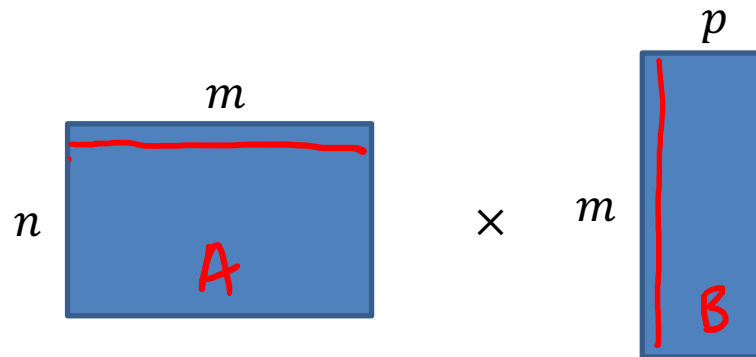


CS4102 Algorithms

Spring 2019

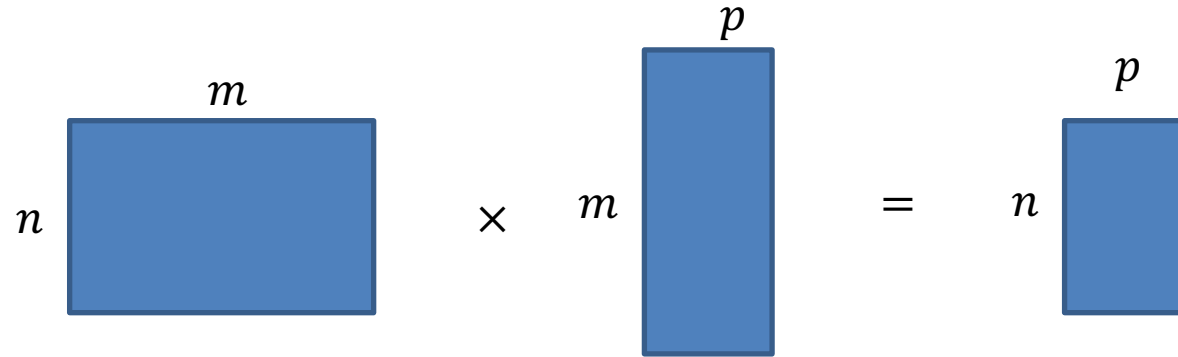
Warm up

How many arithmetic operations are required to multiply a $n \times m$ Matrix with a $m \times p$ Matrix?
(don't overthink this)



m multiplies
m-1 additions
 $a_{11} \cdot b_{11} + a_{21} \cdot b_{12} + \dots$
m

How many arithmetic operations are required to multiply a $n \times m$ Matrix with a $m \times p$ Matrix?



- m multiplications and additions per element
- $n \cdot p$ elements to compute
- Total cost: $m \cdot n \cdot p$

$$n \cdot p (m + m - 1)$$

Today's Keywords

- Dynamic Programming
- Matrix Chaining
- Seam Carving
- Longest Common Subsequence

CLRS Readings

- Chapter 15

Administrativa

- HW5 out by tomorrow morning
 - Due March 27 at 11pm
 - Seam Carving!
 - Dynamic Programming (implementation)
 - Java or Python
- Midterm
 - Grading underway! Should be returned tomorrow
- HW4 grading in-progress

Dynamic Programming

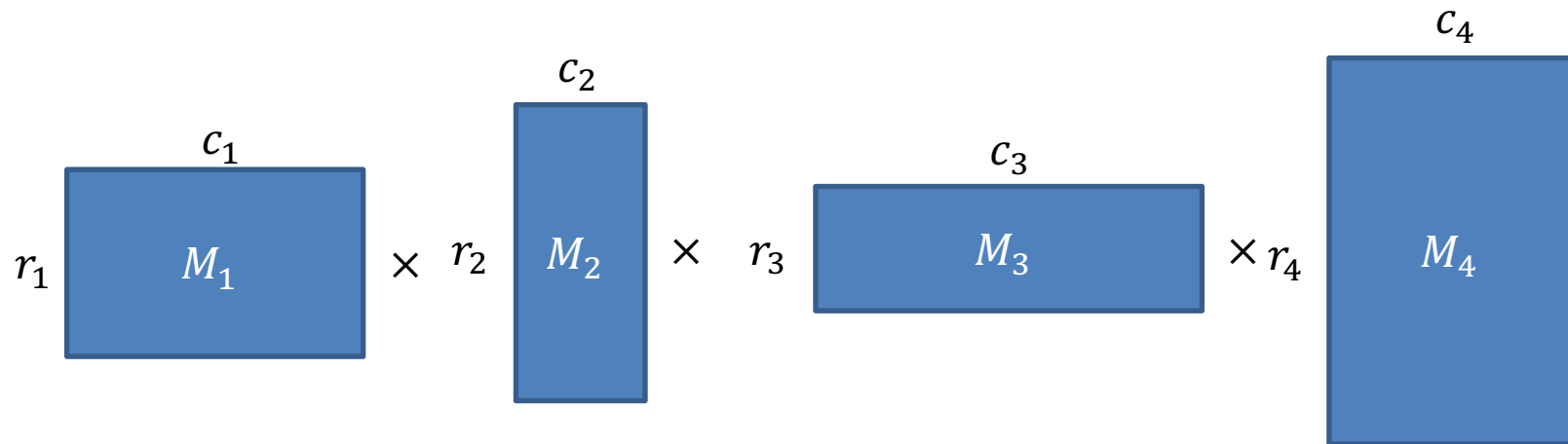
- Requires **Optimal Substructure**
 - Solution to larger problem contains the solutions to smaller ones
- Idea:
 1. Identify recursive structure of the problem
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Generic Top-Down Dynamic Programming Soln

```
mem = {}  
def myDPalgo(problem):  
    if mem[problem] not blank:  
        return mem[problem]  
    if baseCase(problem):  
        solution = solve(problem)  
        mem[problem] = solution  
        return solution  
    for subproblem of problem:  
        subsolutions.append(myDPalgo(subproblem))  
    solution = OptimalSubstructure(subsolutions)  
    mem[problem] = solution  
    return solution
```

Matrix Chaining

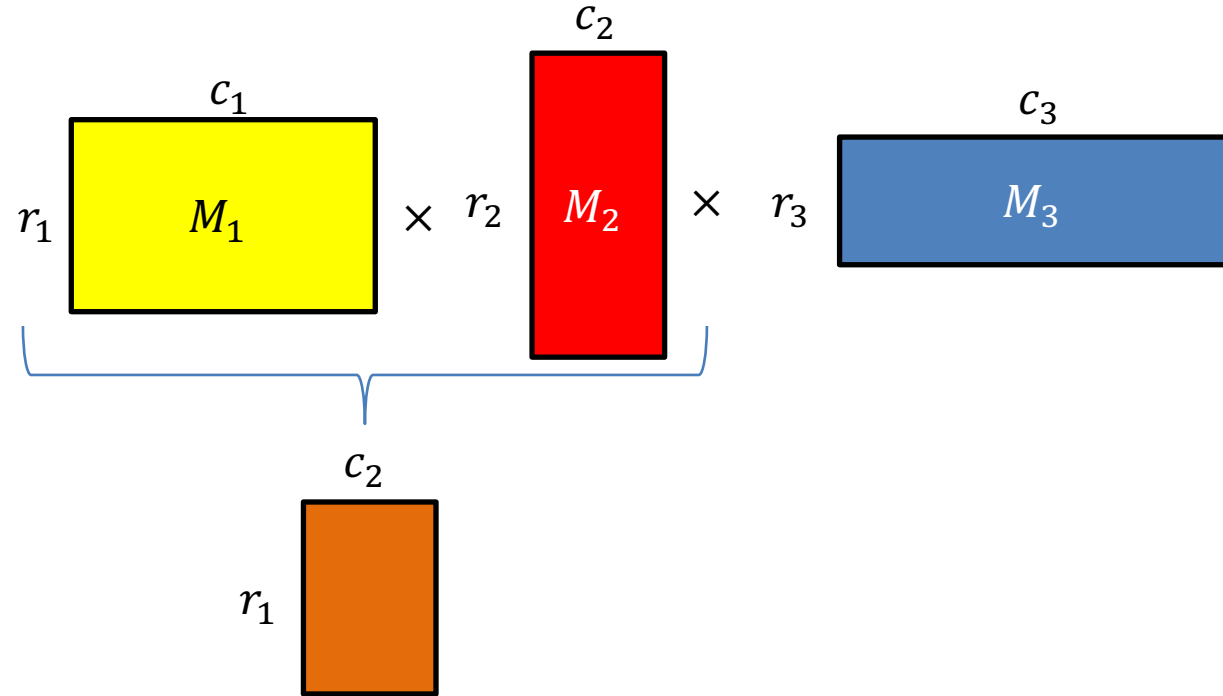
- Given a sequence of Matrices (M_1, \dots, M_n) , what is the most efficient way to multiply them?



$$c_1 = r_2$$

$$c_2 = r_3$$

Order Matters!

