

Lecture 25, 18 November 2025

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Programming and Data Structures with Python

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Inductive definitions, recursive programs, subproblems

- Factorial

- $fact(0) = 1$

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

Inductive definitions, recursive programs, subproblems

■ Factorial

- $fact(0) = 1$

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

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

Inductive definitions, recursive programs, subproblems

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def fact(n):  
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■ Insertion sort

- $isort([]) = []$

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

Inductive definitions, recursive programs, subproblems

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

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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

Tricky - cost of recursive calls

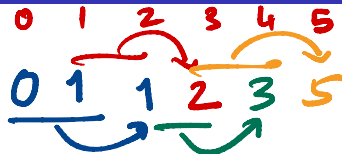
Evaluating subproblems

- Fibonacci numbers

- $fib(0) = 0$

- $fib(1) = 1$

- $fib(n) = fib(n-1) + fib(n-2)$



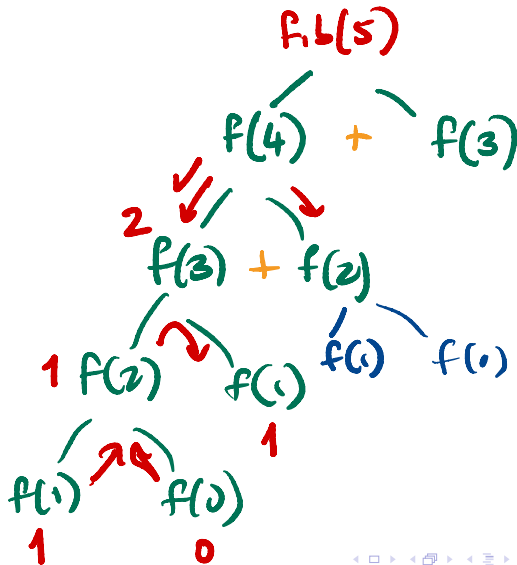
```
def fib(n):  
    if n <= 1:  
        value = n  
    else:  
        value = fib(n-1) + fib(n-2)  
    return(value)
```

Evaluating subproblems

- Fibonacci numbers

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Evaluating subproblems

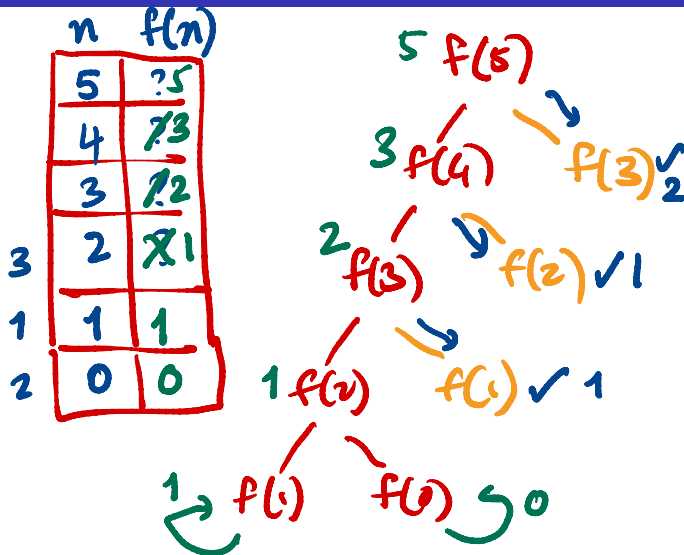
- Build a table of values already computed
 - Memory table

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

← fibtable = {}

```
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)
```

Memoizing recursive implementations

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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

Recursion

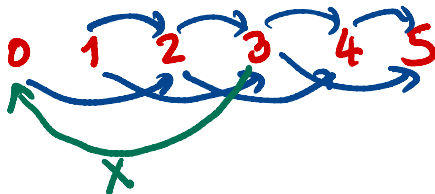
- ① - Wasteful recomputation
- ② - Cost of recursive calls

- ① Memoization ✓
- ② Translate to iteration

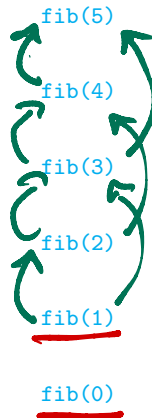
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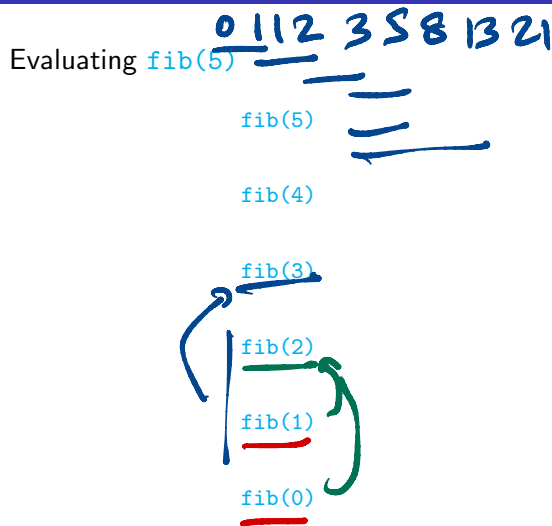


