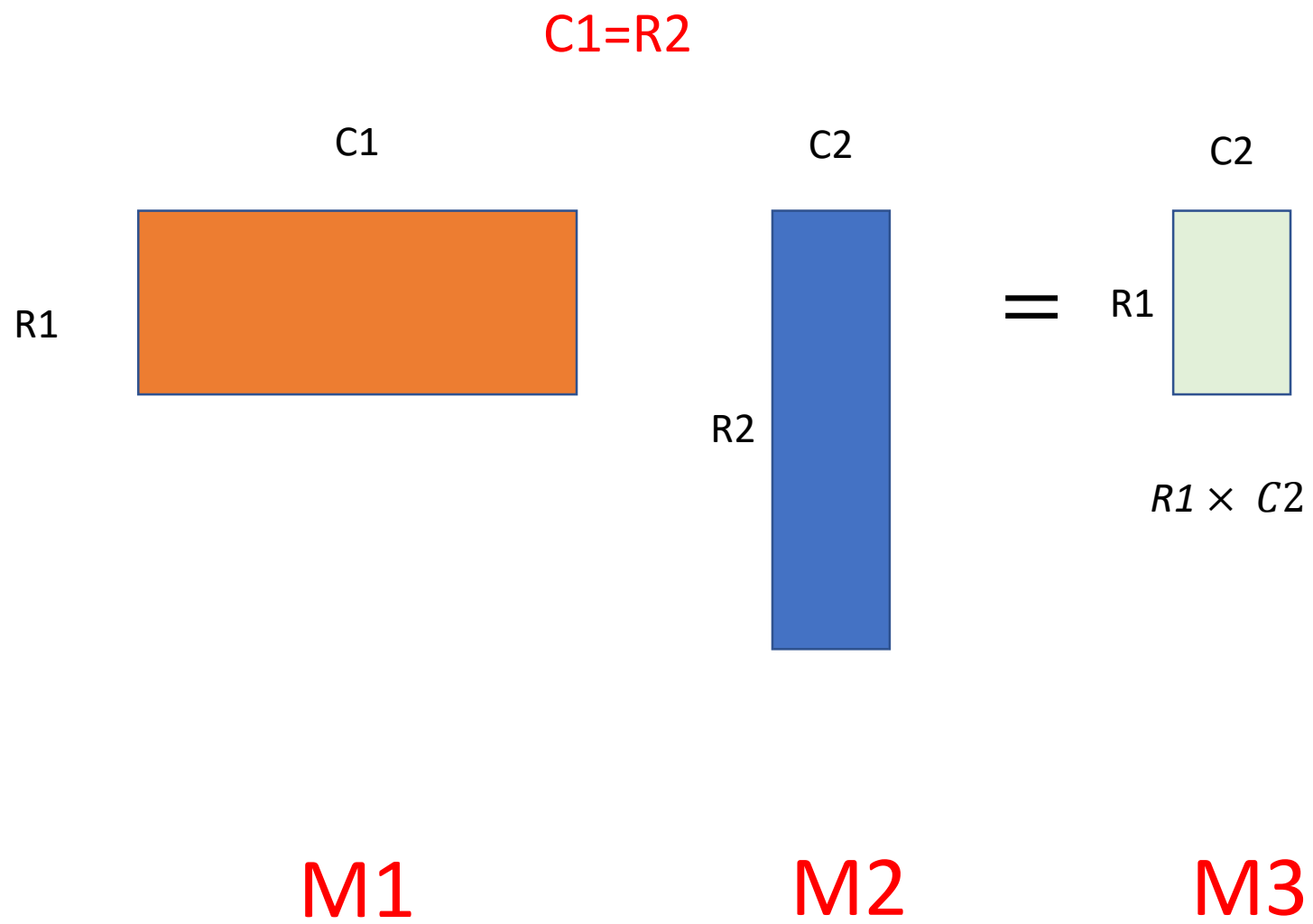
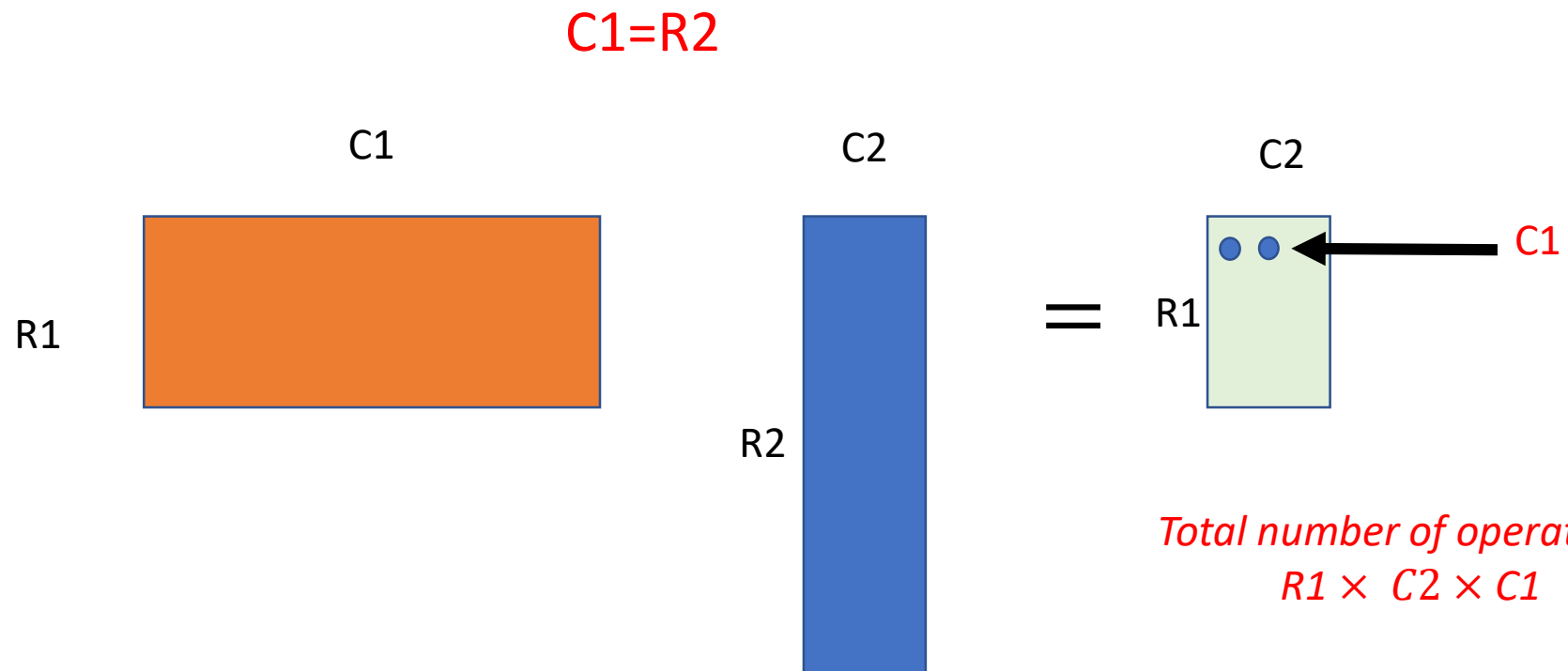


