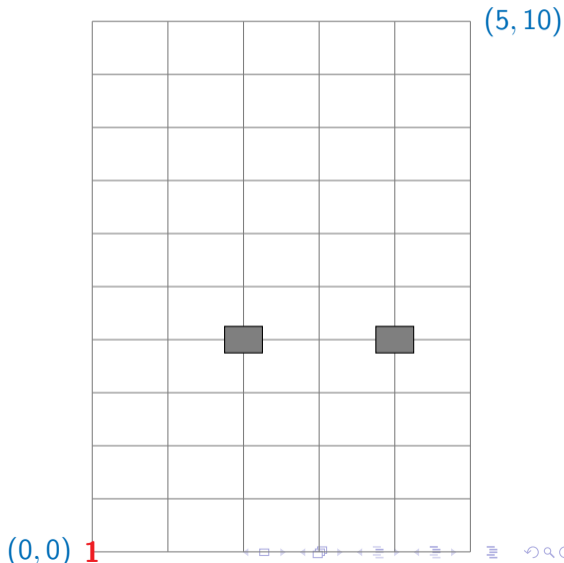
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	1	11	51	181	526	1358	$(5,10)$
	1	10	40	130	345	832	
	1	9	30	90	215	487	
	1	8	21	60	125	272	
	1	7	13	39	65	147	
	1	6	6	26	26	82	
	1	5	0	20	0	56	
	1	4	10	20	35	56	
	1	3	6	10	15	21	
	1	2	3	4	5	6	
$(0,0)$	1	1	1	1	1	1	

# Dynamic programming

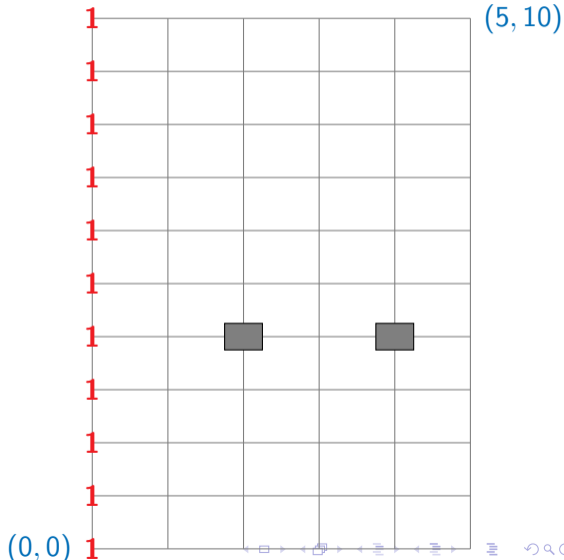
- Identify supproblem structure
- $P(0,0)$  has no dependencies
- Start at  $(0,0)$
- Fill row by row
- Fill column by column