Evaluating `fib(5)`



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



Grid paths

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

$m+n$ steps, each R, U

5 R
10 U

✓ R ✓ U ✓ U ✓ U --- R ✓
1 2 3 --- 15

$$\binom{15}{5}$$

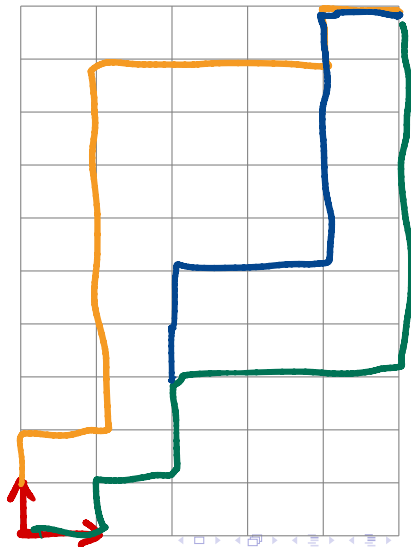
$$\binom{m+n}{n}$$

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

$$\binom{15}{10}$$

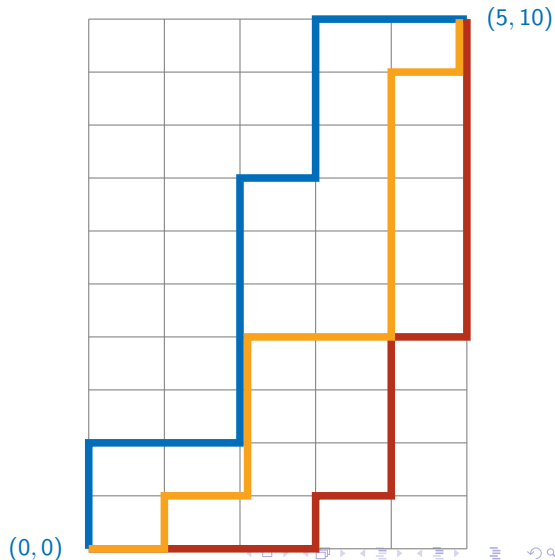
$(0, 0)$

$(5, 10)$



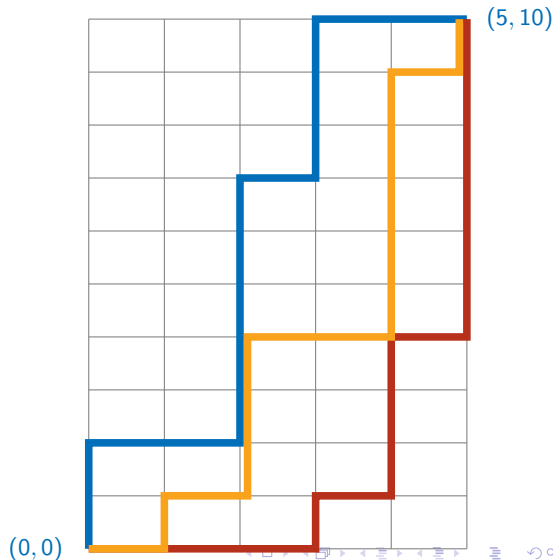
Combinatorial solution

- 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



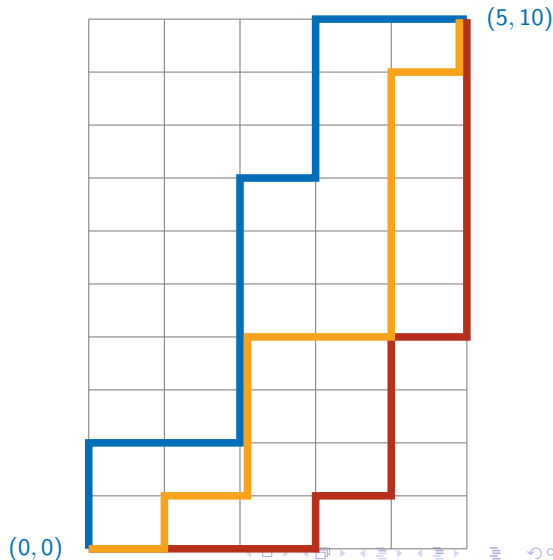
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 - Same as $\binom{15}{10}$ — fix the 10 up moves