Dynamic Programming

lecture 2





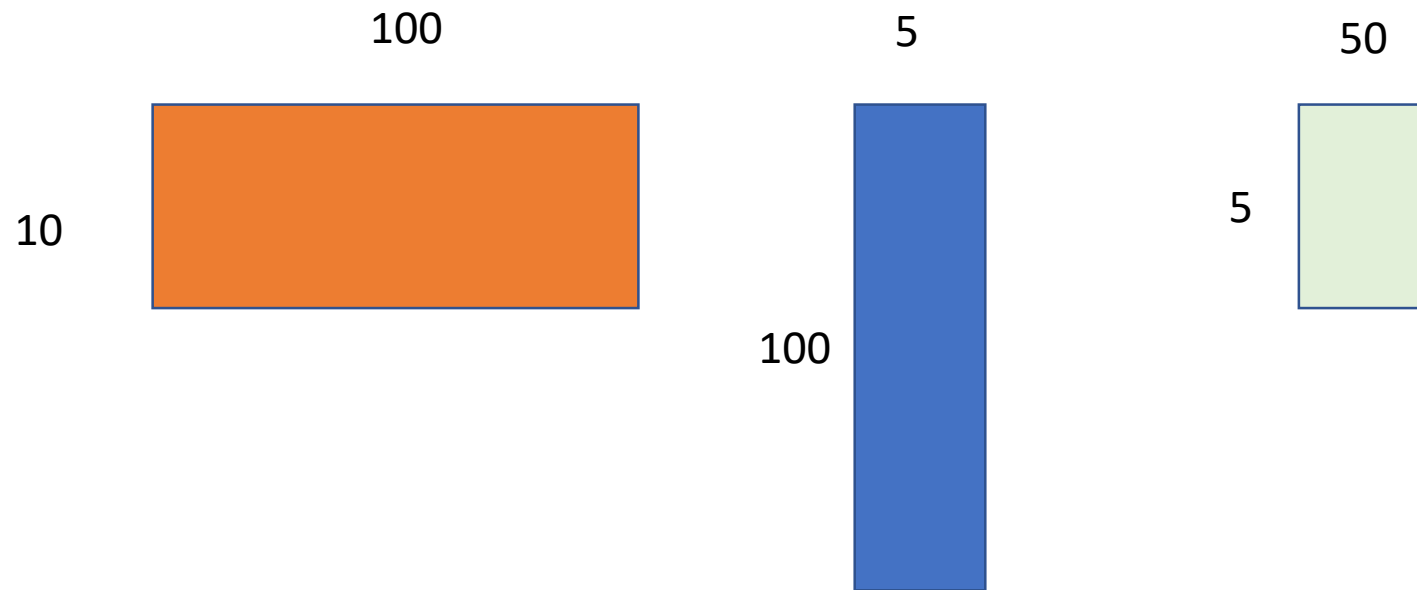
$$A_1 \cdot A_2 \cdot A_3$$

Associative

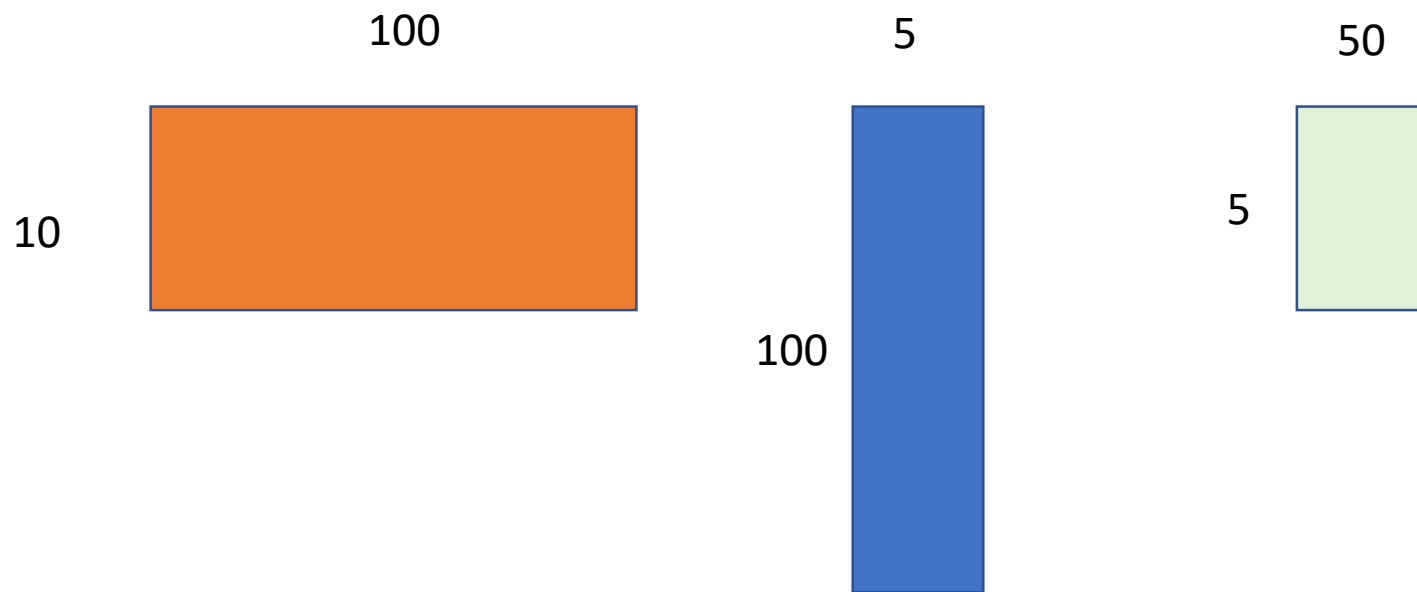
$$(A_1 \cdot A_2) \cdot A_3$$

$$A_1 \cdot (A_2 \cdot A_3)$$

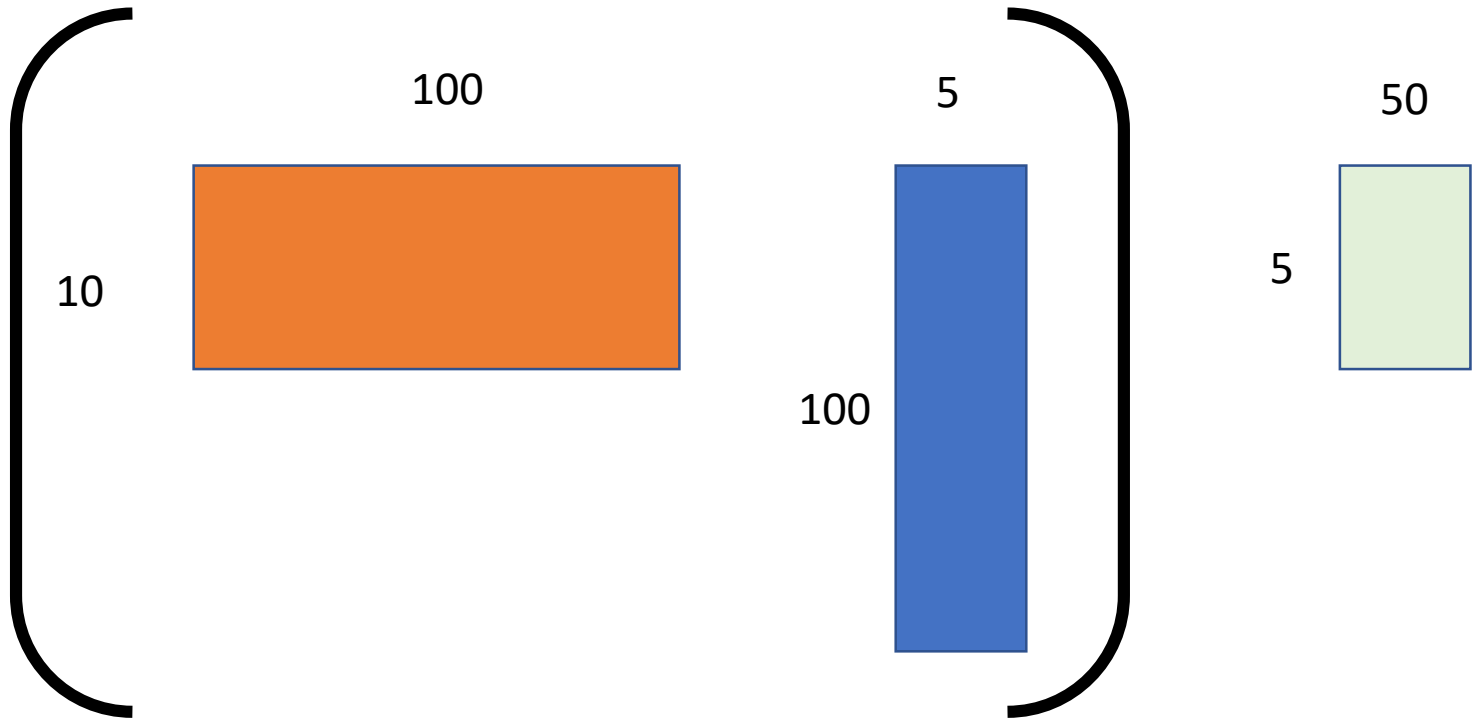
$$A_1 \cdot A_2 \cdot A_3$$



$$(A_1 \cdot A_2) \cdot A_3$$



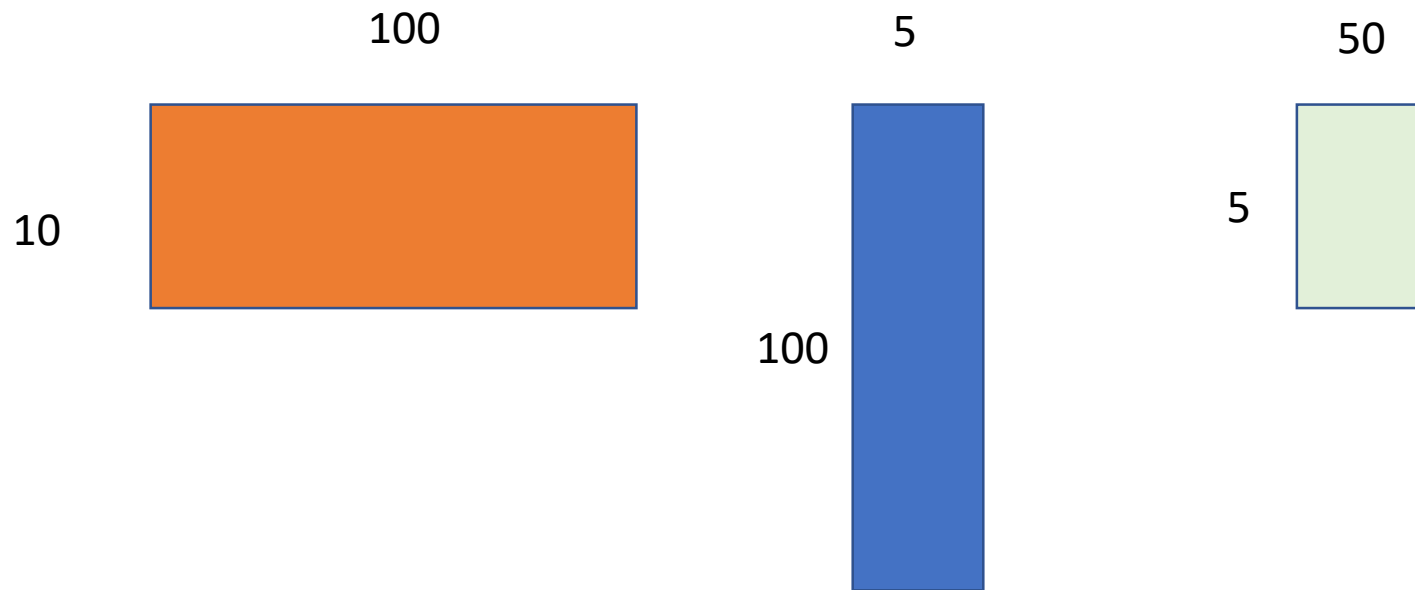
$$(A_1 \cdot A_2) \cdot A_3$$



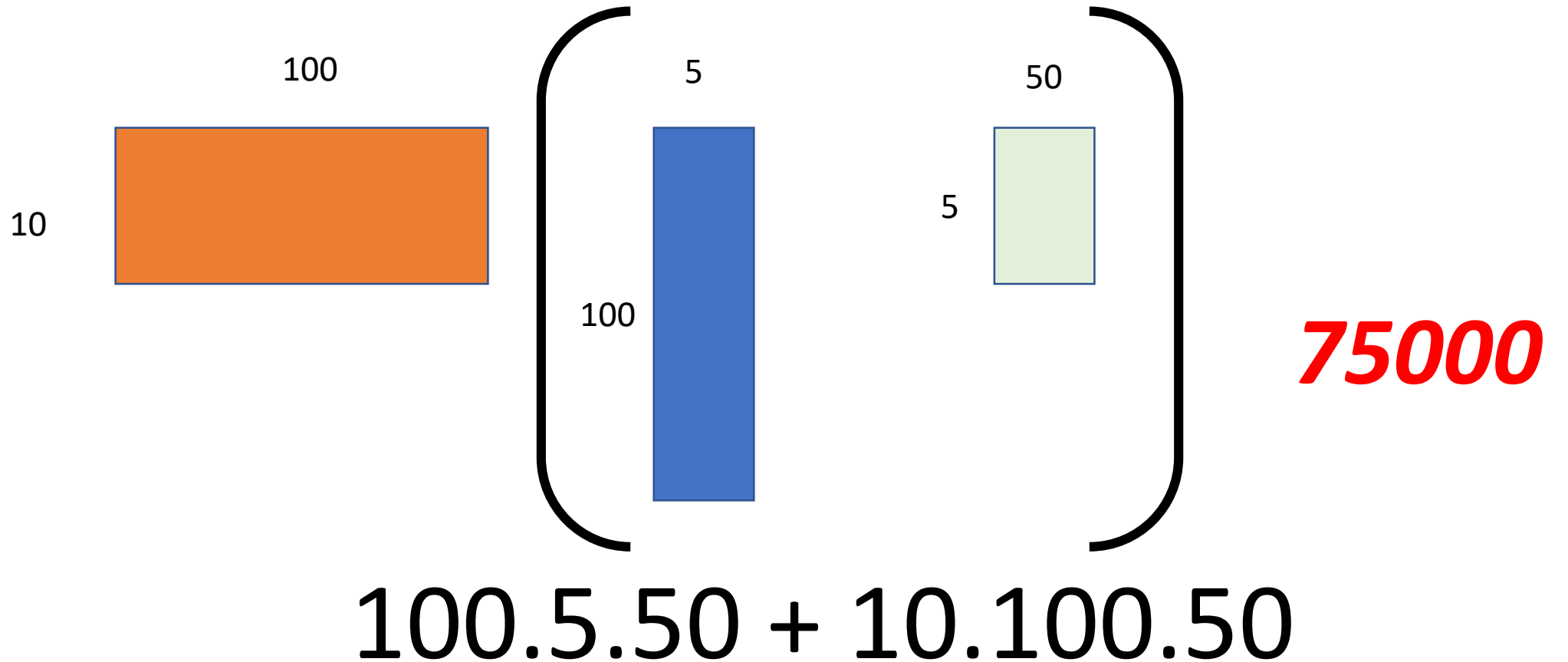
$$10 \cdot 100 \cdot 5 + 10 \cdot 5 \cdot 50$$

7500

$$A_1 \cdot (A_2 \cdot A_3)$$



$$A_1 \cdot (A_2 \cdot A_3)$$



Order Matters

How many ways to multiply:

$$A_1 \cdot A_2 \cdot A_3 \cdot \dots \cdot A_n$$

N-1 multiplication

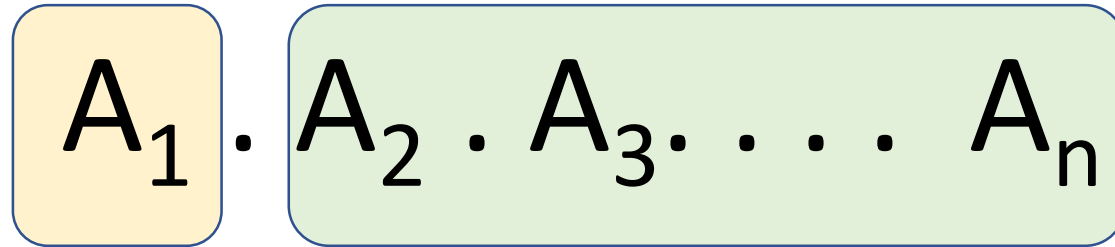
P(n): number of ways to multiply the n matrices

How many ways to multiply:

$$A_1 \cdot A_2 \cdot A_3 \cdot \dots \cdot A_n$$

P(n): number of ways to multiply the n matrices

$$P(n) = P(1) \cdot P(n-1) +$$


$$A_1 \cdot A_2 \cdot A_3 \cdot \dots \cdot A_n$$

How many ways to multiply:

$$A_1 \cdot A_2 \cdot A_3 \cdot \dots \cdot A_n$$

P(n): number of ways to multiply the n matrices

$$P(n) = P(1) \cdot P(n-1) + P(2) \cdot P(n-2) +$$

$$\boxed{A_1 \cdot A_2} \cdot \boxed{A_3 \cdot \dots \cdot A_n}$$

How many ways to multiply:

$$A_1 \cdot A_2 \cdot A_3 \cdot \dots \cdot A_n$$

P(n): number of ways to multiply the n matrices

$$P(n) = P(1) \cdot P(n-1) + P(2) \cdot P(n-2) + P(3) \cdot P(n-3) +$$

$$\boxed{A_1 \cdot A_2 \cdot A_3} \cdot \boxed{A_4 \cdot \dots \cdot A_n}$$

How many ways to multiply:

$$A_1 \cdot A_2 \cdot A_3 \cdot \dots \cdot A_n$$

P(n): number of ways to multiply the n matrices

$$P(n) = P(1) \cdot P(n-1) + P(2) \cdot P(n-2) + P(3) \cdot P(n-3) + \dots + P(n-1)P(1)$$

$$A_1 \cdot A_2 \cdot A_3 \cdot \dots \cdot A_{n-1} \cdot A_n$$

How many ways to multiply:

$$A_1 \cdot A_2 \cdot A_3 \cdot \dots \cdot A_n$$

$P(n)$: number of ways to multiply the n matrices

$$P(n) = P(1) \cdot P(n-1) + P(2) \cdot P(n-2) + P(3) \cdot P(n-3) + \dots + P(n-1)P(1)$$

$$= \sum_{i=1}^{n-1} P(i) \cdot P(n-i) \approx 4^n$$

Optimal Way to Compute

$$A_1 \cdot A_2 \cdot A_3 \cdots A_l \cdot A_{l+1} \cdot \cdots A_n$$

Optimal Way to Compute

$$\overset{C_1}{A_1} \overset{R_1}{\cdot} \overset{C_2}{A_2} \overset{R_2}{\cdot} \overset{C_3}{A_3} \cdots \cdots \overset{C_l}{A_l} \overset{R_{l+1}}{\cdot} \overset{C_{l+1}}{A_{l+1}} \cdots \cdots \overset{C_n}{A_n} \overset{R_n}{\cdot}$$