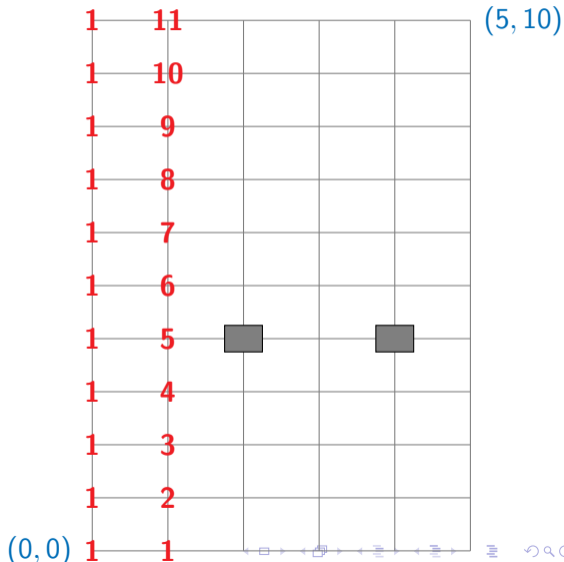
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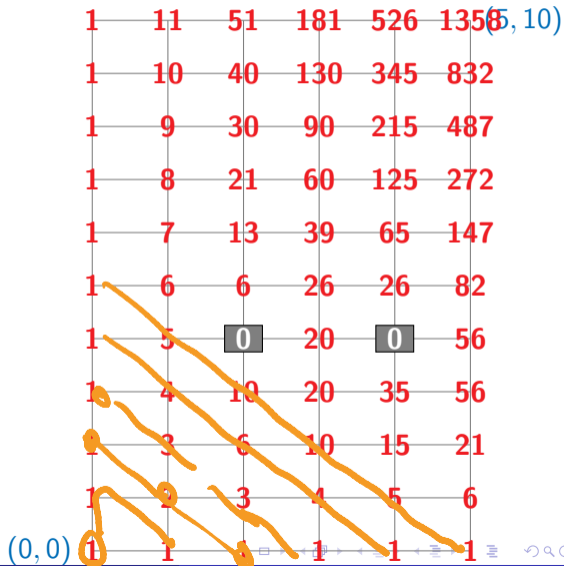
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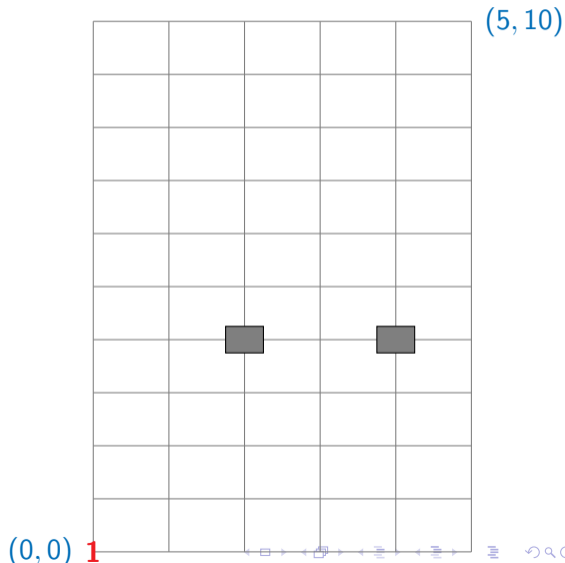
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Yet another order



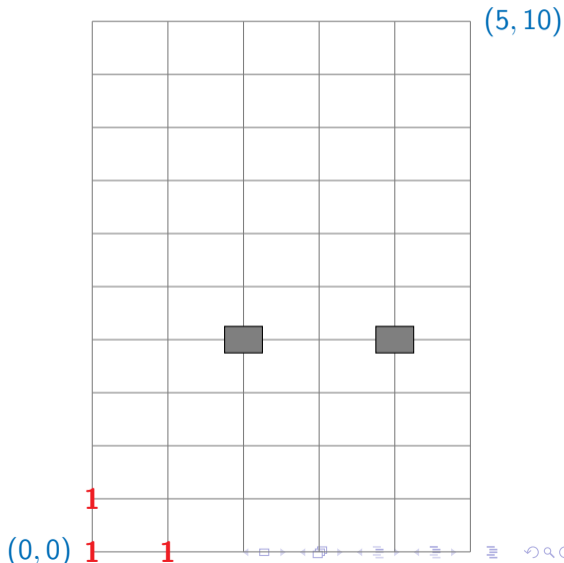
# Dynamic programming

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



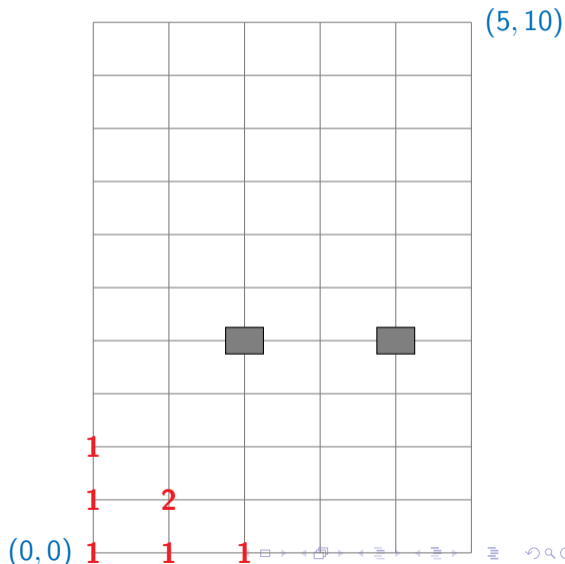
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- Start at  $(0,0)$
- Fill row by row
- Fill column by column
- Fill diagonal by diagonal