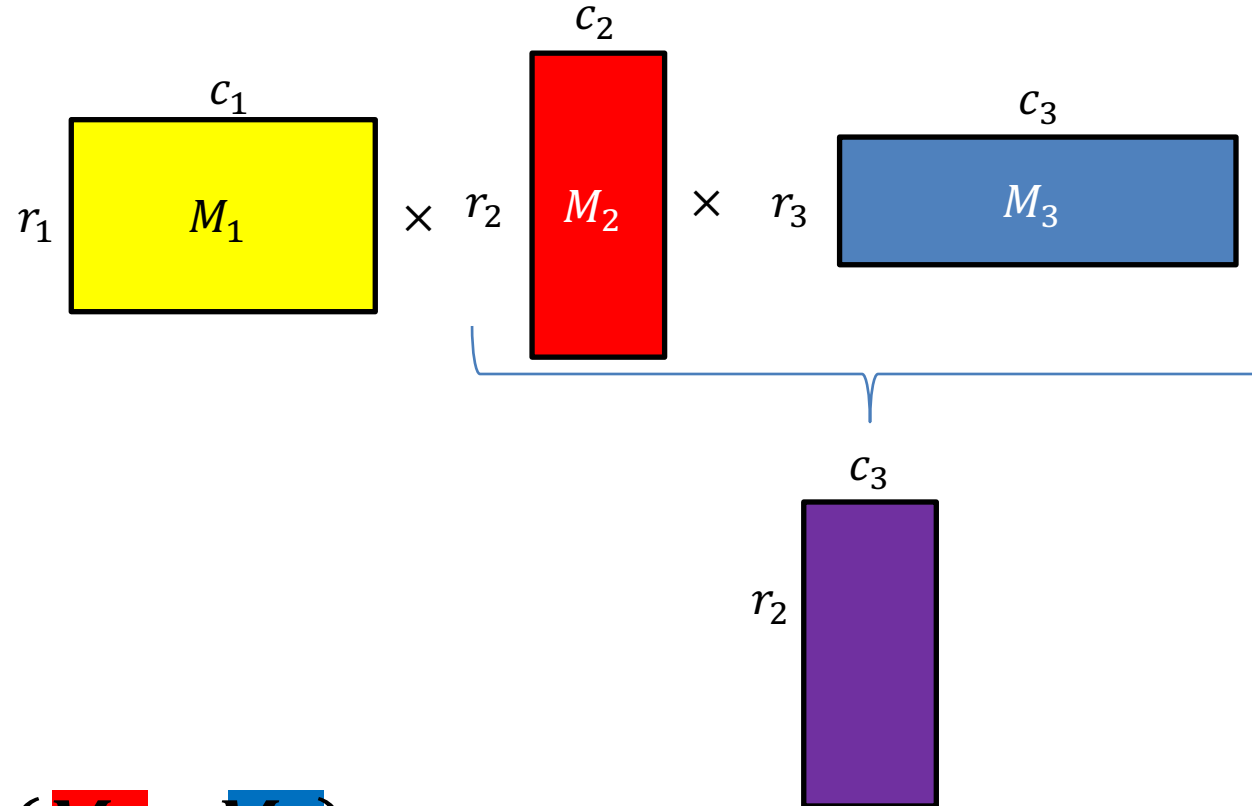


- $(M_1 \times M_2) \times M_3$
 – uses $(c_1 \cdot r_1 \cdot c_2) + c_2 \cdot r_1 \cdot c_3$ operations

$$c_1 = r_2$$

$$c_2 = r_3$$

Order Matters!



- $M_1 \times (M_2 \times M_3)$
 – uses $c_1 \cdot r_1 \cdot c_3 + (c_2 \cdot r_2 \cdot c_3)$ operations

$$c_1 = r_2$$

$$c_2 = r_3$$

Order Matters!

- $(M_1 \times M_2) \times M_3$
 - uses $(c_1 \cdot r_1 \cdot c_2) + c_2 \cdot r_1 \cdot c_3$ operations
 - $(10 \cdot 7 \cdot 20) + 20 \cdot 7 \cdot 8 = 2520$
- $M_1 \times (M_2 \times M_3)$
 - uses $c_1 \cdot r_1 \cdot c_3 + (c_2 \cdot r_2 \cdot c_3)$ operations
 - $10 \cdot 7 \cdot 8 + (20 \cdot 10 \cdot 8) = 2160$

$$\begin{aligned}M_1 &= 7 \times 10 \\M_2 &= 10 \times 20 \\M_3 &= 20 \times 8\end{aligned}$$

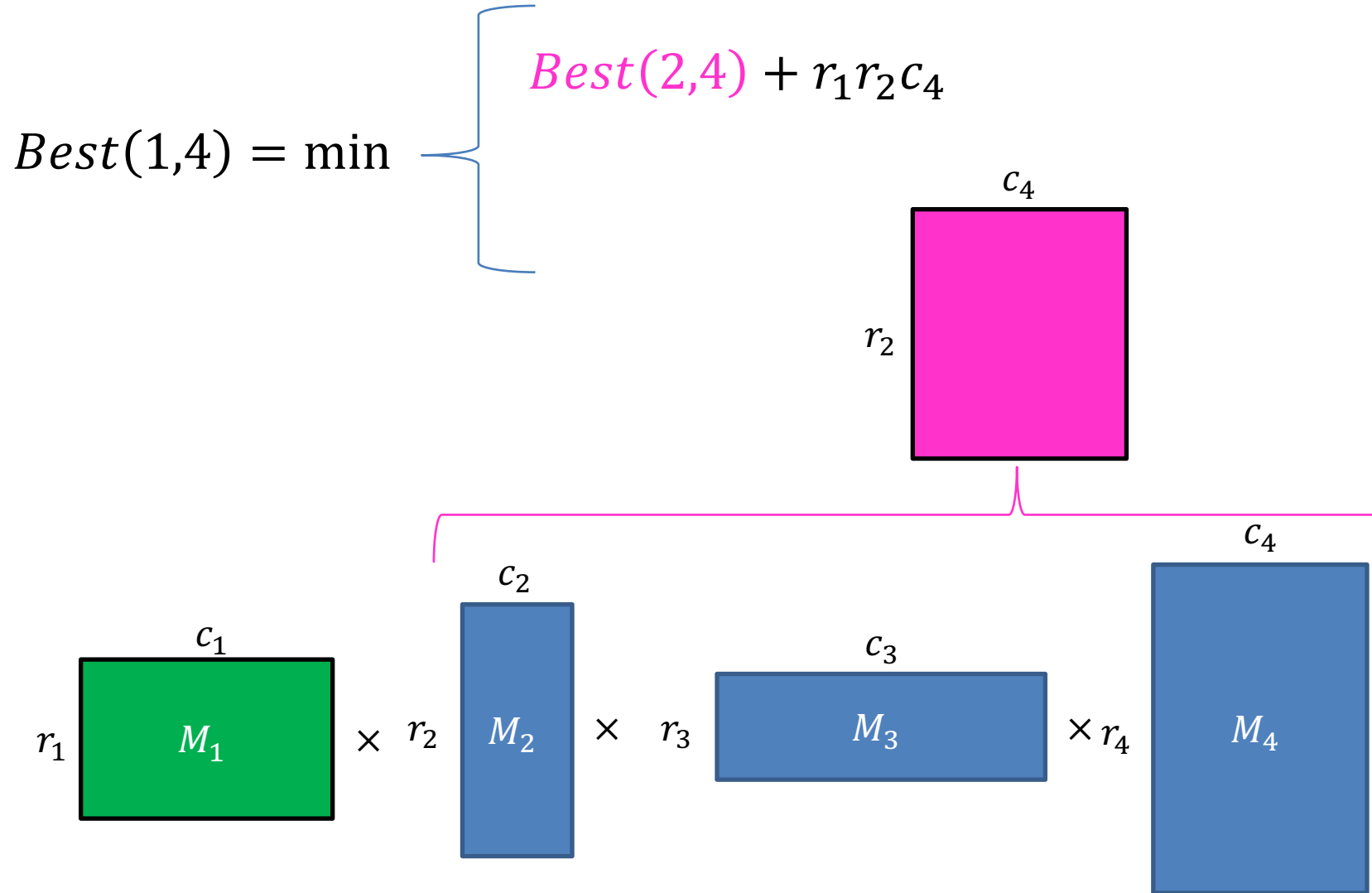
$$\begin{aligned}c_1 &= 10 \\c_2 &= 20 \\c_3 &= 8 \\r_1 &= 7 \\r_2 &= 10 \\r_3 &= 20\end{aligned}$$