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



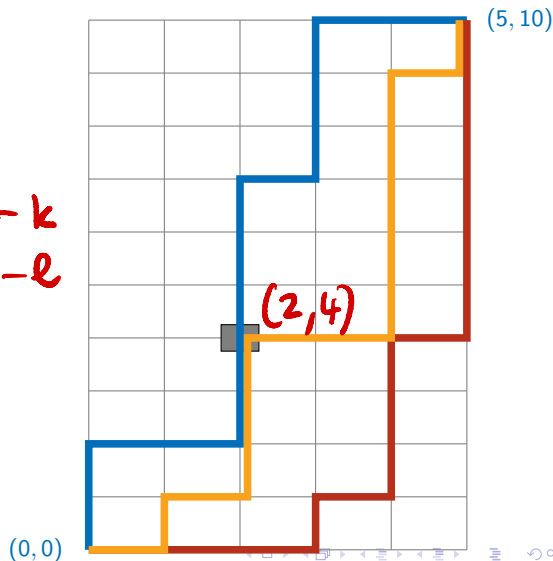
Holes

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

Count paths $(0,0) \rightarrow (2,4) = k$
 $(2,4) \rightarrow (5,10) = l$

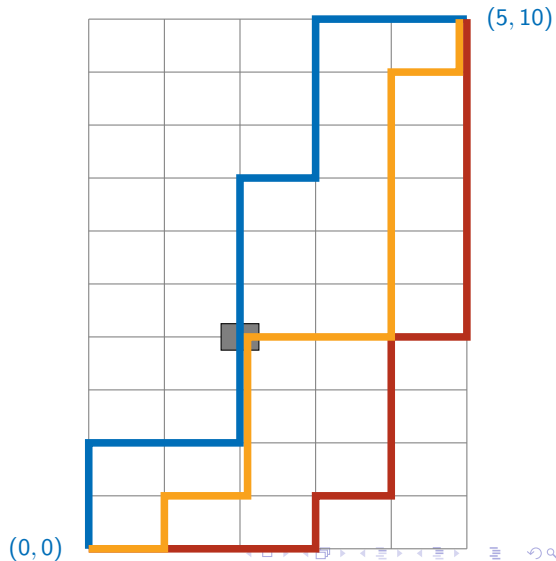
$k \cdot l$ bad paths

$$\binom{m+n}{n} - k \cdot l$$



Combinatorial solution for holes

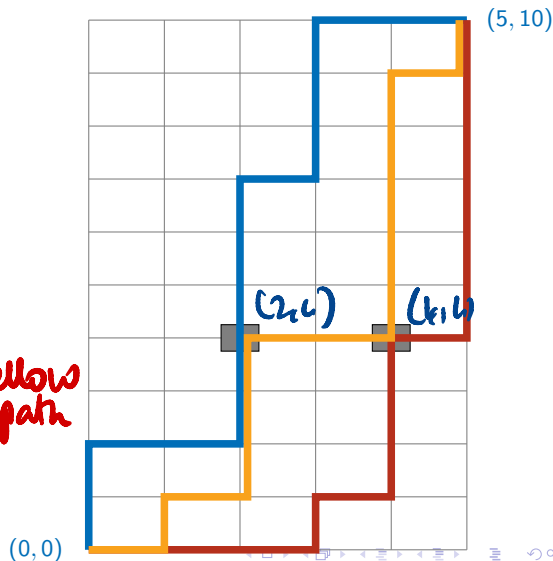
- Discard paths passing through $(2, 4)$



More holes

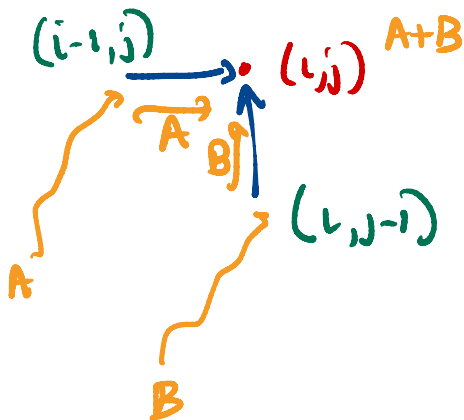
- What if two intersections are blocked?
- Discard paths via $(2, 4)$, $(4, 4)$
 - Some paths are counted twice
- Add back the paths that pass through both holes
- Inclusion-exclusion — counting is messy

$$\begin{array}{ll} (2, 4) & k_1 \cdot l_1 = A \\ (4, 4) & k_2 \cdot l_2 = B \end{array} \quad \text{Yellow path}$$



Inductive formulation

- How can a path reach (i, j)

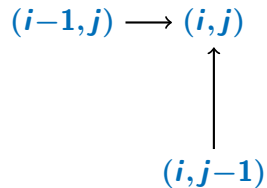


Inductive formulation

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

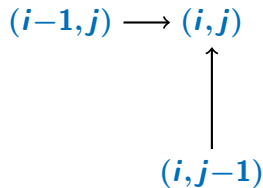
Inductive formulation

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



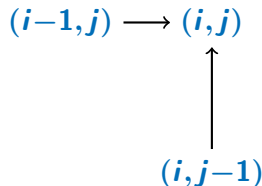
Inductive formulation

- 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)



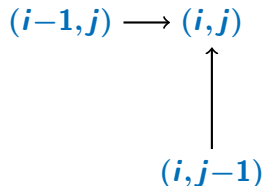
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- Recurrence for $P(i, j)$, number of paths from $(0, 0)$ to (i, j)
 - $P(i, j) = P(i - 1, j) + P(i, j - 1)$



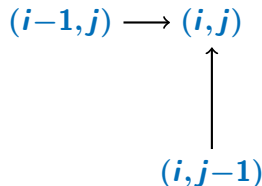
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 - $P(0, 0) = 1$ — base case



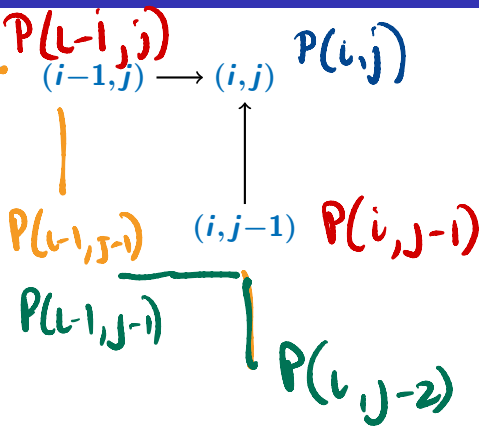
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 - $P(i, 0) = P(i - 1, 0)$ — bottom row



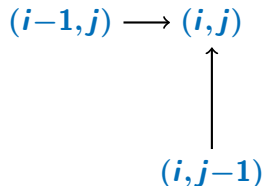
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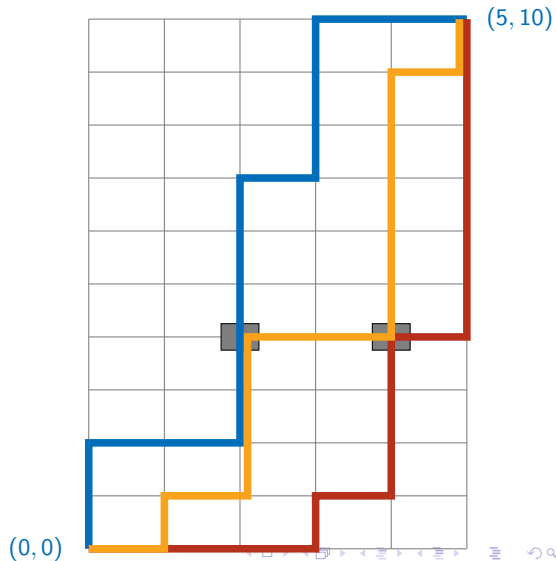
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 - $P(i, 0) = P(i - 1, 0)$ — bottom row
 - $P(0, j) = P(0, j - 1)$ — left column
- $P(i, j) = 0$ if there is a hole at (i, j)