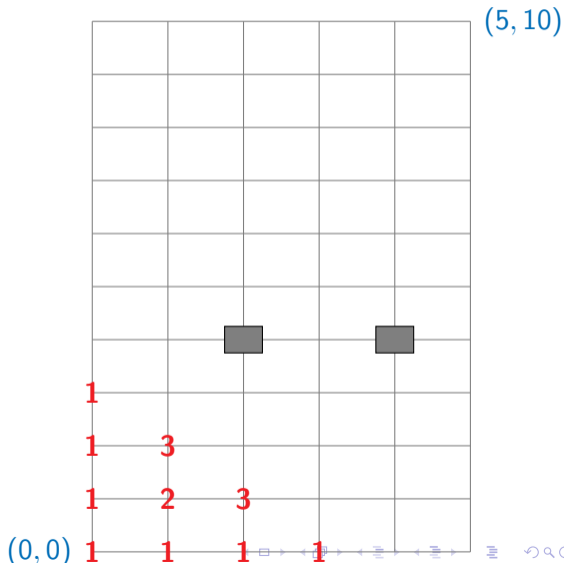
# Dynamic programming

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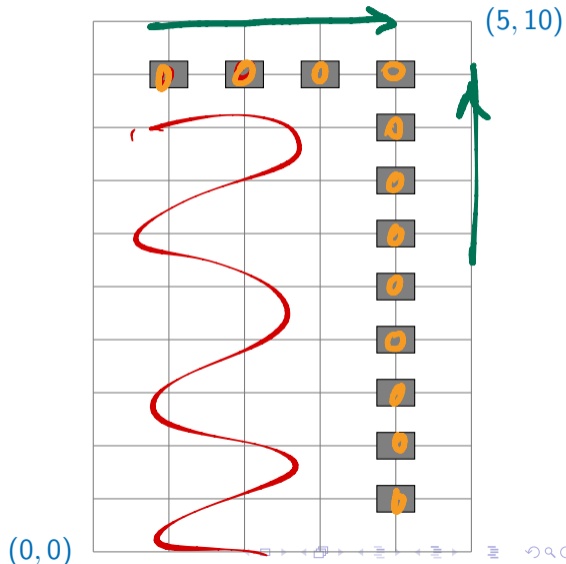
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# Memoization vs dynamic programming

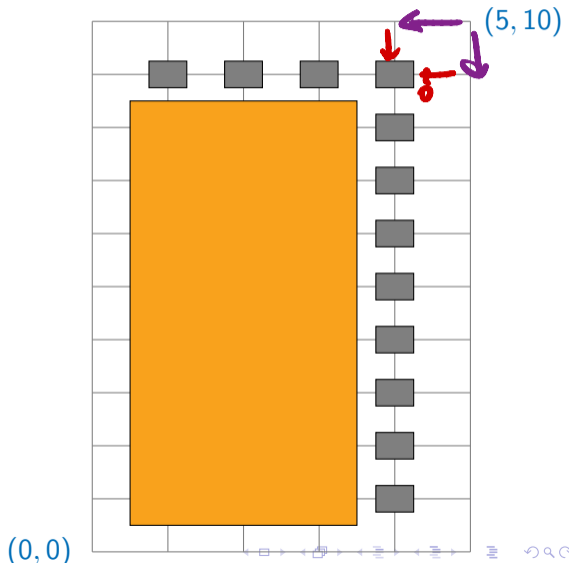
- Barrier of holes just inside the border





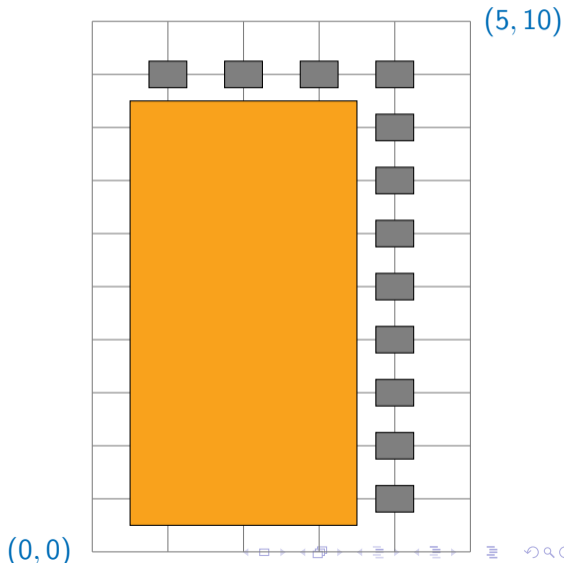
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- Barrier of holes just inside the border
- Memoization never explores the shaded region