Dynamic Programming

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1. Identify the Recursive Structure of the Problem

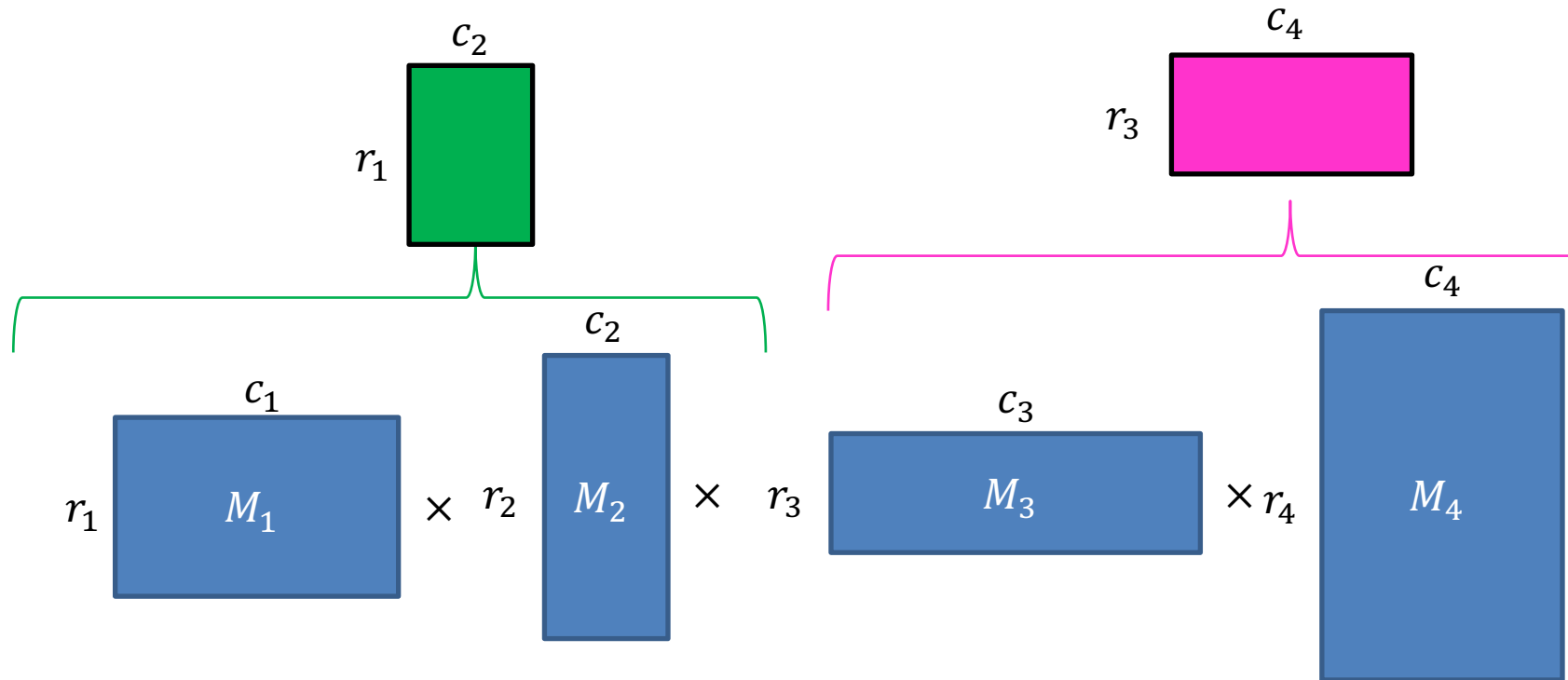
$Best(1, n)$ = cheapest way to multiply together M_1 through M_n



1. Identify the Recursive Structure of the Problem

$Best(1, n)$ = cheapest way to multiply together M_1 through M_n

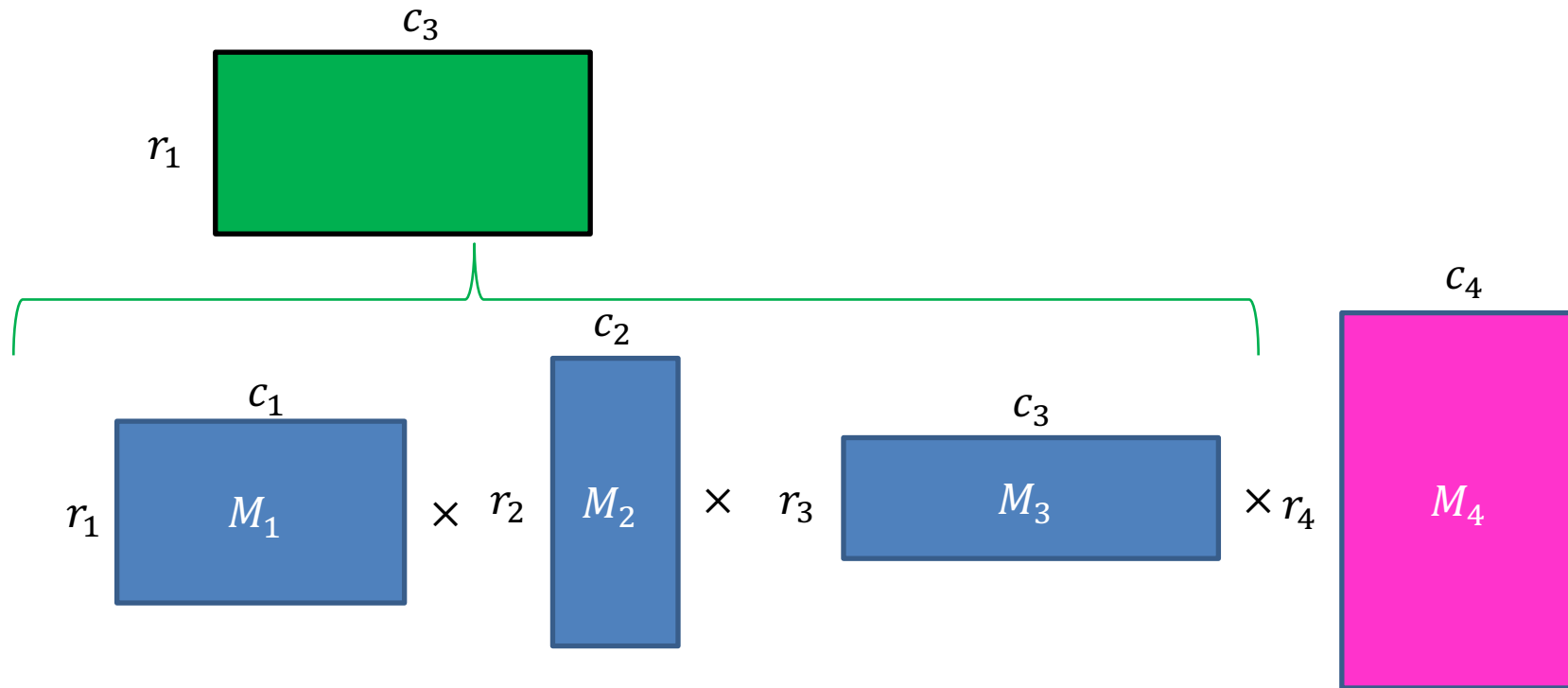
$$Best(1, 4) = \min \left\{ \begin{array}{l} Best(2, 4) + r_1 r_2 c_4 \\ Best(1, 2) + Best(3, 4) + r_1 r_3 c_4 \end{array} \right.$$