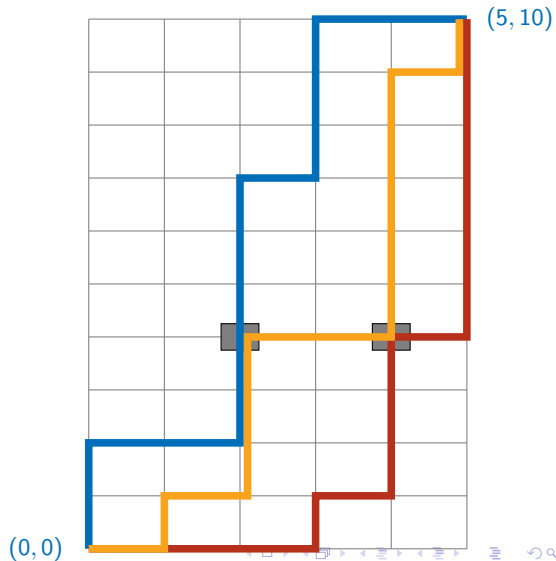
Computing $P(i,j)$

- Naive recursion recomputes same subproblem repeatedly



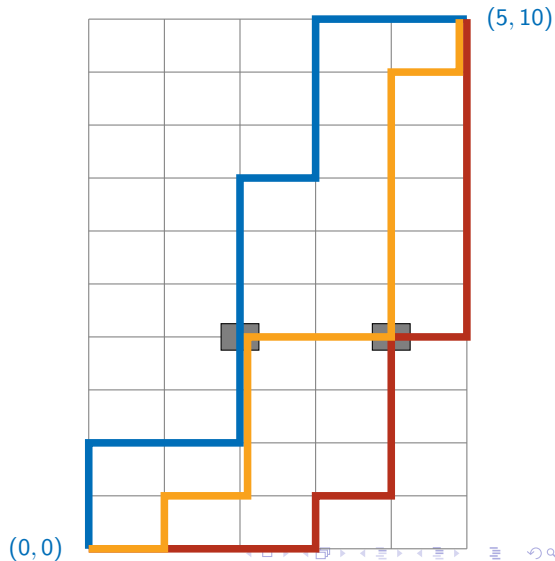
Computing $P(i, j)$

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



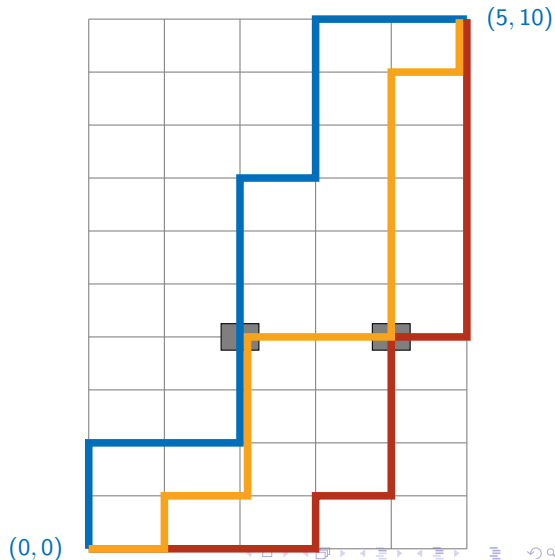
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- Naive recursion recomputes same subproblem repeatedly
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 - Both $P(4, 10)$, $P(5, 9)$ require $P(4, 9)$



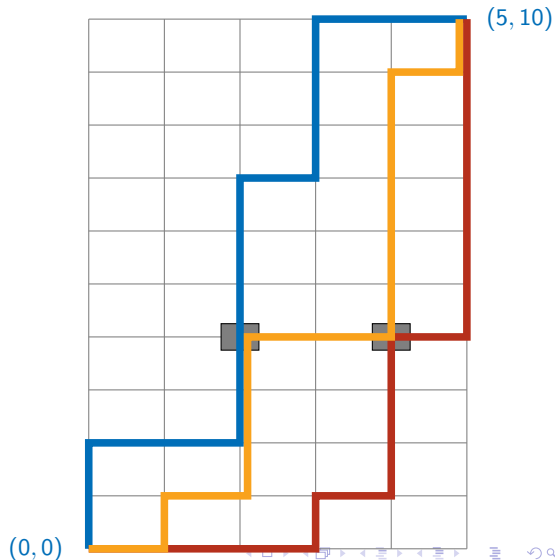
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- Use memoization ...



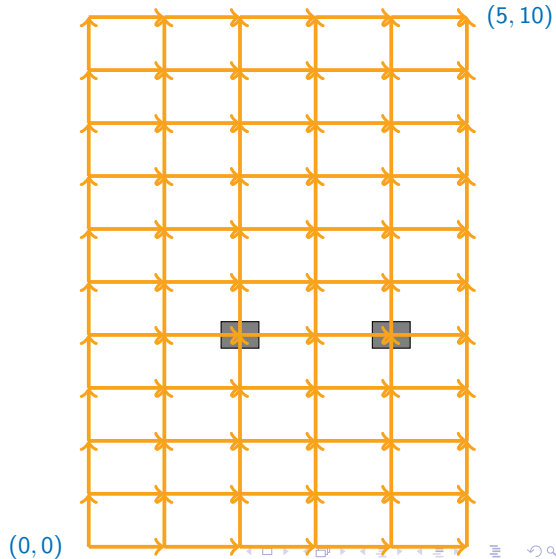
Computing $P(i, j)$

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 - $P(5, 10)$ 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