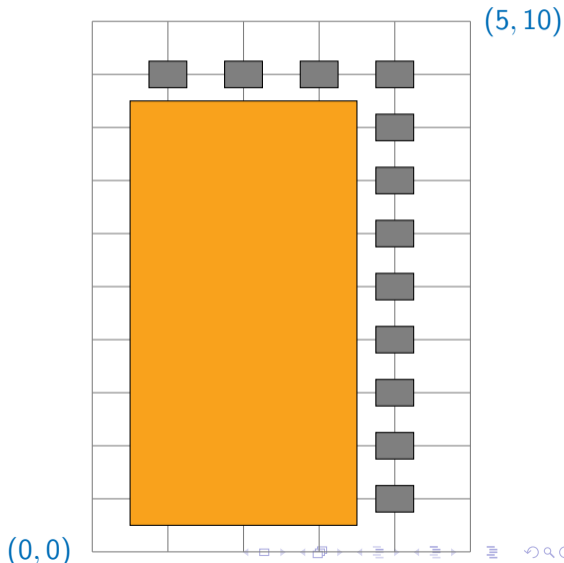
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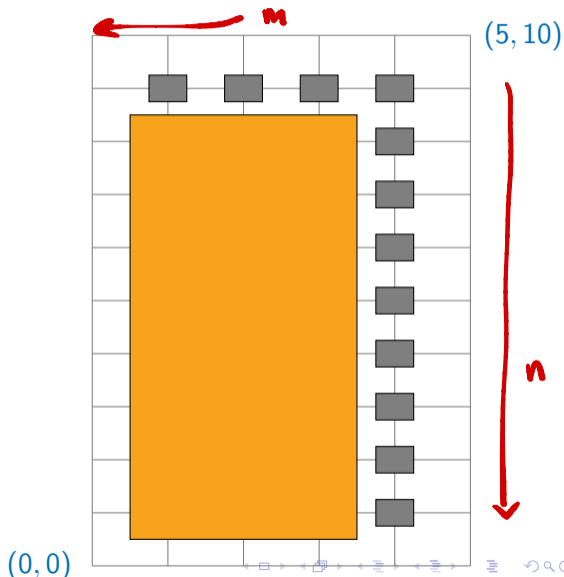
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- Memoization never explores the shaded region
- Memo table has  $O(m + n)$  entries
- Dynamic programming blindly fills all  $mn$  cells of the table
- Tradeoff between recursion and iteration
  - “Wasteful” dynamic programming still better in general



# Longest common subword

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

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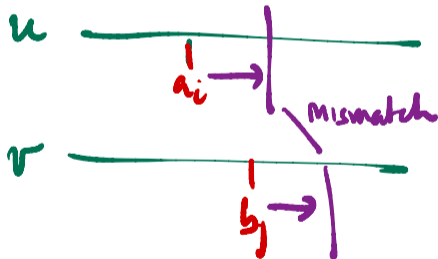
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  - Find the largest such  $k$  — length of the longest common subword



# Brute force

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

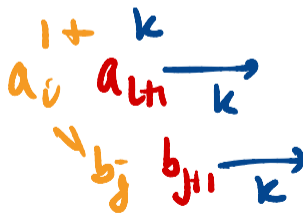
# Inductive structure

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- $LCW(i, j)$  — length of longest common subword in  $a_ia_{i+1} \dots a_{m-1}$ ,  $b_jb_{j+1} \dots b_{n-1}$ 
  - If  $a_i \neq b_j$ ,  $LCW(i, j) = 0$
  - If  $a_i = b_j$ ,  $LCW(i, j) = 1 + LCW(i+1, j+1)$

$LCW(i, j)$  is longest ending  
at  $a_i, b_j$



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

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

Handwritten annotations:  $0$  (purple) above the first column,  $n$  (purple) to the left of the first column,  $m$  (purple) above the last column, and three purple arrows pointing down from the last column to the second column, with a purple  $0$  and a question mark below the last cell.

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$$1 + LCW(i+1, j+1)$$

		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	0

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

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

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



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

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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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## 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	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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## 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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		s	e	c	r	e	t	•
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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

# 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):
        for i in range(m-1,-1,-1):
            if u[i] == v[j]:
                lcw[i,j] = 1 + lcw[i+1,j+1]
            else:
                lcw[i,j] = 0
            if lcw[i,j] > maxlcw:
                maxlcw = lcw[i,j]

    return(maxlcw)
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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