1. Identify the Recursive Structure of the Problem

$Best(1, n)$ = cheapest way to multiply together M_1 through M_n

$$Best(1, 4) = \min \begin{cases} Best(2, 4) + r_1 r_2 c_4 \\ Best(1, 2) + Best(3, 4) + r_1 r_3 c_4 \\ Best(1, 3) + r_1 r_4 c_4 \end{cases}$$



1. Identify the Recursive Structure of the Problem

- In general:

$Best(i, j)$ = cheapest way to multiply together M_i through M_j

$$Best(i, j) = \min_{k=i}^{j-1} (\overset{r_i \times c_k}{Best(i, k)} + \overset{r_{k+1} \times c_j}{Best(k+1, j)} + r_i r_{k+1} c_j)$$

$$c_k = r_{k+1}$$

$$Best(i, i) = 0$$

$$Best(1, n) = \min \left\{ \begin{array}{l} Best(2, n) + r_1 r_2 c_n \\ Best(1, 2) + Best(3, n) + r_1 r_3 c_n \\ Best(1, 3) + Best(4, n) + r_1 r_4 c_n \\ Best(1, 4) + Best(5, n) + r_1 r_5 c_n \\ \dots \\ Best(1, n-1) + r_1 r_n c_n \end{array} \right.$$

Dynamic Programming

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1. Identify the Recursive Structure of the Problem

- In general:

$Best(i, j)$ = cheapest way to multiply together M_i through M_j

$$Best(i, j) = \min_{k=i}^{j-1} (Best(i, k) + Best(k+1, j) + r_i r_{k+1} c_j)$$

$$Best(i, i) = 0$$

Save to $M[n]$

Read from $M[n]$
if present

$$Best(1, n) = \min$$

$$Best(2, n) + r_1 r_2 c_n$$

$$Best(1, 2) + Best(3, n) + r_1 r_3 c_n$$

$$Best(1, 3) + Best(4, n) + r_1 r_4 c_n$$

$$Best(1, 4) + Best(5, n) + r_1 r_5 c_n$$

...

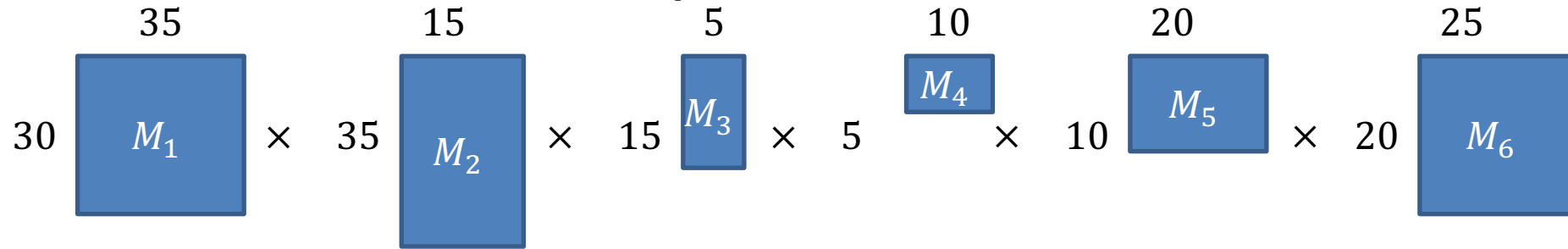
$$Best(1, n-1) + r_1 r_n c_n$$

$O(4^n)$

Dynamic Programming

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2. Select a good order for solving subproblems

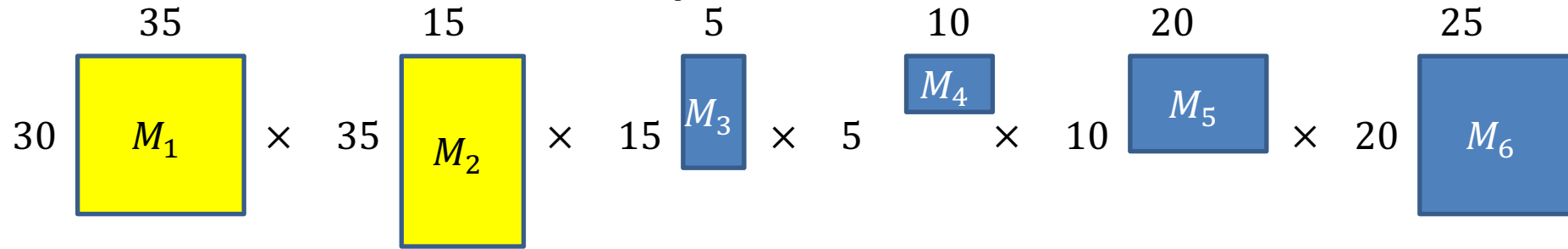


$$Best(i, j) = \min_{k=i}^{j-1} (Best(i, k) + Best(k+1, j) + r_i r_{k+1} c_j)$$

$$Best(i, i) = 0$$

$j =$						
1	2	3	4	5	6	$= i$
0						1
	0					2
		0				3
			0			4
				0		5
					0	6

2. Select a good order for solving subproblems



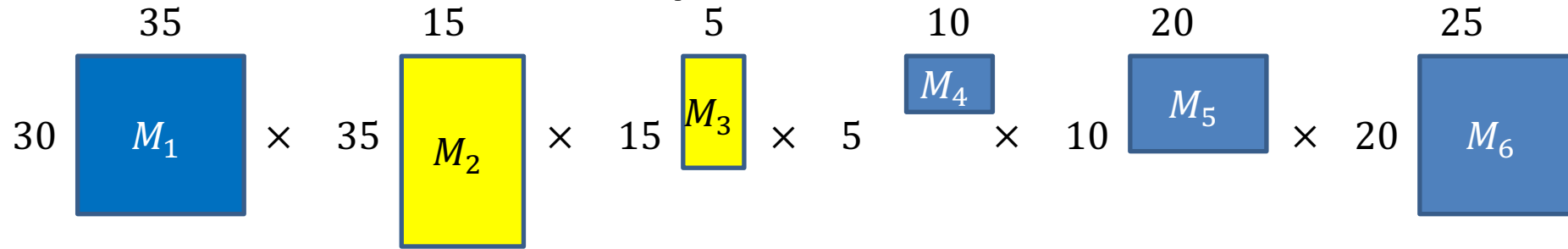
$$Best(i, j) = \min_{k=i}^{j-1} (Best(i, k) + Best(k+1, j) + r_i r_{k+1} c_j)$$

$$Best(i, i) = 0$$

$j =$						
1	2	3	4	5	6	$= i$
0	15750					1
	0					2
		0				3
			0			4
				0		5
					0	6