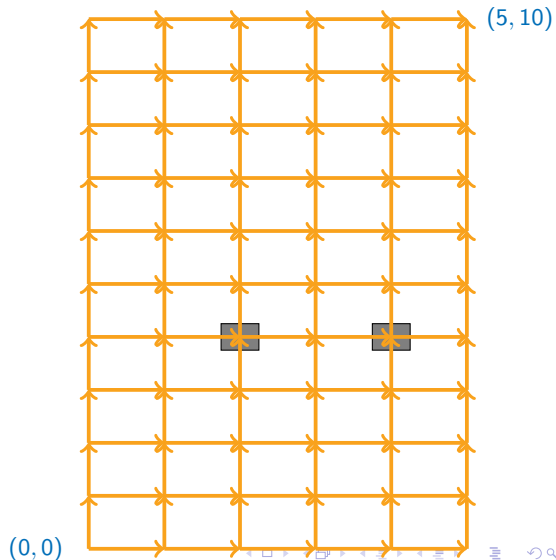
Dynamic programming

- Identify subproblem structure



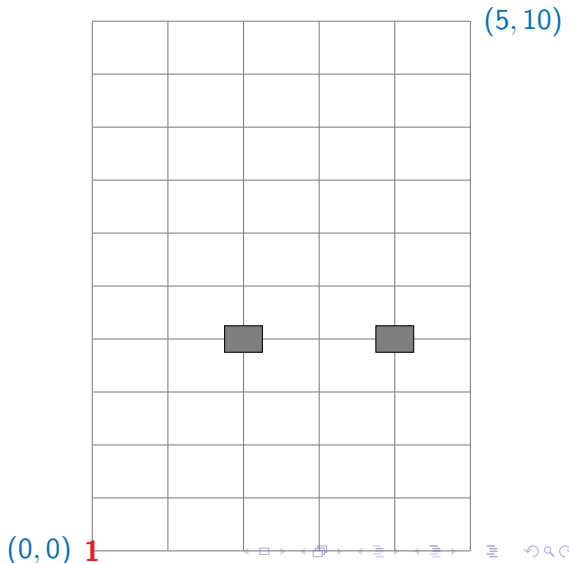
Dynamic programming

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



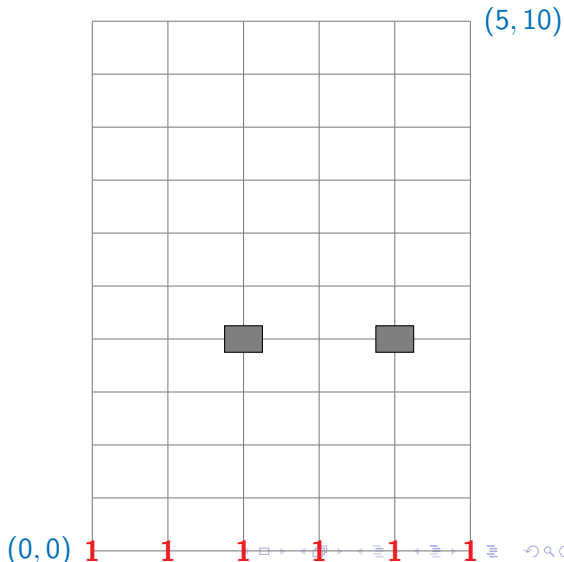
Dynamic programming

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



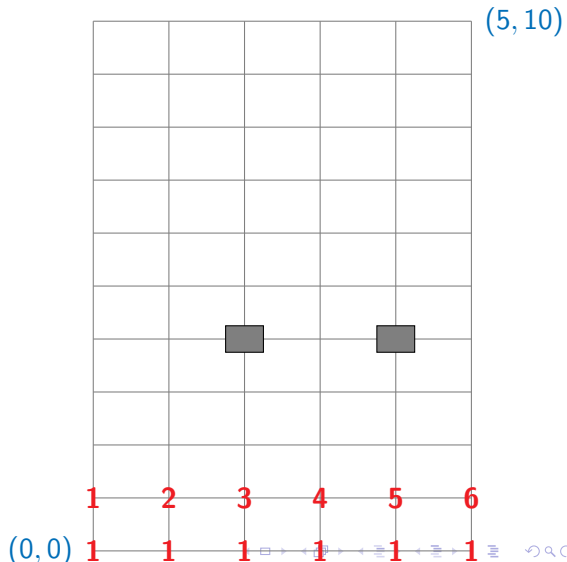
Dynamic programming

- Identify subproblem structure
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- Fill row by row