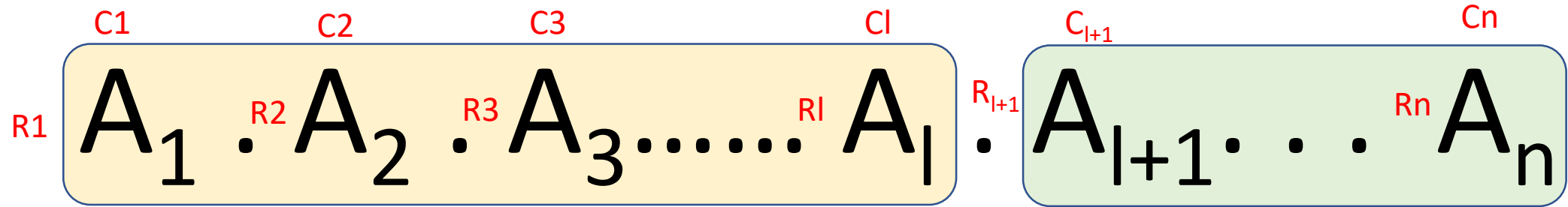
B[1,n]= smallest number of operations needed to multiply the chain

Optimal Way to Compute

$$\overset{C_1}{A_1} \overset{R_1}{\cdot} \overset{C_2}{A_2} \overset{R_2}{\cdot} \overset{C_3}{A_3} \cdots \cdots \overset{C_l}{A_l} \overset{R_{l+1}}{\cdot} \overset{C_{l+1}}{A_{l+1}} \cdots \cdots \overset{C_n}{A_n} \overset{R_n}{\cdot}$$

$B[1,n]$ = smallest number of operations needed to multiply the chain

Optimal Way to Compute

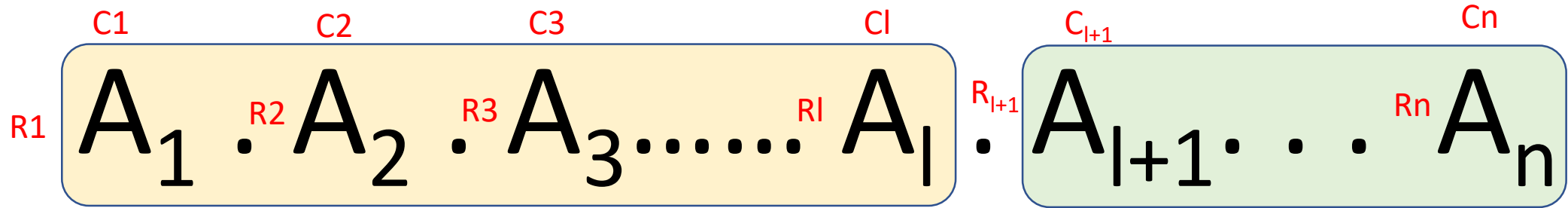


Optimal last step: $A[1\dots l] \cdot A[l+1, \dots n]$

$B[1,n]$ = smallest number of operations needed to multiply the chain

$$B[1,n] = B[1,l] + B[l+1,n] + R_1 \cdot C_l \cdot C_{l+1}$$

Optimal Way to Compute



Optimal last step: $A[1\dots l] \cdot A[l+1, \dots n]$

$B[1,n]$ = smallest number of operations needed to multiply the chain

$$B[1,n] = B[1,l] + B[l+1,n] + R_1 \cdot C_l \cdot C_{l+1}$$

How many choices we have for l ?
 $l \in [1, n-1]$

Optimal Way to Compute

$${}^{R_1}A_1 \overset{C_1}{\cdot} \overset{C_2}{{}^{R_2}A_2} \overset{C_3}{\cdot} A_3 \cdots \cdots \overset{C_l}{{}^{R_l}A_l} \overset{C_{l+1}}{\cdot} A_{l+1} \cdot \cdot \cdot \overset{C_n}{{}^{R_n}A_n}$$

B[1,n]= smallest number of operations needed to multiply the chain

B[1,1]	B[1,2]			B[1,n-2]	B[1,n-1]
B[2,n]	B[3,n]	B[n-1,n]	B[n,n]
R₁C₁C_n	R₁C₂C_n			R₁C_{n-2}C_n	R₁C_{n-1}C_n

Which Order to Solve?

$$A_1 \cdot A_2 \cdot A_3 \cdot \dots \cdot A_{n-1} \cdot A_n$$

$$B(i,i)=0$$

$$B(i,j)=\min_{k=i}^{j-1} B(i,k) + B(k+1, j) + R_i C_k C_j$$

$$\overset{R_1}{A_1} \overset{C_1}{\cdot} \overset{R_2}{A_2} \overset{C_2}{\cdot} \overset{R_3}{A_3} \dots \overset{R_k}{A_k} \overset{C_k}{\cdot} \overset{R_{k+1}}{A_{k+1}} \dots \overset{R_{n-1}}{A_{n-1}} \overset{C_{n-1}}{\cdot} \overset{R_n}{A_n} \overset{C_n}$$

Which Order to Solve?

$$A_1 \cdot A_2 \cdot A_3 \cdot \dots \cdot A_{n-1} \cdot A_n$$

$$B(i,i)=0$$

$$B(i,j) = \min_{k=i}^{j-1} B(i,k) + B(k+1, j) + R_i C_k C_j$$

$$i=2$$

$$j=n-1$$

$$\begin{array}{ccccccc}
 & C_1 & & C_2 & & C_3 & & & C_k & & C_{k+1} & & C_{n-1} & & C_n \\
 R_1 & A_1 & \cdot & A_2 & \cdot & A_3 & \dots & \cdot & A_k & \cdot & A_{k+1} & \dots & A_{n-1} & \cdot & A_n \\
 & & & R_2 & & R_3 & & & R_k & & R_{k+1} & & R_{n-1} & & R_n
 \end{array}$$

Which Order to Solve?

$$A_1 \cdot A_2 \cdot A_3 \cdot \dots \cdot A_{n-1} \cdot A_n$$

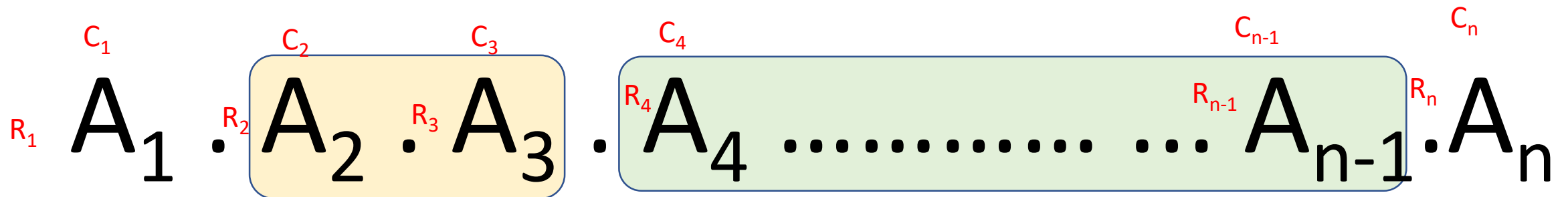
$$B(i,i)=0$$

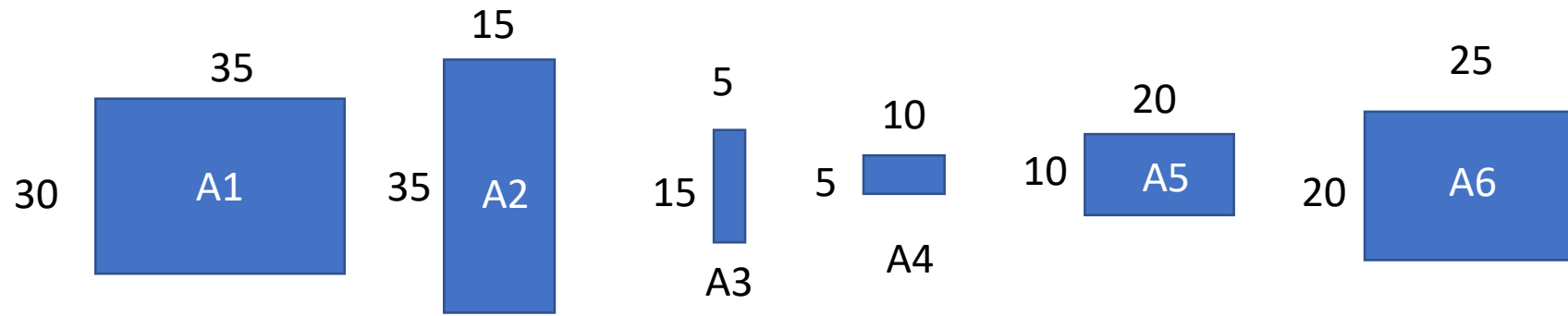
$$B(i,j) = \min_{k=i}^{j-1} B(i,k) + B(k+1, j) + R_i C_k C_j$$

$$i=2$$

$$j=n-1$$

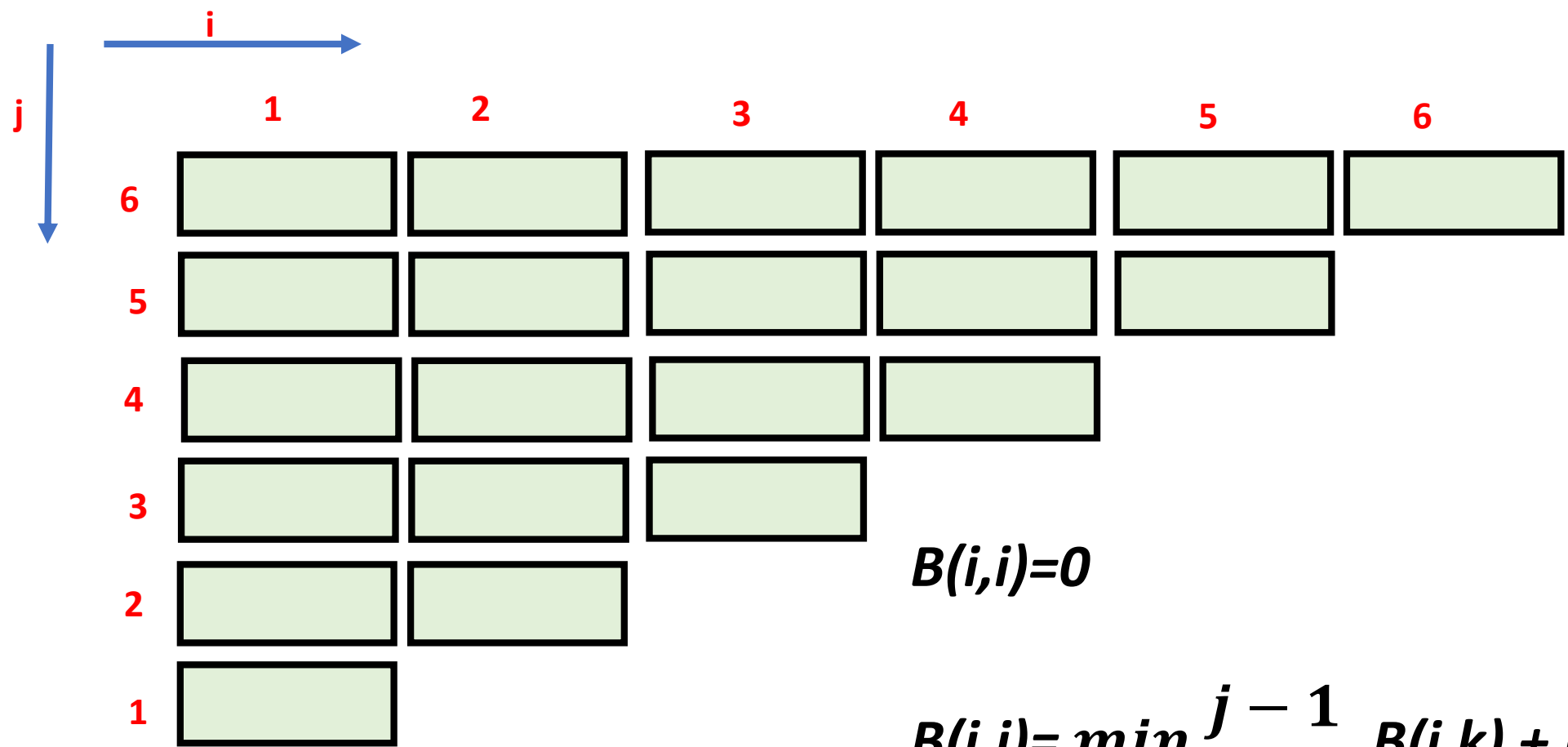
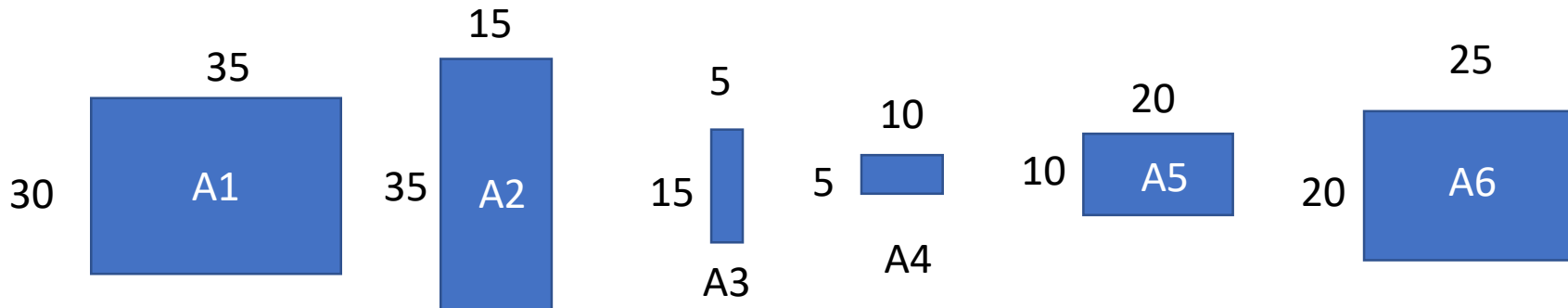
$$K=3$$