$$Best(1, 2) = \min \left\{ Best(1, 1) + Best(2, 2) + r_1 r_2 c_2 \right\}$$

2. Select a good order for solving subproblems



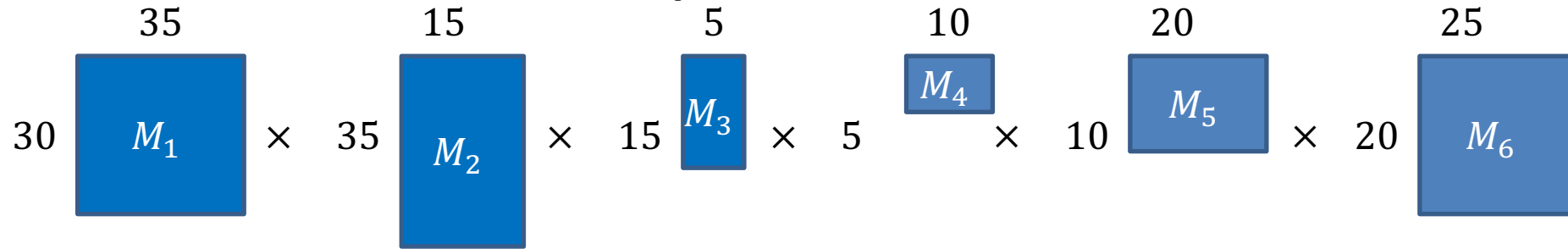
$$Best(i, j) = \min_{k=i}^{j-1} (Best(i, k) + Best(k+1, j) + r_i r_{k+1} c_j)$$

$$Best(i, i) = 0$$

$j =$	1	2	3	4	5	6	$= i$
1	0	15750					1
2		0	2625				2
3			0				3
4				0			4
5					0		5
6						0	6

$$Best(2, 3) = \min \left\{ Best(2, 2) + Best(3, 3) + r_2 r_3 c_3 \right\}$$

2. Select a good order for solving subproblems

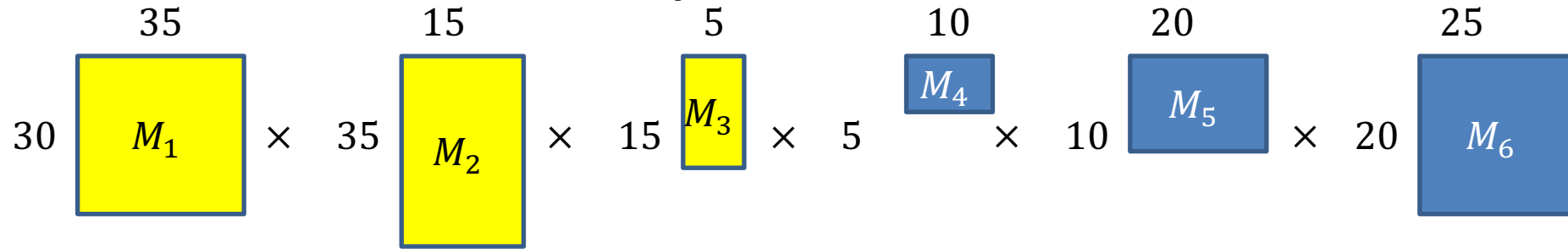


$$Best(i, j) = \min_{k=i}^{j-1} (Best(i, k) + Best(k + 1, j) + r_i r_{k+1} c_j)$$

$$Best(i, i) = 0$$

$j =$						
1	2	3	4	5	6	$= i$
0	15750					1
	0	2625				2
		0	750			3
			0	1000		4
				0	5000	5
					0	6

2. Select a good order for solving subproblems



$$Best(i, j) = \min_{k=i}^{j-1} (Best(i, k) + Best(k+1, j) + r_i r_{k+1} c_j)$$

$$Best(i, i) = 0$$

$$r_1 r_2 c_3 = 30 \cdot 35 \cdot 5 = 5250$$

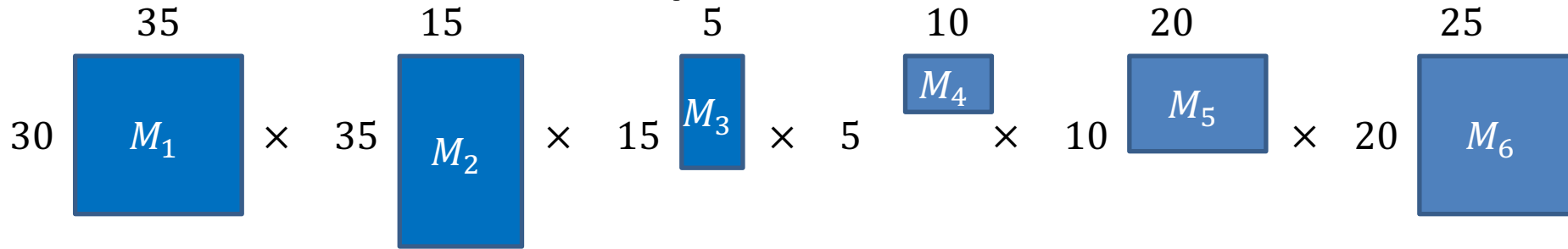
$$r_1 r_3 c_3 = 30 \cdot 15 \cdot 5 = 2250$$

$$Best(1, 3) = \min \begin{cases} 0 & 2625 \\ Best(1, 1) + Best(2, 3) + r_1 r_2 c_3 \\ Best(1, 2) + Best(3, 3) + r_1 r_3 c_3 \end{cases}$$

15750 0

$j =$	1	2	3	4	5	6	$= i$
1	0	15750	7875				1
2		0	2625				2
3			0	750			3
4				0	1000		4
5					0	5000	5
6						0	6

2. Select a good order for solving subproblems



$$Best(i, j) = \min_{k=i}^{j-1} (Best(i, k) + Best(k+1, j) + r_i r_{k+1} c_j)$$

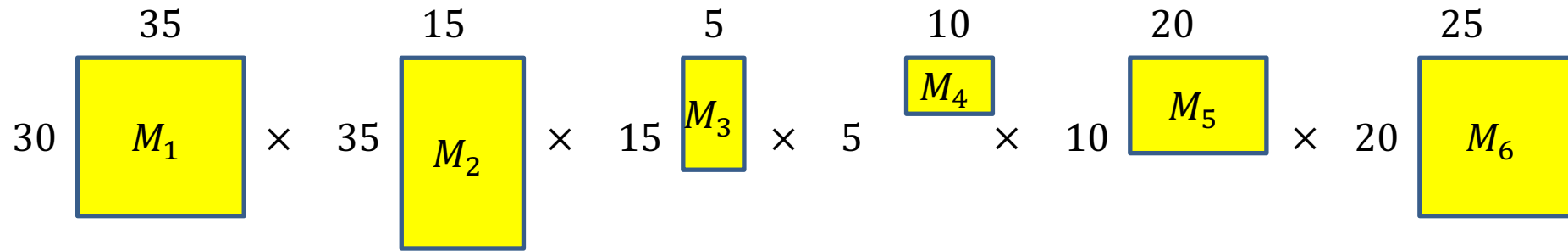
$$Best(i, i) = 0$$

$j =$	1	2	3	4	5	6	$= i$
1	0	15750	7875				
2		0	2625				
3			0	750			
4				0	1000		
5					0	5000	
6						0	

To find $Best(i, j)$: Need all preceding terms of row i and column j

Conclusion: solve in order of diagonal

Longest Common Subsequence



$$Best(i, j) = \min_{k=i}^{j-1} (Best(i, k) + Best(k+1, j) + r_i r_{k+1} c_j)$$

$$Best(i, i) = 0$$

	$j = 1$	2	3	4	5	6	i
1	0	15750	7875	9375	11875	15125	1
2		0	2625	4375	7125	10500	2
3			0	750	2500	5375	3
4				0	1000	3500	4
5					0	5000	5
6						0	6

$Best(1,6) = \min$

- $Best(1,1) + Best(2,6) + r_1 r_2 c_6$
- $Best(1,2) + Best(3,6) + r_1 r_3 c_6$
- $Best(1,3) + Best(4,6) + r_1 r_4 c_6$
- $Best(1,4) + Best(5,6) + r_1 r_5 c_6$
- $Best(1,5) + Best(6,6) + r_1 r_6 c_6$

Run Time

1. Initialize $Best[i, i]$ to be all 0s
2. Starting at the main diagonal, working to the upper-right, fill in each cell using:

$\Theta(n^2)$ cells in the Array

1. $Best[i, i] = 0$

2. $Best[i, j] = \min_{k=i}^{j-1} (Best(i, k) + Best(k + 1, j) + r_i r_{k+1} c_j)$

$\Theta(n)$ options for each cell

$\Theta(n^3)$ overall run time

Backtrack to find the best order

“remember” which choice of k was the minimum at each cell

$$Best(i, j) = \min_{k=i}^{j-1} (Best(i, k) + Best(k+1, j) + r_i r_{k+1} c_j)$$

$$Best(i, i) = 0$$

	$j = 1$	2	3	4	5	6	
	0	15750	7875 <small>1</small>	9375	11875	15125 <small>3</small>	1
		0	2625	4375	7125	10500	2
			0	750	2500	5375	3
				0	1000	3500 <small>5</small>	4
					0	5000	5
						0	6

$= i$

$Best(1,6) = \min$

- $Best(1,1) + Best(2,6) + r_1 r_2 c_6$
- $Best(1,2) + Best(3,6) + r_1 r_3 c_6$
- $Best(1,3) + Best(4,6) + r_1 r_4 c_6$
- $Best(1,4) + Best(5,6) + r_1 r_5 c_6$
- $Best(1,5) + Best(6,6) + r_1 r_6 c_6$

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Movie Time!

In Season 9 Episode 7 “The Slicer” of the hit 90s TV show *Seinfeld*, George discovers that, years prior, he had a heated argument with his new boss, Mr. Kruger. This argument ended in George throwing Mr. Kruger’s boombox into the ocean. How did George make this discovery?