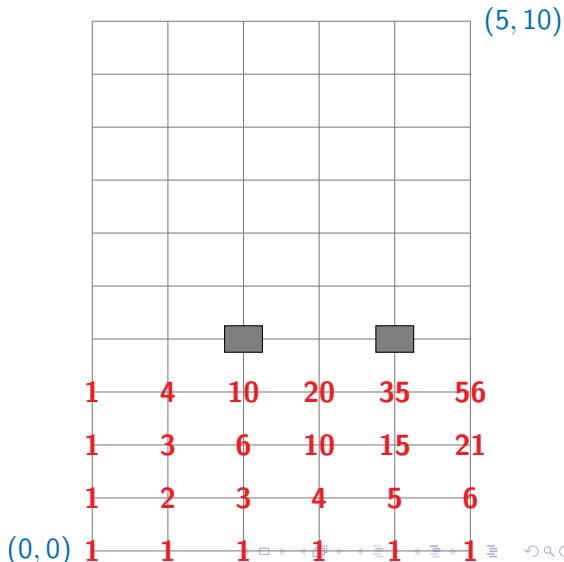
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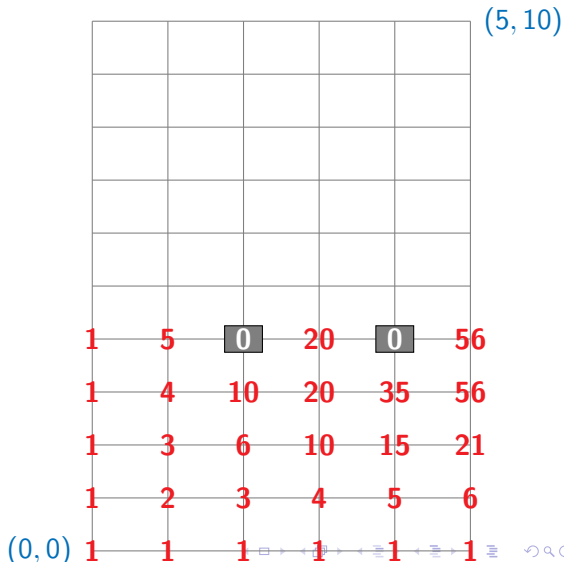
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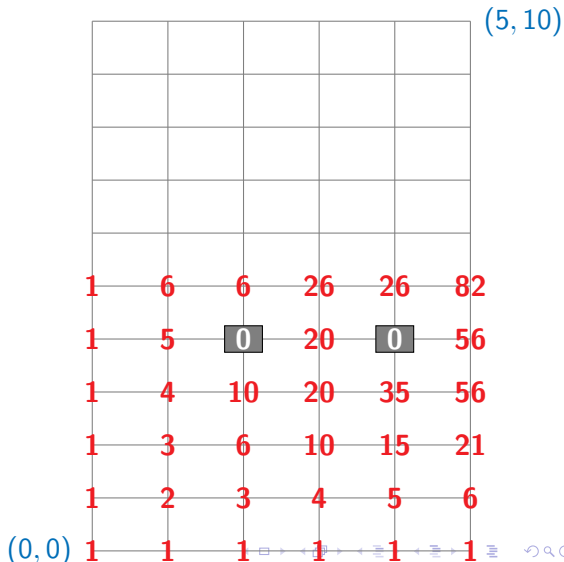
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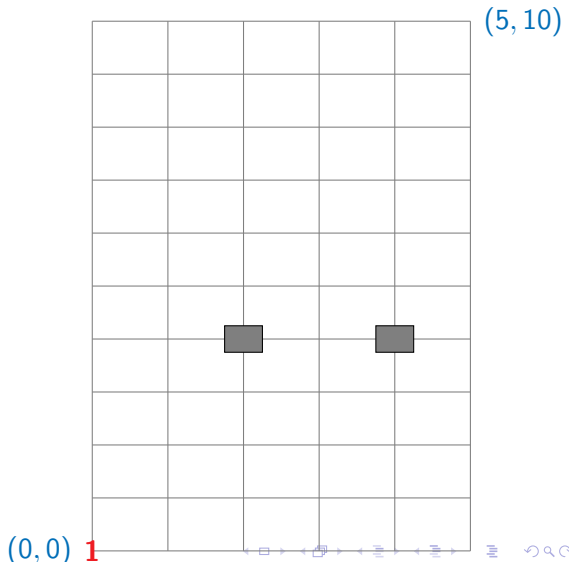
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(5, 10)

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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

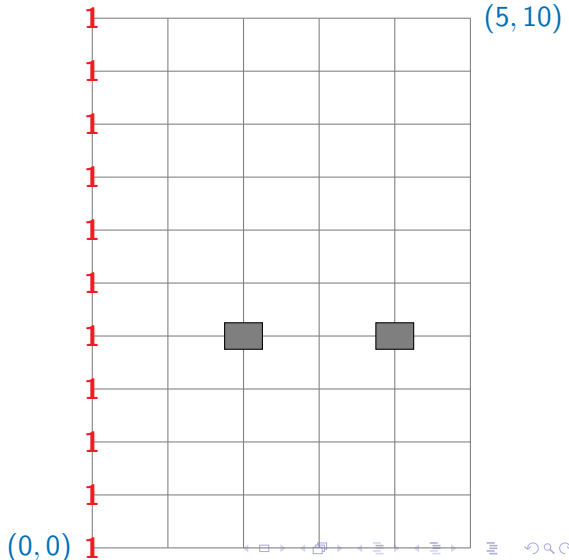
Dynamic programming

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



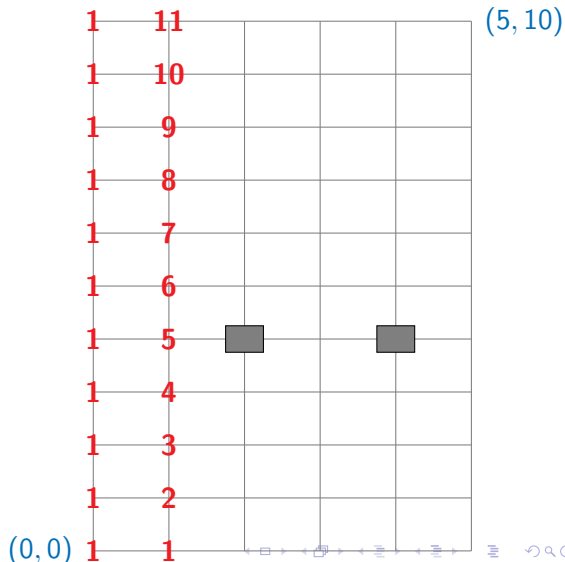
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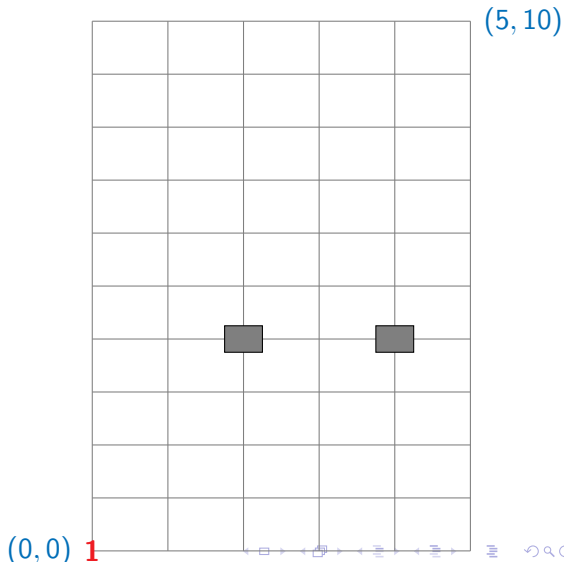
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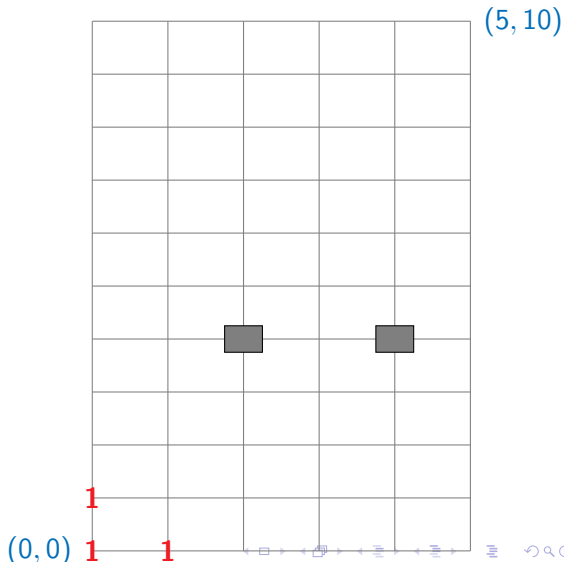
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- Fill diagonal by diagonal