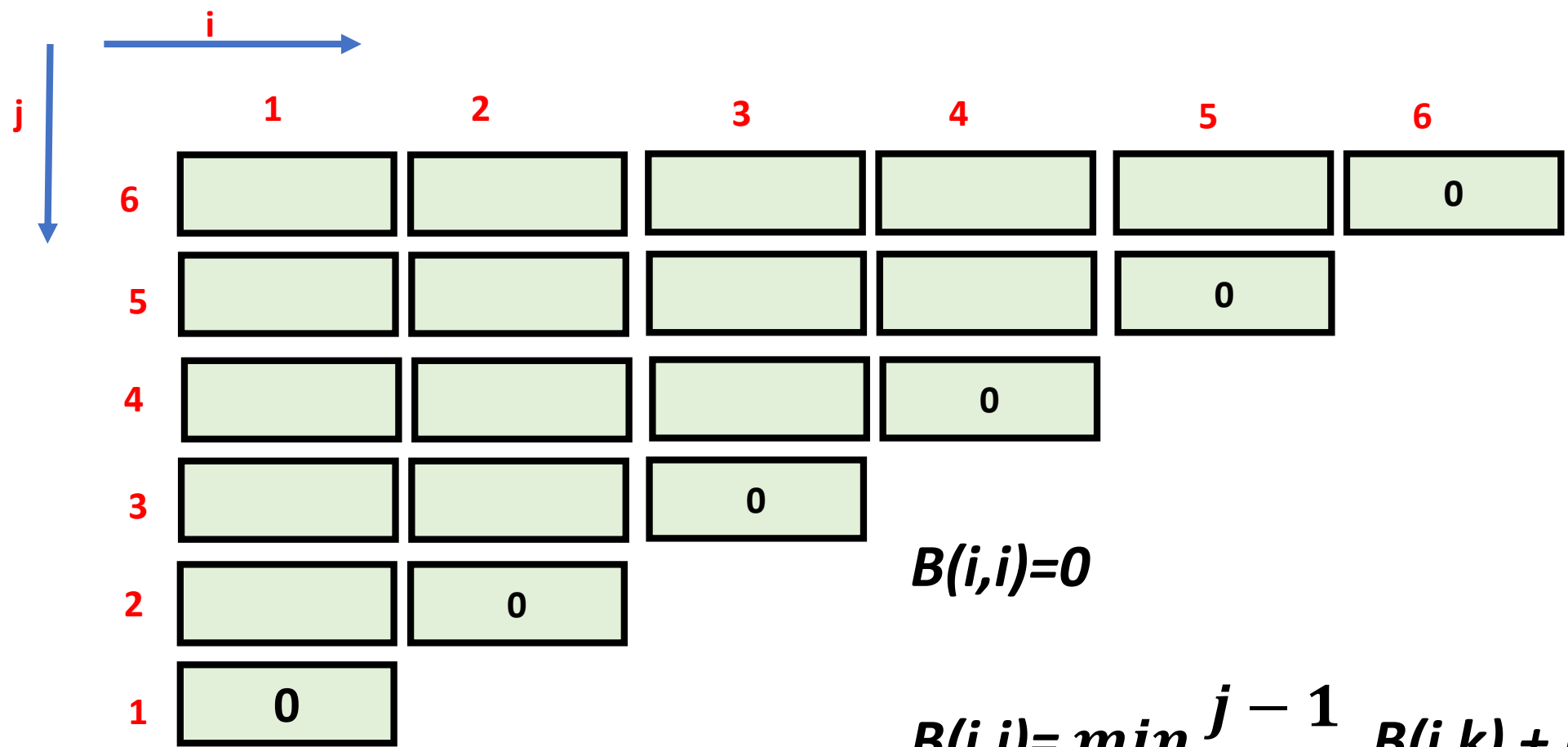
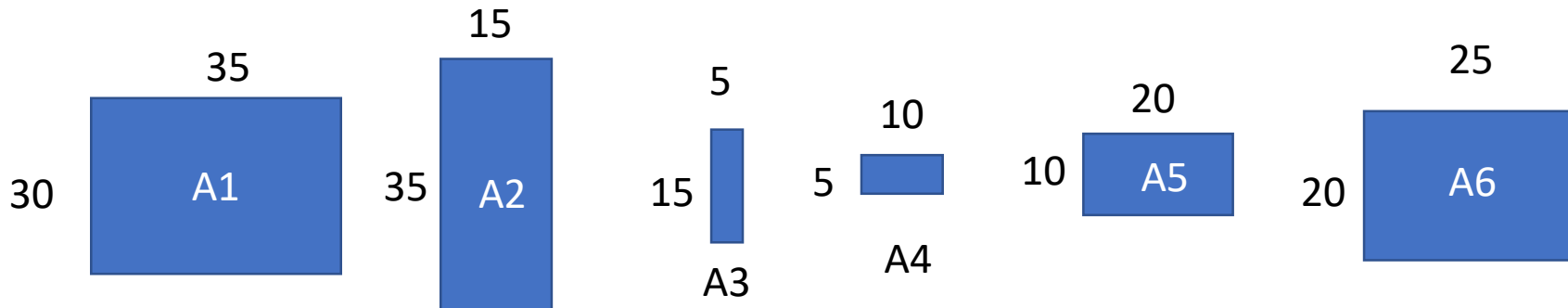
$$B(i,i)=0$$

$$B(i,j)=\min_{k=i}^{j-1} B(i,k) + B(k+1, j) + R_i C_k C_j$$



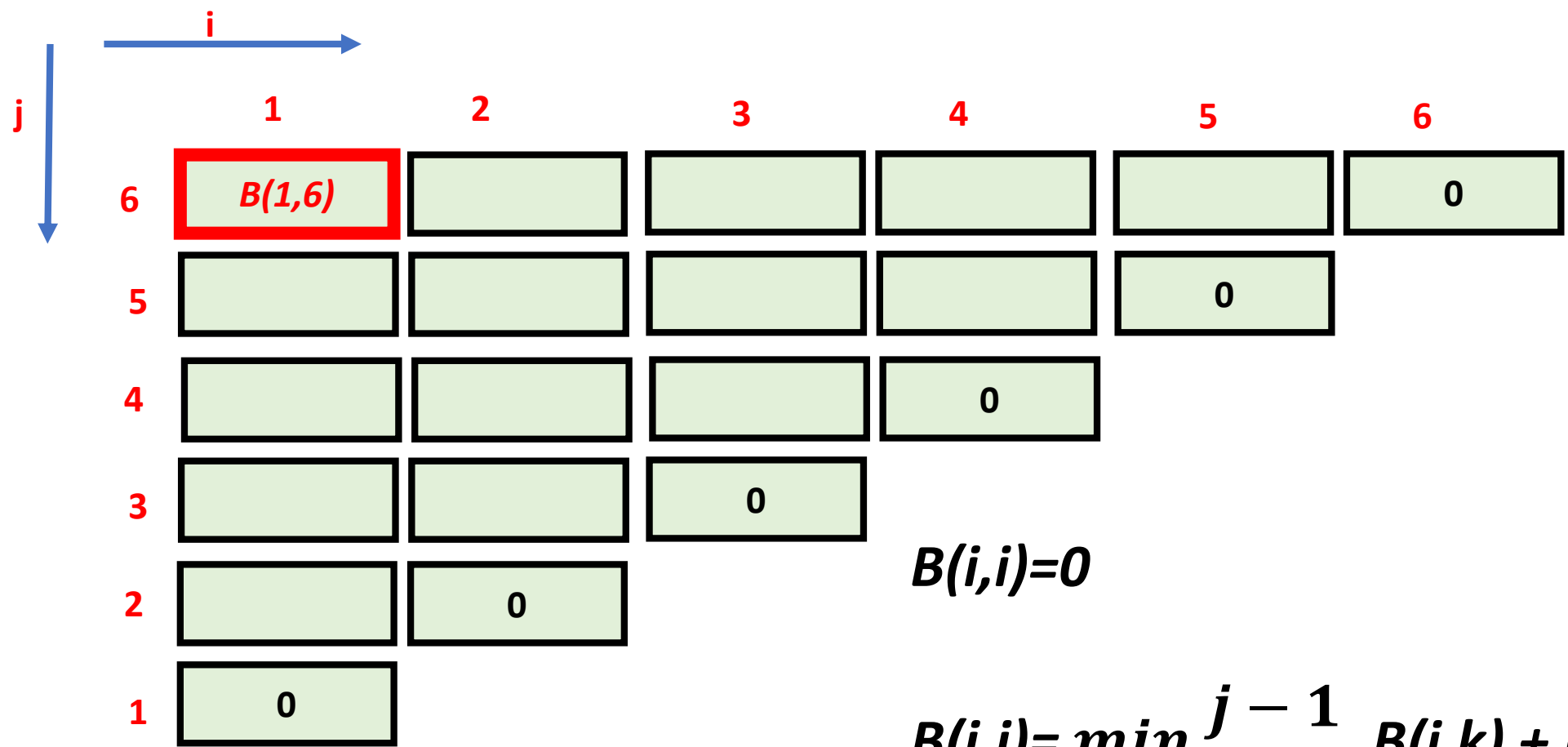
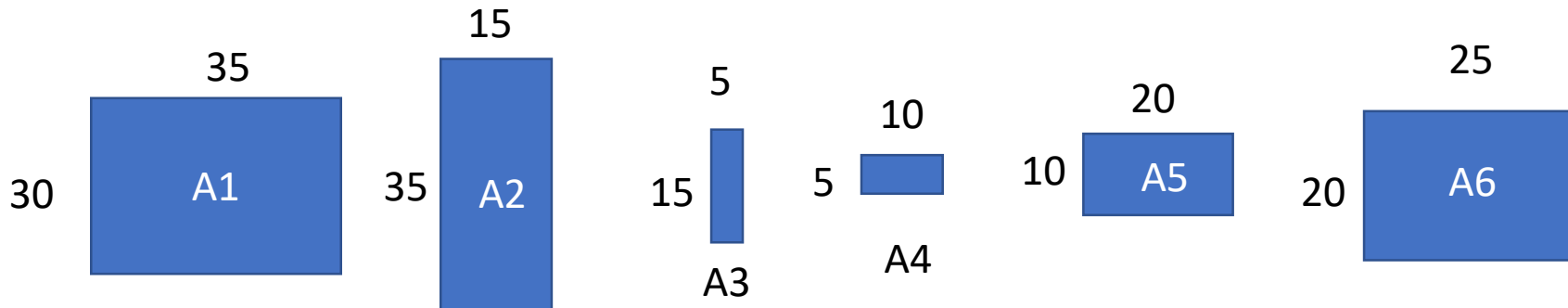
$$B(i,i)=0$$