Seam Carving

- Method for image resizing that doesn't scale/crop the image

Seam Carving

- Method for image resizing that doesn't scale/crop the image



Seam Carving

- Method for image resizing that doesn't scale/crop the image

Cropped



Scaled

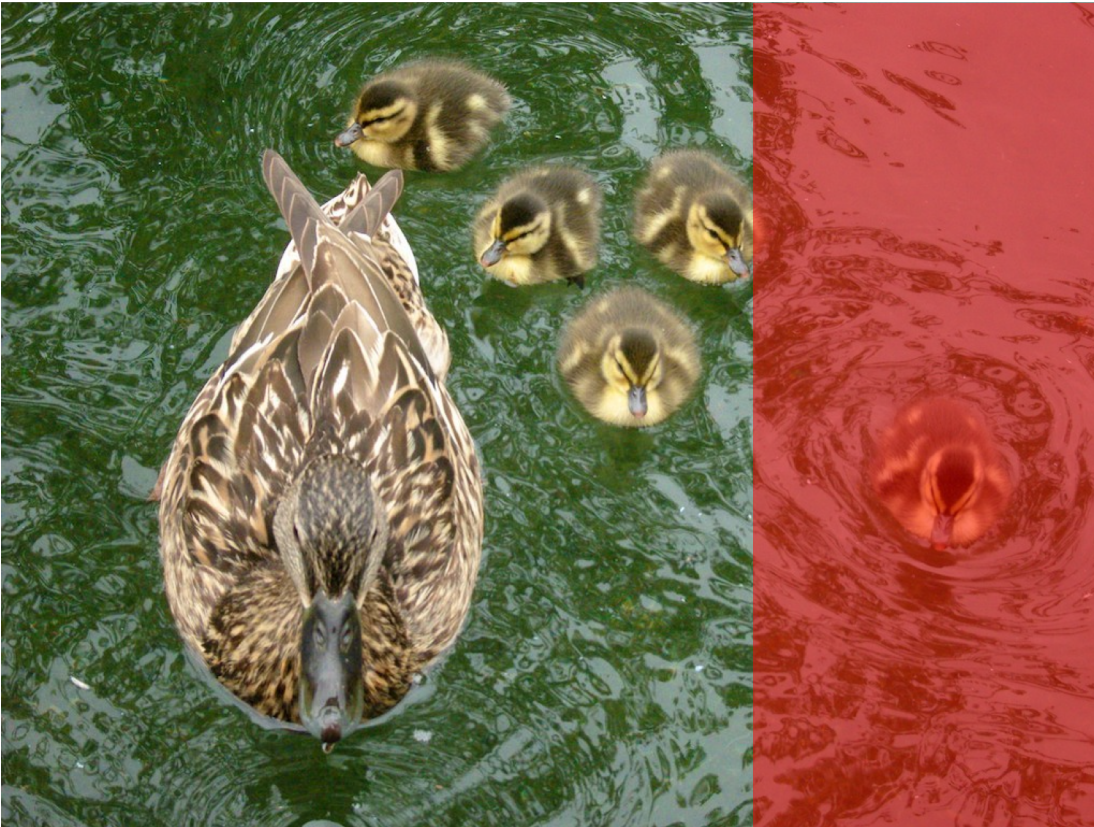


Carved

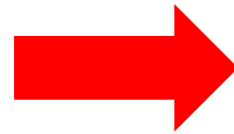


Cropping

- Removes a “block” of pixels

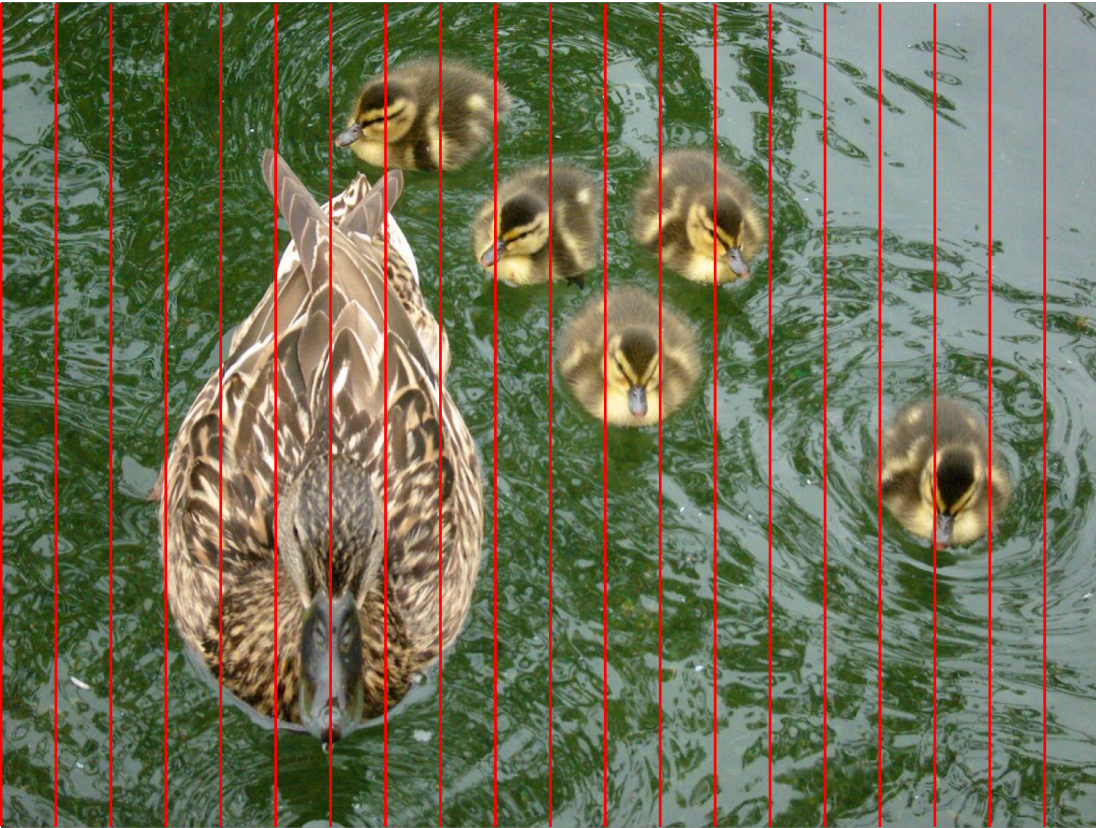


Cropped



Scaling

- Removes “stripes” of pixels

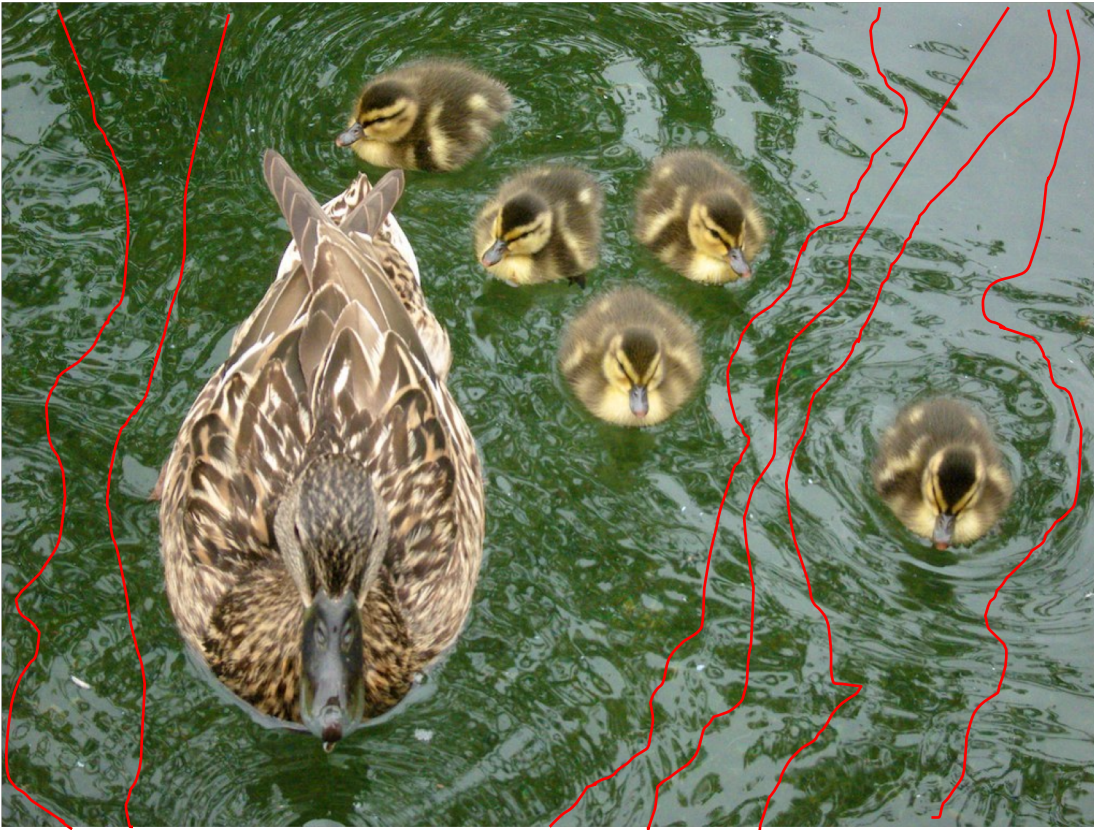


Scaled



Seam Carving

- Removes “least energy seam” of pixels
- <http://rsizr.com/>



Carved



Seattle Skyline

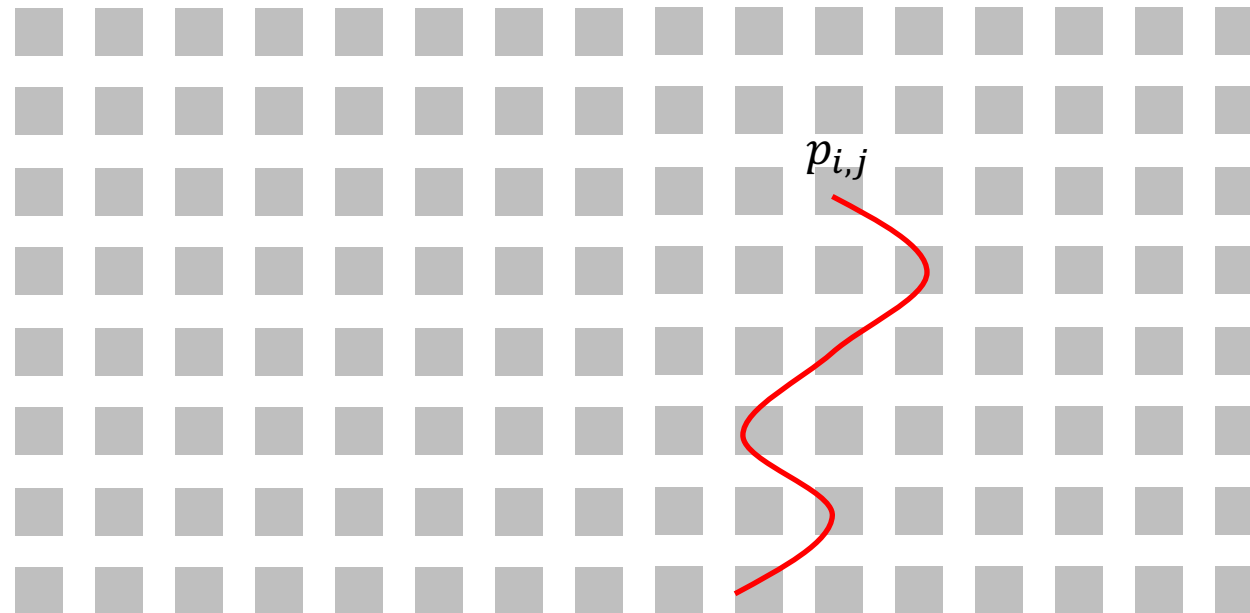


Energy of a Seam

- Sum of the energies of each pixel
 - $e(p)$ = energy of pixel p
- Many choices
 - E.g.: change of gradient (how much the color of this pixel differs from its neighbors)
 - Particular choice doesn't matter, we use it as a “black box”

Identify Recursive Structure

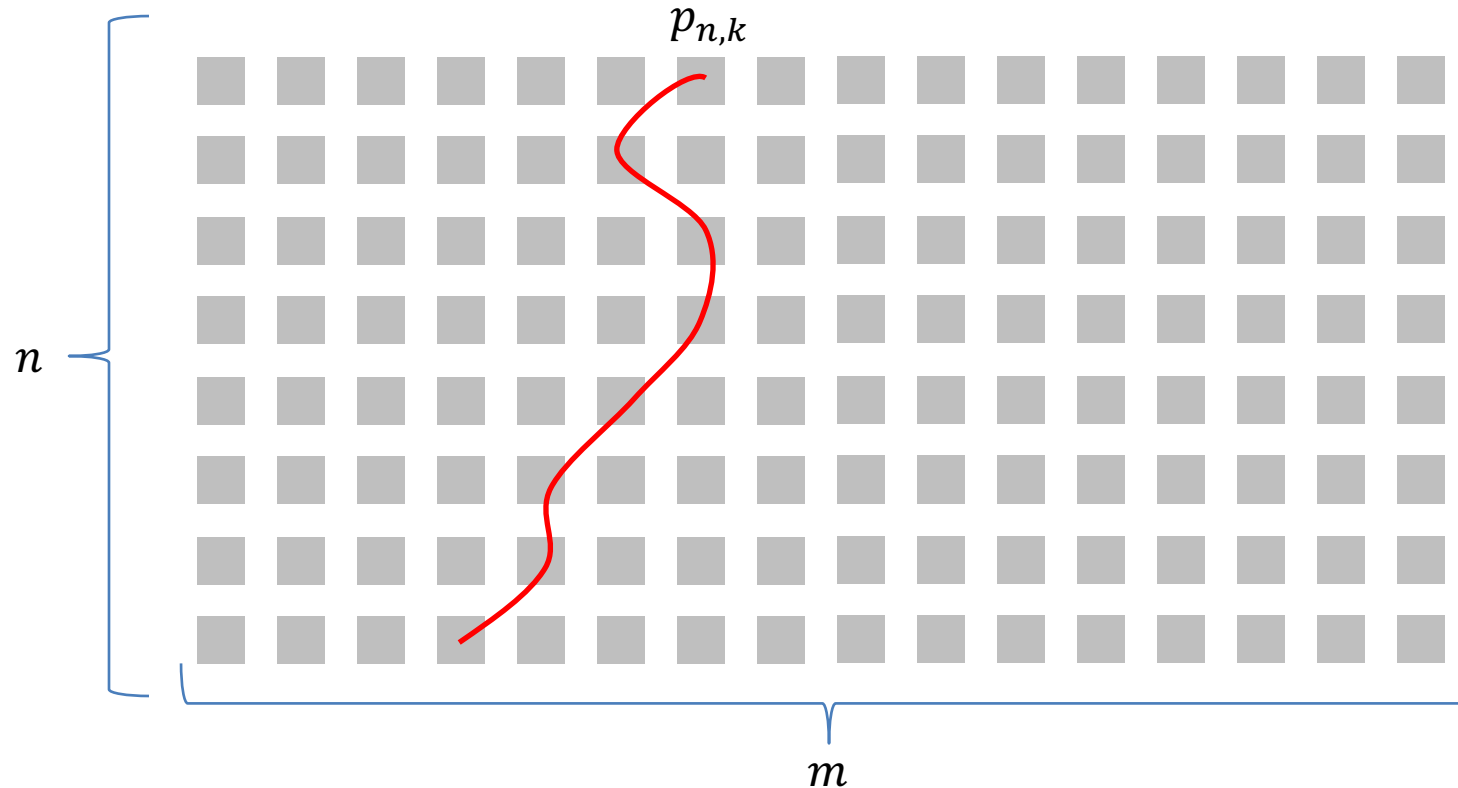
Let $S(i, j)$ = least energy seam from the bottom of the image up to pixel $p_{i,j}$