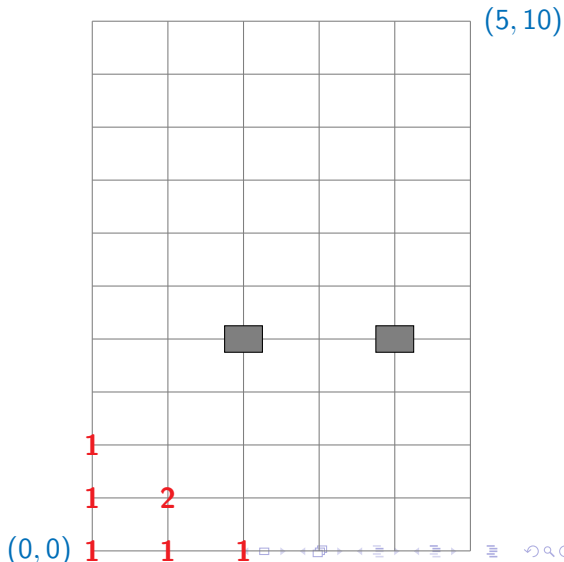
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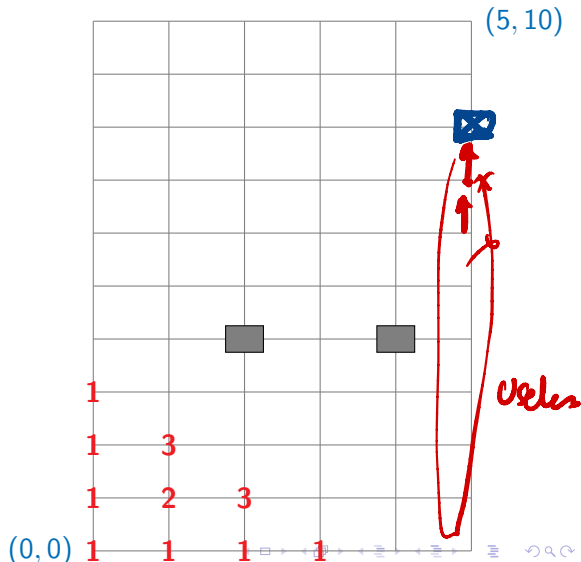
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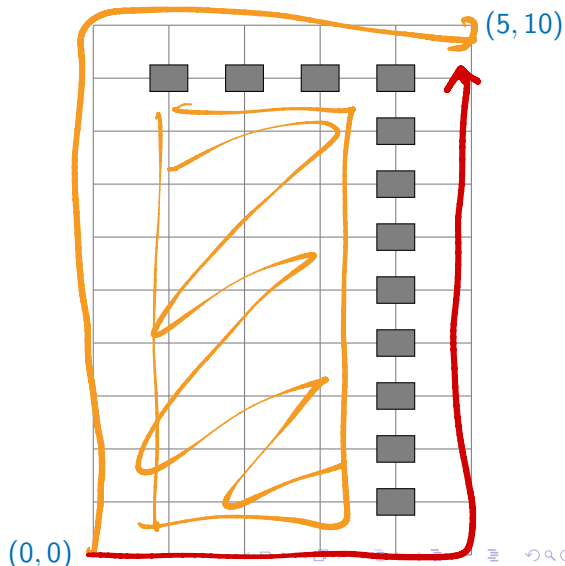
Dynamic programming