$$B(i,j)= \min_{k=i}^{j-1} B(i,k) + B(k+1, j) + R_i C_k C_j$$



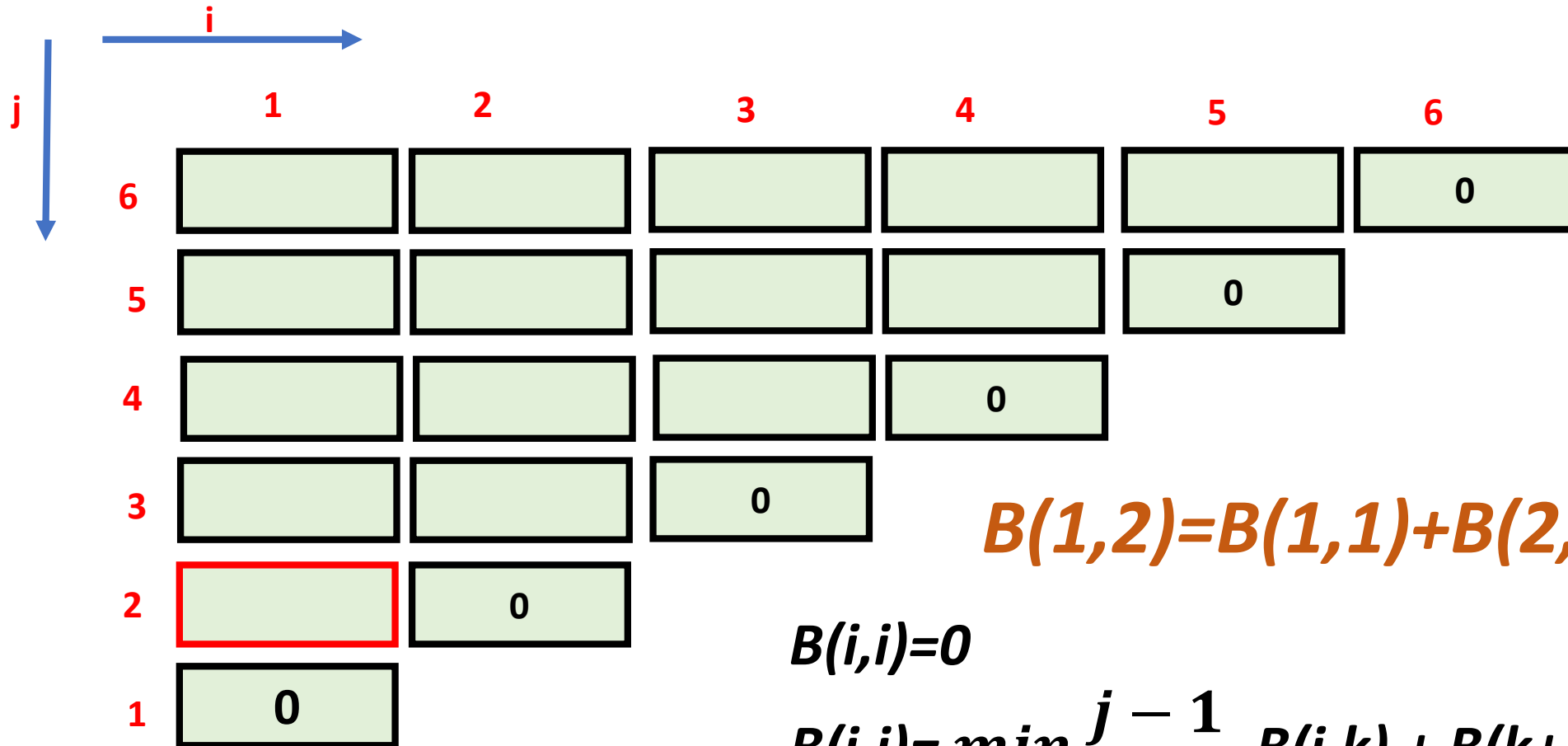
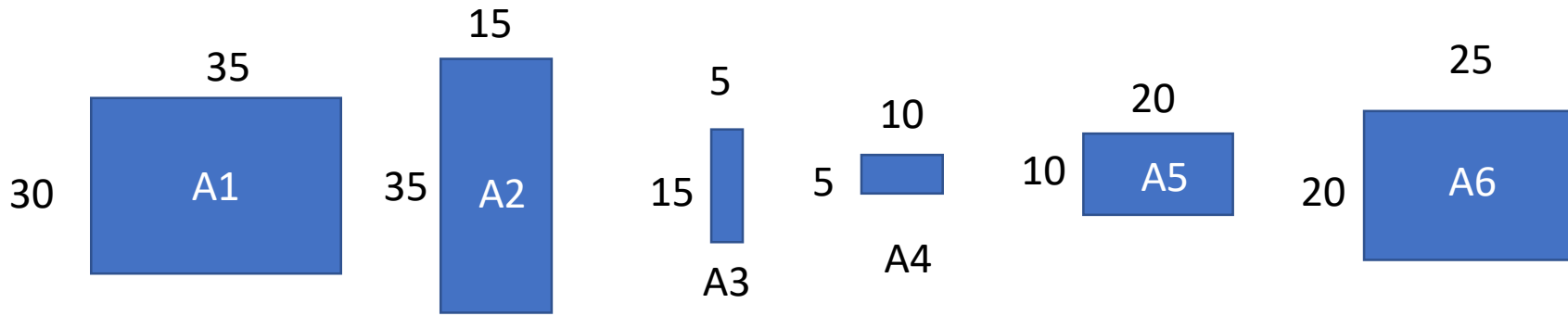
$$B(i,i)=0$$

$$B(i,j)=\min_{k=i}^{j-1} B(i,k) + B(k+1, j) + R_i C_k C_j$$



$$B(i,i)=0$$

$$B(i,j)= \min_{k=i}^{j-1} B(i,k) + B(k+1, j) + R_i C_k C_j$$



$$B(1,2) = B(1,1) + B(2,2) + 30 \cdot 35 \cdot 15$$

$$B(i,i) = 0$$

$$B(i,j) = \min_{k=i}^{j-1} B(i,k) + B(k+1, j) + R_i C_k C_j$$

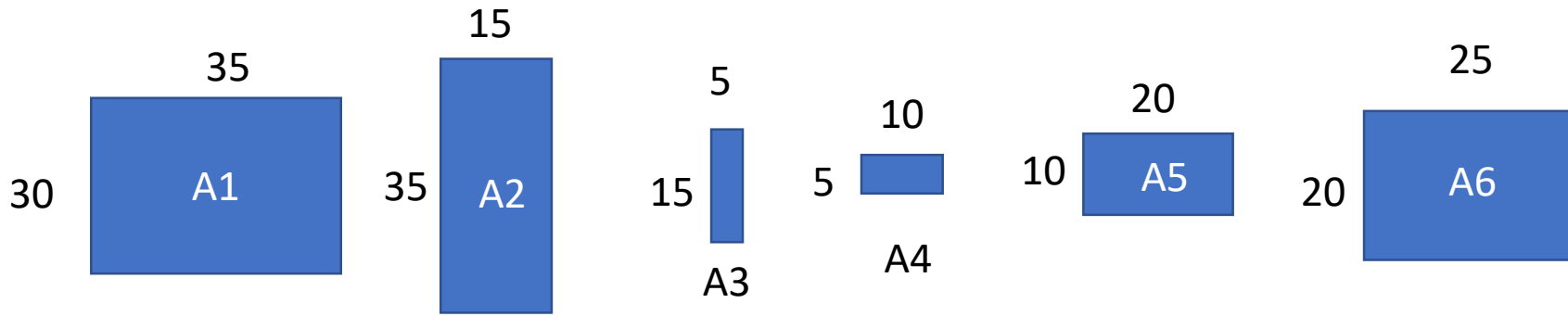


Diagram illustrating the dynamic programming table for matrix chain multiplication. The table is indexed by i (horizontal axis) and j (vertical axis). The cells contain the minimum number of scalar multiplications required to compute the product of matrices from i to j .

	1	2	3	4	5	6
6						0
5					0	
4				0		
3			0			
2	15750	0				
1	0					

$$B(1,2) = B(1,1) + B(2,2) + 30 \cdot 35 \cdot 15$$

$$B(i,i) = 0$$

$$B(i,j) = \min_{k=i}^{j-1} B(i,k) + B(k+1, j) + R_i C_k C_j$$

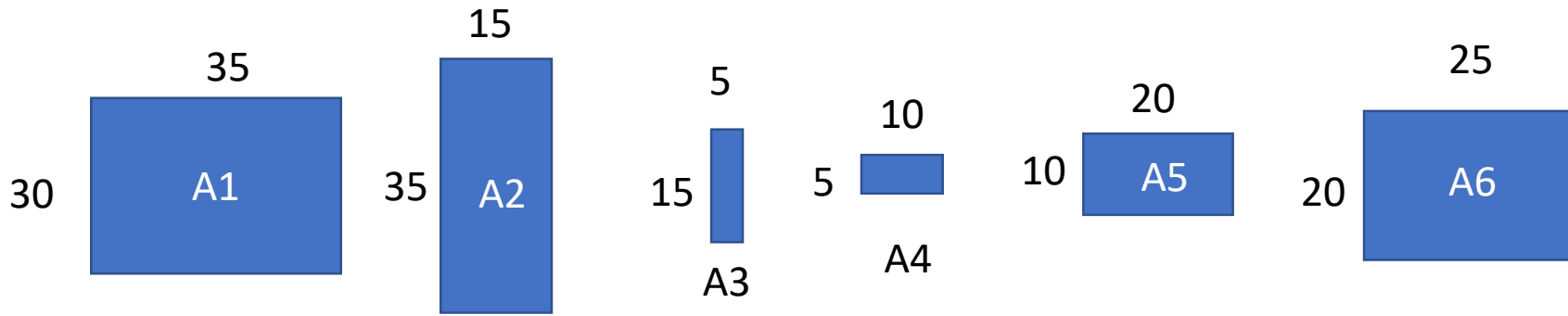


Diagram illustrating the dynamic programming table for matrix chain multiplication. The table is indexed by i (horizontal axis) and j (vertical axis). The cells are green, and the value 0 is shown in several cells, indicating the base case $B(i,i)=0$.

	1	2	3	4	5	6
6						0
5					0	
4				0		
3			0			
2	15750	0				
1	0					

$$B(2,3) = B(2,2) + B(3,3) + 35 \cdot 15 \cdot 5$$

$$B(i,i) = 0$$

$$B(i,j) = \min_{k=i}^{j-1} B(i,k) + B(k+1, j) + R_i C_k C_j$$

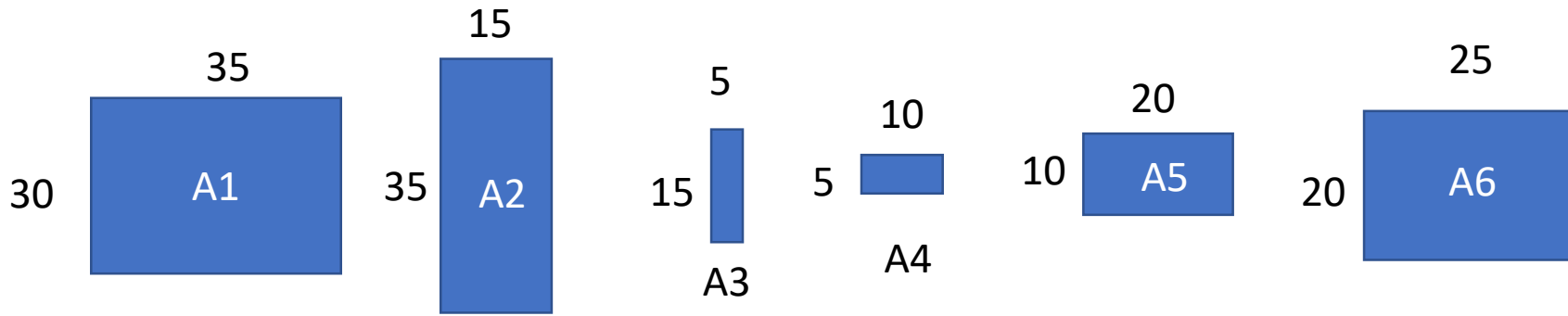


Diagram illustrating the dynamic programming table for matrix chain multiplication. The table is indexed by i (horizontal axis) and j (vertical axis). The cells contain the minimum number of scalar multiplications required to compute the product of matrices from i to j .