Finding the Least Energy Seam

Want the least energy seam going from bottom to top, so delete:

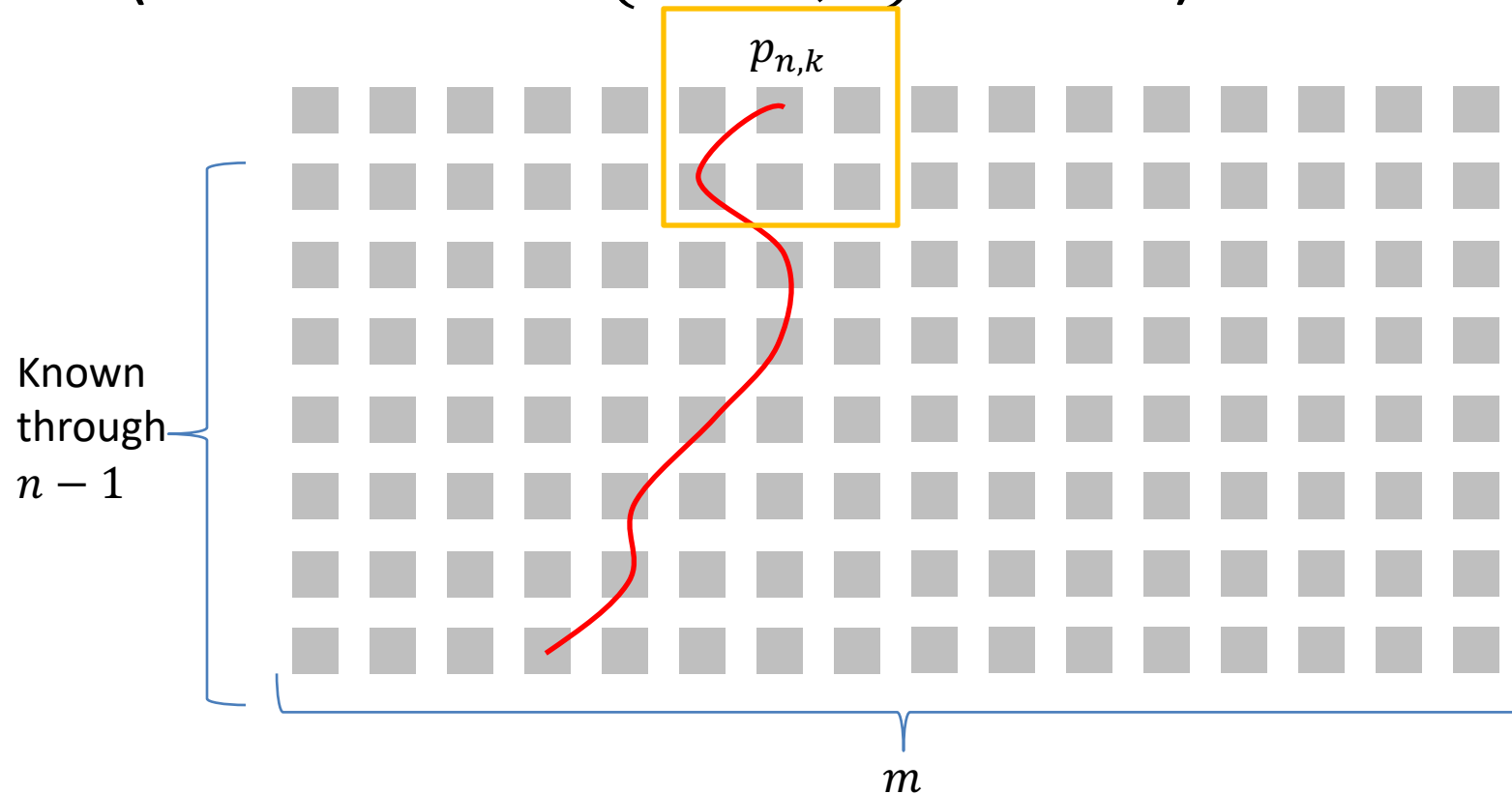
$$\min_{k=1}^m (S(n, k))$$



Computing $S(n, k)$

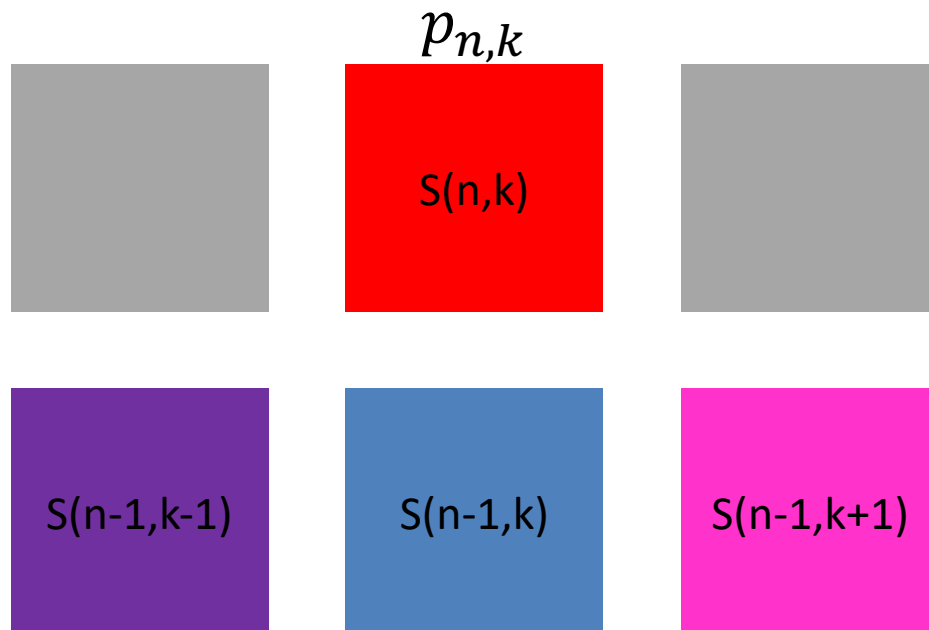
Assume we know the least energy seams for all of row $n - 1$

(i.e. we know $S(n - 1, \ell)$ for all ℓ)



Computing $S(n, k)$

Assume we know the least energy seams for all of row $n - 1$ (i.e. we know $S(n - 1, \ell)$ for all ℓ)



Repeated Seam Removal

Only need to update **pixels dependent** on the **removed seam**

$2n$ pixels change

$\Theta(2n)$ time to update pixels

$\Theta(n + m)$ time to find min+backtrack