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



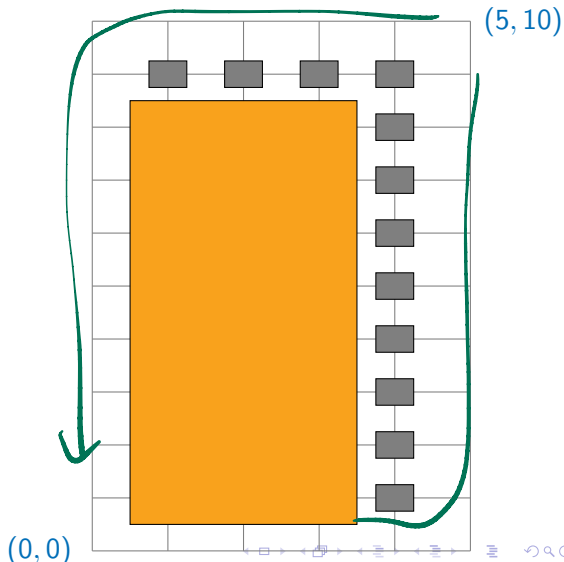
Memoization vs dynamic programming

- Barrier of holes just inside the border



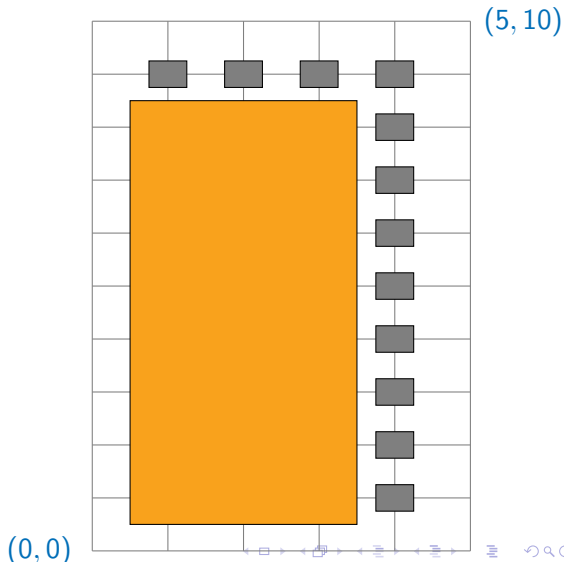
Memoization vs dynamic programming

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



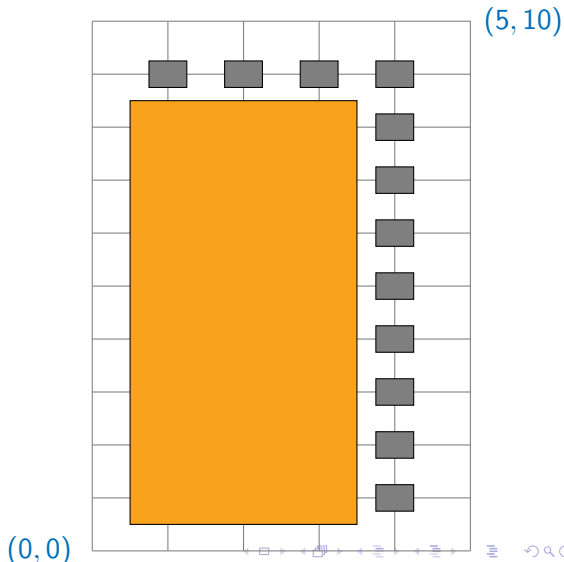
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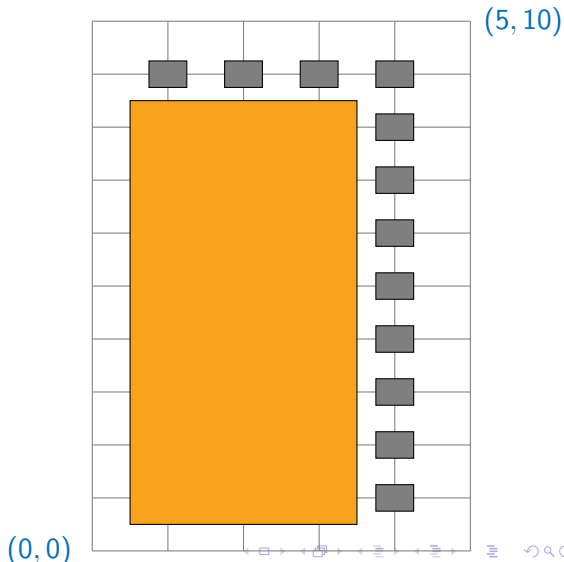
Memoization vs dynamic programming

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Memoization vs dynamic programming

- 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", "trisection" — "isect", length 5
 - "bisect", "secret" — "sec", length 3
 - "director", "secretary" — "ec", "re", length 2

ect

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

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 - $u = a_0a_1 \dots a_{m-1}$
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 $a_ia_{i+1}a_{i+2} \dots a_{i+k-1} = b_jb_{j+1}b_{j+2} \dots b_{j+k-1}$

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 $a_ia_{i+1}a_{i+k-1} = b_jb_{j+1}b_{j+k-1}$
 - Find the largest such k — length of the longest common subword

Brute force

- $u = a_0a_1 \dots a_{m-1}$
- $v = b_0b_1 \dots b_{n-1}$
- 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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- 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
- Assuming $m > n$, this is $O(mn^2)$
 - mn pairs of starting positions
 - From each starting position, scan could be $O(n)$

aa-- ab/a
aa - - - ab/a

m.n starting pos

n^3 if $m \approx n$

Inductive structure

- $u = a_0 a_1 \dots a_{m-1}$
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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 $a_i = b_j$, $LCW(i,j) = 1 + LCW(i+1,j+1)$

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

(i, j)
↖
 $(i+1, j+1)$

Subproblem dependency

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

Subproblem dependency

- Subproblems are $LCW(i, j)$, 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					o		
2	s							
3	e							
4	c							
5	t							
6	•							

Subproblem dependency

- Subproblems are $LCW(i, j)$, for $0 \leq i \leq m, 0 \leq j \leq n$
- 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		✓					
2	s			?				
3	e							
4	c							
5	t							
6	•							

Subproblem dependency

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- Table of $(m+1) \cdot (n+1)$ values
- $LCW(i, j)$ depends on $LCW(i+1, j+1)$
- Start at bottom right and fill row by row or column by column

$$LCW(m, n) = 0$$

$$(i, n) = 0$$

$$(m, j) = 0$$

		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	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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		0	1	2	3	4	5	6
		s	e	<u>c</u>	<u>r</u>	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	<u>c</u>				0	0	0	0
5	t				0	0	1	0
6	•				0	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	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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- 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	0	0	0	0	0
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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		0	1	2	3	4	5	6
		s	e	c	r	e	t	•
0	b	0	0	0	0	0	0	0
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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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- Start at bottom right and fill row by row or column by column

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

Subproblem dependency

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- $LCW(i,j)$ depends on $LCW(i+1,j+1)$
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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

Subproblem dependency

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		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

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

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```

Complexity

- Recall that brute force was $O(mn^2)$

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Complexity

- Recall that brute force was $O(mn^2)$
- Inductive solution is $O(mn)$, using dynamic programming or memoization

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def LCW(u,v):
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                maxlcw = lcw[i,j]

    return(maxlcw)
```

Handwritten annotations: A red arrow points to the range `range(n-1,-1,-1)` with the word "Flip". The text "NOT NEEDED" is written in orange next to the `else:` block.



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