	1	2	3	4	5	6
6						0
5					0	
4				0		
3		2625	0			
2	15750	0				
1	0					

$$B(2,3) = B(2,2) + B(3,3) + 35 \cdot 15 \cdot 5$$

$$B(i,i) = 0$$

$$B(i,j) = \min_{k=i}^{j-1} B(i,k) + B(k+1, j) + R_i C_k C_j$$

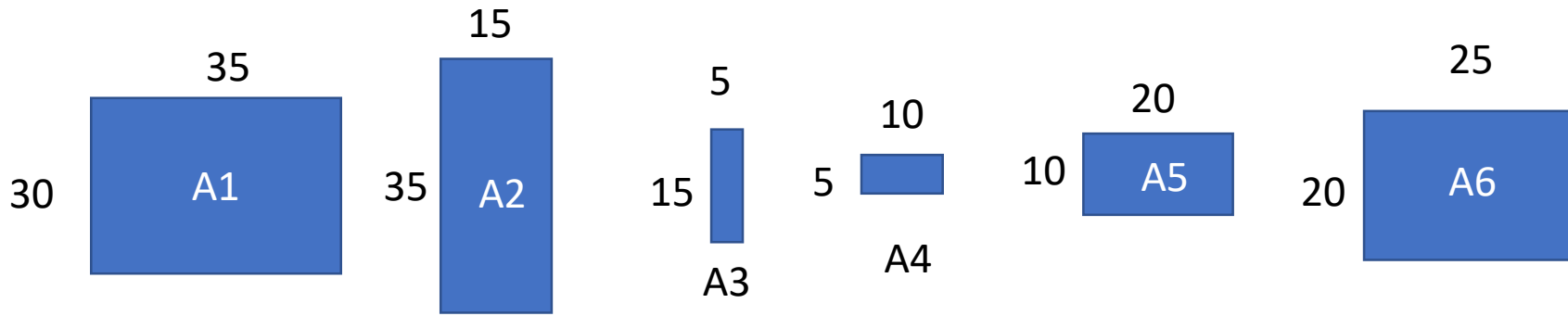


Diagram showing the dimensions of matrices A1 through A6 and a dynamic programming table for matrix chain multiplication.

Matrix dimensions (Row x Column):

- A1: 30 x 35
- A2: 35 x 15
- A3: 15 x 5
- A4: 5 x 10
- A5: 10 x 20
- A6: 20 x 25

Dynamic Programming Table (B[i][j]):

	1	2	3	4	5	6
6						0
5					0	
4				0		
3		2625	0			
2	15750	0				
1	0					

$$B(3,4) = B(3,3) + B(4,4) + 15.5.10$$

$$B(i,i) = 0$$

$$B(i,j) = \min_{k=i}^{j-1} B(i,k) + B(k+1, j) + R_i C_k C_j$$

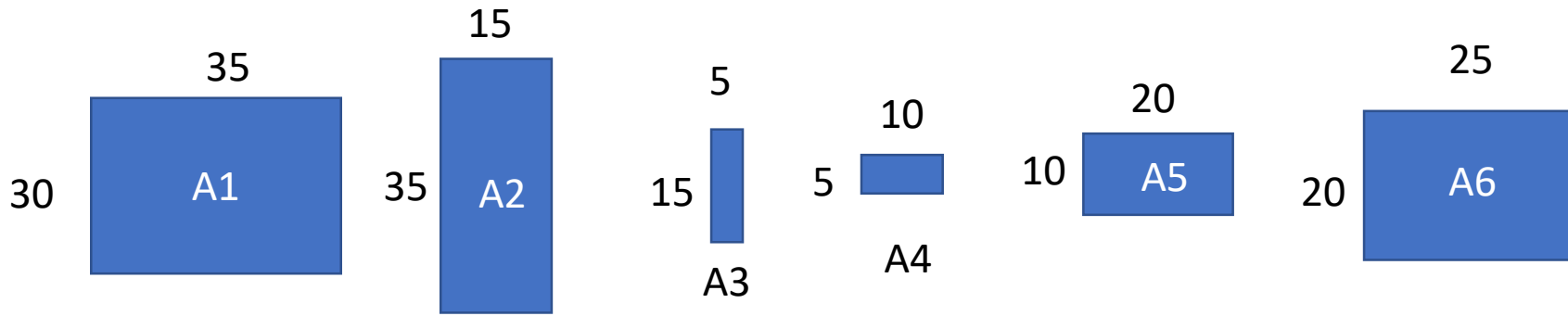


Diagram showing the dimensions of matrices A1 through A6 and a dynamic programming table for matrix chain multiplication.

Matrix dimensions:

- A1: 30x35
- A2: 35x15
- A3: 15x5
- A4: 5x10
- A5: 10x20
- A6: 20x25

Dynamic programming table (B[i,j]):

	1	2	3	4	5	6
6						0
5					0	
4			750	0		
3		2625	0			
2	15750	0				
1	0					

$$B(3,4) = B(3,3) + B(4,4) + 15.5.10$$

$$B(i,i) = 0$$

$$B(i,j) = \min_{k=i}^{j-1} B(i,k) + B(k+1, j) + R_i C_k C_j$$

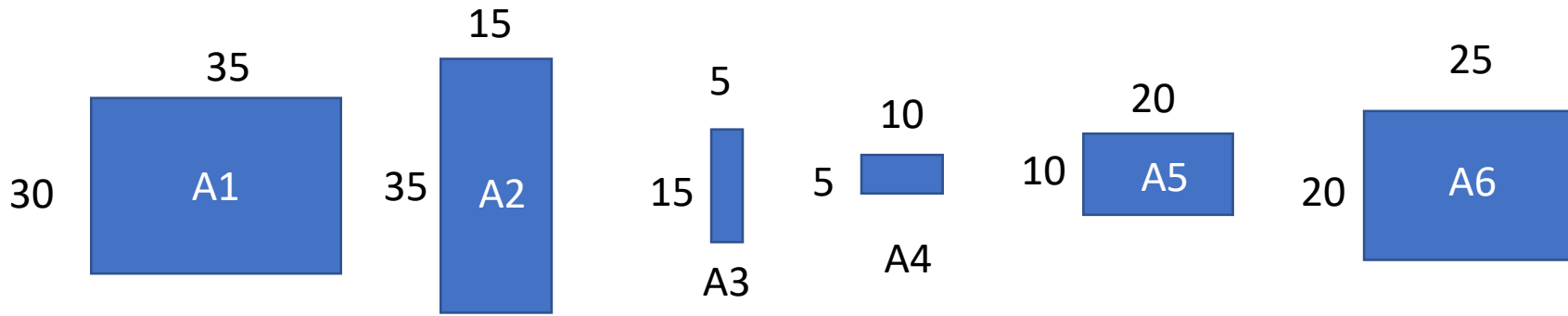


Diagram showing the dimensions of matrices A1 through A6 and a dynamic programming table for matrix chain multiplication.

Matrix dimensions:

- A1: 30x35
- A2: 35x15
- A3: 15x5
- A4: 5x10
- A5: 10x20
- A6: 20x25

Dynamic programming table (B[i,j]):

	1	2	3	4	5	6
6					5000	0
5				1000	0	
4			750	0		
3		2625	0			
2	15750	0				
1	0					

$$B(4,5) = B(4,4) + B(5,5) + 5 \cdot 10 \cdot 20$$

$$B(5,6) = B(5,5) + B(6,6) + 10 \cdot 20 \cdot 25$$

$$B(i,i) = 0$$

$$B(i,j) = \min_{k=i}^{j-1} B(i,k) + B(k+1, j) + R_i C_k C_j$$

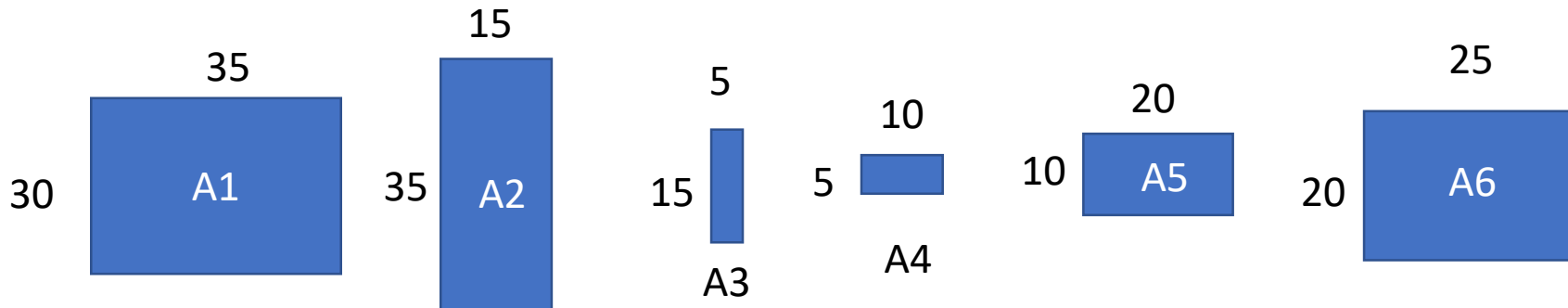


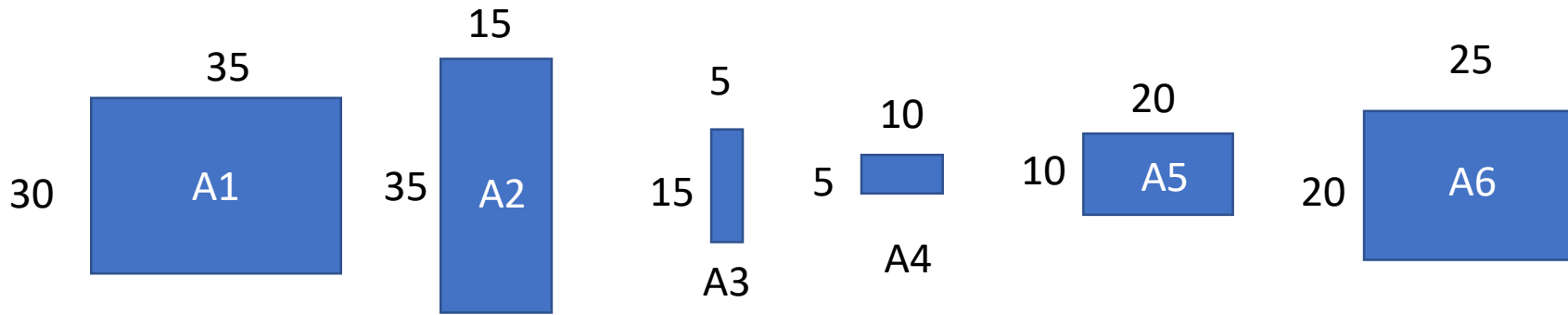
Diagram showing the dimensions of matrices A1 through A6 and a dynamic programming table for matrix chain multiplication. The table is indexed by i (horizontal axis) and j (vertical axis).

	1	2	3	4	5	6
6					5000	0
5				1000	0	
4			750	0		
3		2625	0			
2	15750	0				
1	0					

$B(1,3)$

$$B(i,i)=0$$

$$B(i,j)=\min_{k=i}^{j-1} B(i,k) + B(k+1, j) + R_i C_k C_j$$



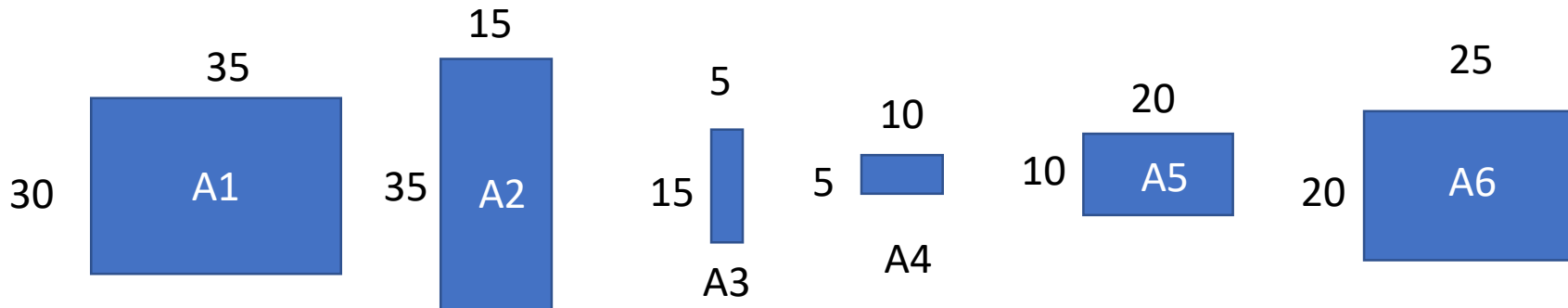
DP Table (B[i][j]):

	1	2	3	4	5	6
6					5000	0
5				1000	0	
4			750	0		
3		2625	0			
2	15750	0				
1	0					

$B(i,i) = 0$
 $B(i,j) = \min_{k=i}^{j-1} B(i,k) + B(k+1, j) + R_i C_k C_j$

For $B(1,3)$, the minimum is achieved by:

- $K=2$: $B(1,2) + B(3,3) + 30 \cdot 15 \cdot 5$
- $K=1$: $B(1,1) + B(2,3) + 30 \cdot 35 \cdot 5$



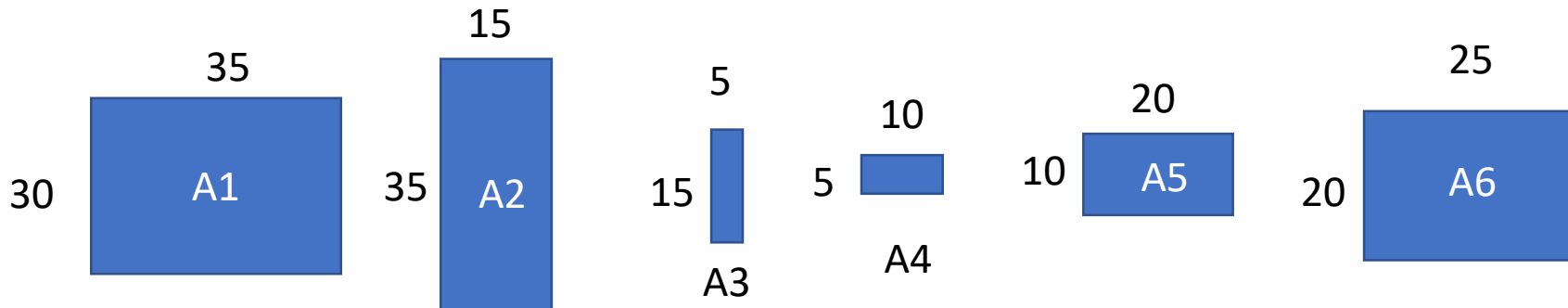
Dynamic Programming Table for Matrix Chain Multiplication (B[i,j]):

	1	2	3	4	5	6
6					5000	0
5				1000	0	
4			750	0		
3		2625	0			
2	15750	0				
1	0					

$B(i,i) = 0$
 $B(i,j) = \min_{k=i}^{j-1} B(i,k) + B(k+1, j) + R_i C_k C_j$

Calculation for $B(1,3)$:

 $B(1,3) = \min \left\{ \begin{aligned} &B(1,2) + B(3,3) + 30 \cdot 15 \cdot 5 = 2250 \\ &B(1,1) + B(2,3) + 30 \cdot 35 \cdot 5 = 2625 \end{aligned} \right.$

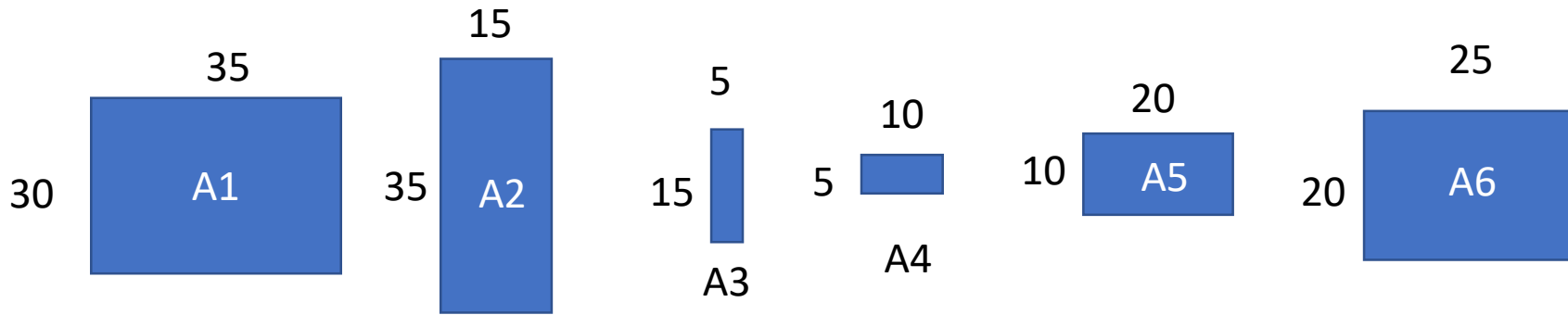


DP Table (B[i][j]):

	1	2	3	4	5	6
6					5000	0
5				1000	0	
4			750	0		
3	7875	2625	0			
2	15750	0				
1	0					

$B(i,i) = 0$
 $B(i,j) = \min_{k=i}^{j-1} B(i,k) + B(k+1, j) + R_i C_k C_j$

$B(1,3) = \min \left\{ \begin{aligned} &15750 \quad 2250 \\ &B(1,2) + B(3,3) + 30 \cdot 15 \cdot 5 \\ &B(1,1) + B(2,3) + 30 \cdot 35 \cdot 5 \\ &2625 \quad 5250 \end{aligned} \right.$



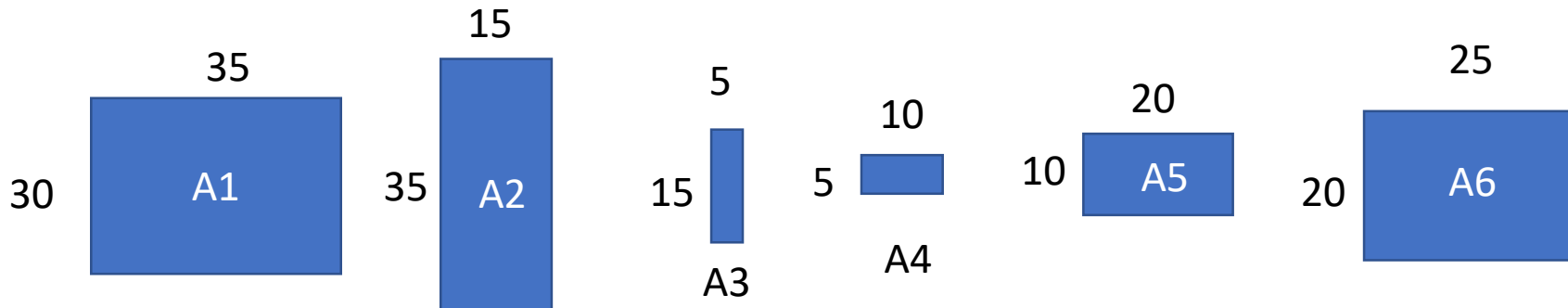
Dynamic Programming Table (B[i][j]):

	1	2	3	4	5	6
6					5000	0
5				1000	0	
4			750	0		
3	7875	2625	0			
2	15750	0				
1	0					

$B(i,i) = 0$
 $B(i,j) = \min_{k=i}^{j-1} B(i,k) + B(k+1, j) + R_i C_k C_j$

For $B(2,4)$, the minimum is achieved by $K=2$ or $K=3$:

- $K=2$: $B(2,2) + B(3,4) + 35 \cdot 15 \cdot 10$
- $K=3$: $B(2,3) + B(4,4) + 35 \cdot 5 \cdot 10$

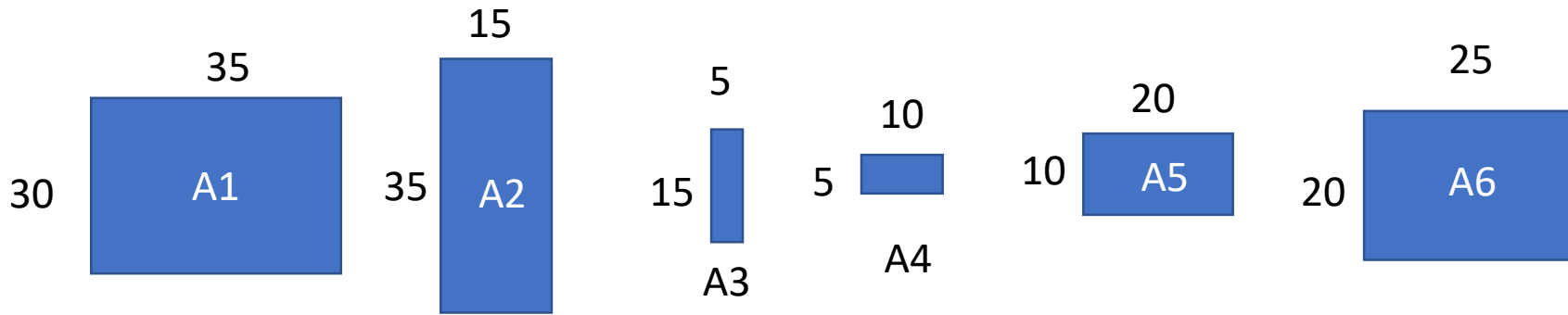


DP Table (B[i][j]):

	1	2	3	4	5	6
6					5000	0
5				1000	0	
4			750	0		
3	7875	2625	0			
2	15750	0				
1	0					

$B(i,i) = 0$
 $B(i,j) = \min_{k=i}^{j-1} B(i,k) + B(k+1, j) + R_i C_k C_j$

$B(2,4) = \min \left\{ \begin{aligned} &B(2,3) + B(4,4) + 35 \cdot 5 \cdot 10 \\ &B(2,2) + B(3,4) + 35 \cdot 15 \cdot 10 \end{aligned} \right.$



Dynamic Programming Table for Matrix Chain Multiplication (B[i,j]):

	1	2	3	4	5	6
6					5000	0
5				1000	0	
4		4375	750	0		
3	7875	2625	0			
2	15750	0				
1	0					

$B(i,i) = 0$
 $B(i,j) = \min_{k=i}^{j-1} B(i,k) + B(k+1, j) + R_i C_k C_j$

For $B(2,4)$, the minimum is achieved by:

- $B(2,3) + B(4,4) + 35 \cdot 5 \cdot 10$
- $B(2,2) + B(3,4) + 35 \cdot 15 \cdot 10$

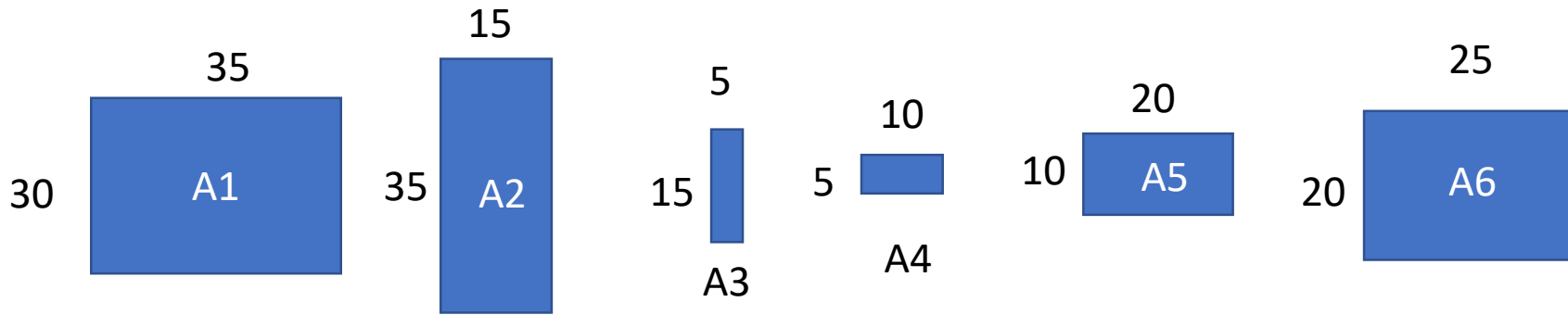


Diagram showing the dimensions of matrices A1 through A6 and a dynamic programming table B(i,j) for matrix chain multiplication. The table is indexed by i (horizontal axis) and j (vertical axis).

	1	2	3	4	5	6
6					5000	0
5				1000	0	
4		4375	750	0		
3	7875	2625	0			
2	15750	0				
1	0					

$B(3,5)=$

$$B(i,i)=0$$

$$B(i,j)=\min_{k=i}^{j-1} B(i,k) + B(k+1, j) + R_i C_k C_j$$

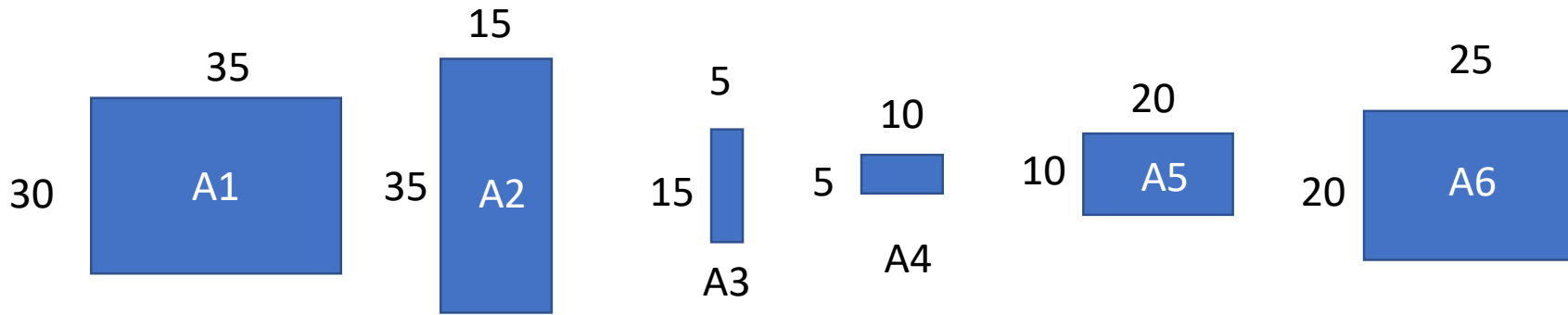


Diagram showing the dimensions of matrices A1 through A6 and a dynamic programming table for matrix chain multiplication. The table is indexed by i (horizontal axis) and j (vertical axis).

	1	2	3	4	5	6
6					5000	0
5			2500	1000	0	
4		4375	750	0		
3	7875	2625	0			
2	15750	0				
1	0					

$B(3,5)=$

$$B(i,i)=0$$

$$B(i,j)=\min_{k=i}^{j-1} B(i,k) + B(k+1, j) + R_i C_k C_j$$

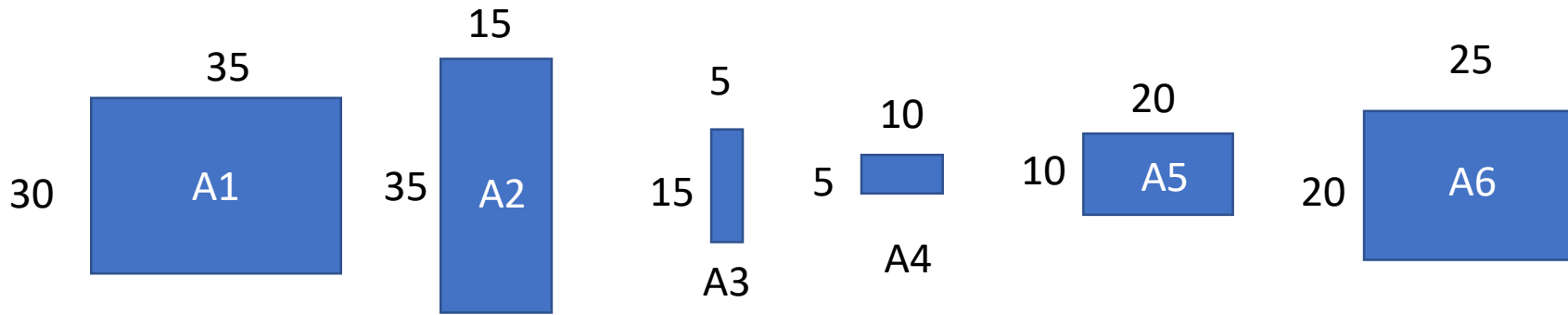
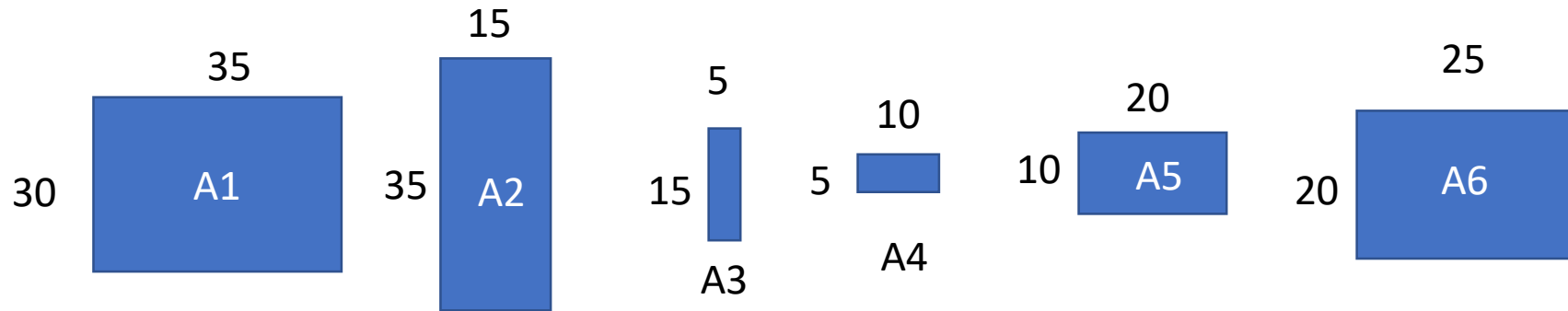


Diagram showing the dimensions of the matrices A1 through A6, and a dynamic programming table B(i,j) for matrix chain multiplication. The table is indexed by i (horizontal axis) and j (vertical axis), representing the sequence of matrices from 1 to 6.

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

$$B(i,i)=0$$

$$B(i,j)=\min_{k=i}^{j-1} B(i,k) + B(k+1, j) + R_i C_k C_j$$

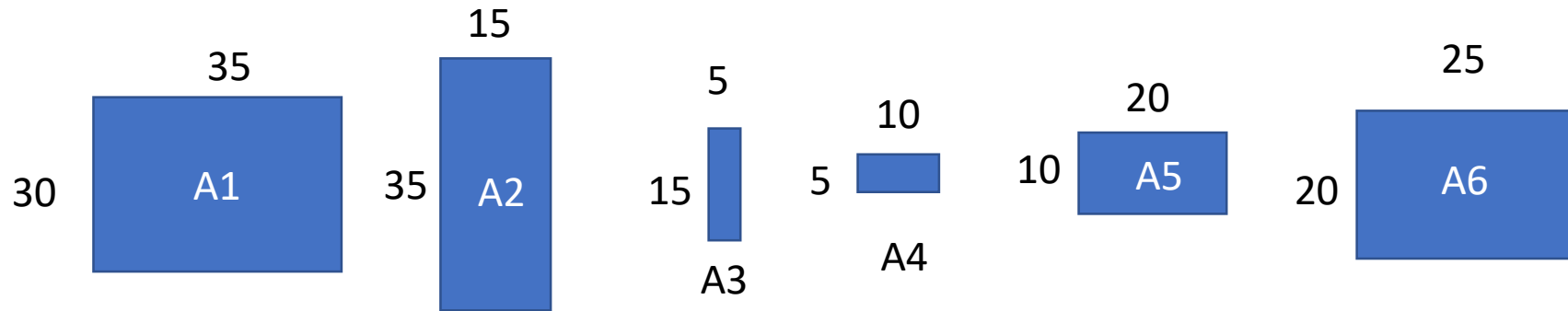


DP Table (B(i,j)) with dimensions i (horizontal) and j (vertical):

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

$B(1,6) = \min$

- $K=1 \ B(1,1)+B(2,6)+R1C1C6$
- $K=2 \ B(1,2)+B(3,6)+R1C2C6$
- $K=3 \ B(1,3)+B(4,6)+R1C3C6$
- $K=4 \ B(1,4)+B(5,6)+R1C4C6$
- $K=5 \ B(1,5)+B(6,6)+R1C5C6$



DP Table (B[i][j]):

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

$B(1,6) = \min$

- $K=1 \ B(1,1)+B(2,6)+R1C1C6$
- $K=2 \ B(1,2)+B(3,6)+R1C2C6$
- $K=3 \ B(1,3)+B(4,6)+R1C3C6$
- $K=4 \ B(1,4)+B(5,6)+R1C4C6$
- $K=5 \ B(1,5)+B(6,6)+R1C5C6$

Matrix Chain Multiplication

Initialize array $m[x,y]$ to zero

Starting at diagonal, working toward upper left

$\theta(n^2)$

Compute $B[i,j]$ according to:

$$B(i,i)=0$$

$$B(i,j) = \min_{k=i}^{j-1} B(i,k) + B(k+1, j) + R_i C_k C_j$$

$\theta(n)$

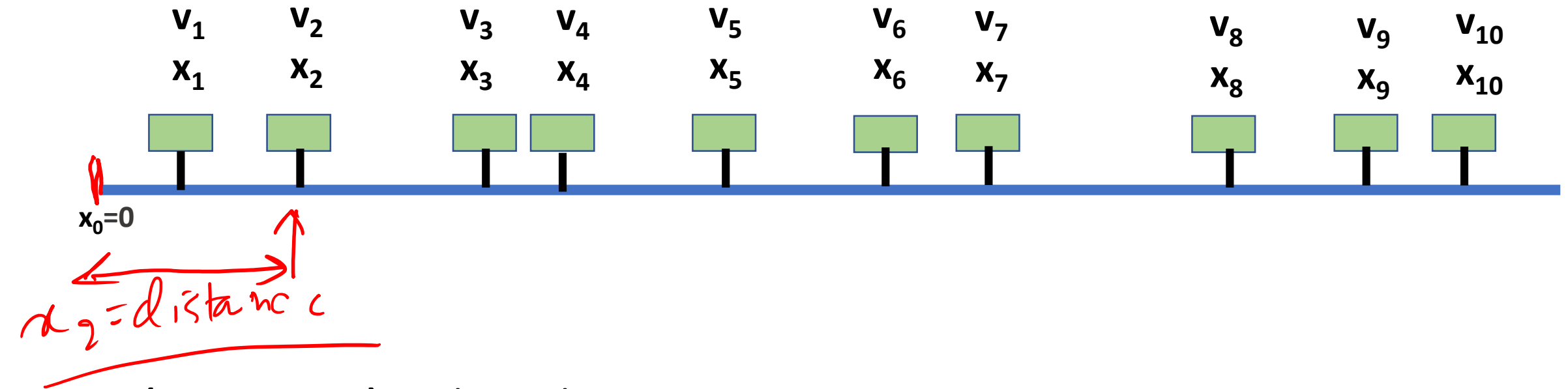
Runtime: $\theta(n^3)$

Dynamic Programming

lecture 3

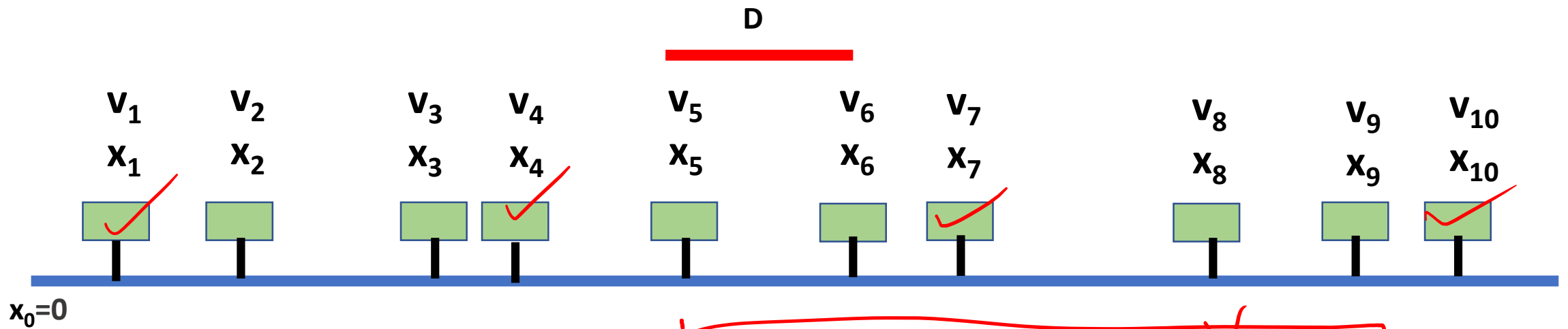


✓



$(x_1, x_2, x_3, \dots, x_n)$: mile markers

$(v_1, v_2, v_3, \dots, v_n)$: Viewership, e.g., v_i = number of people that view billboard at x_i



$$v_1 + v_4 + v_7 + v_{10} \quad \text{e.g.}$$

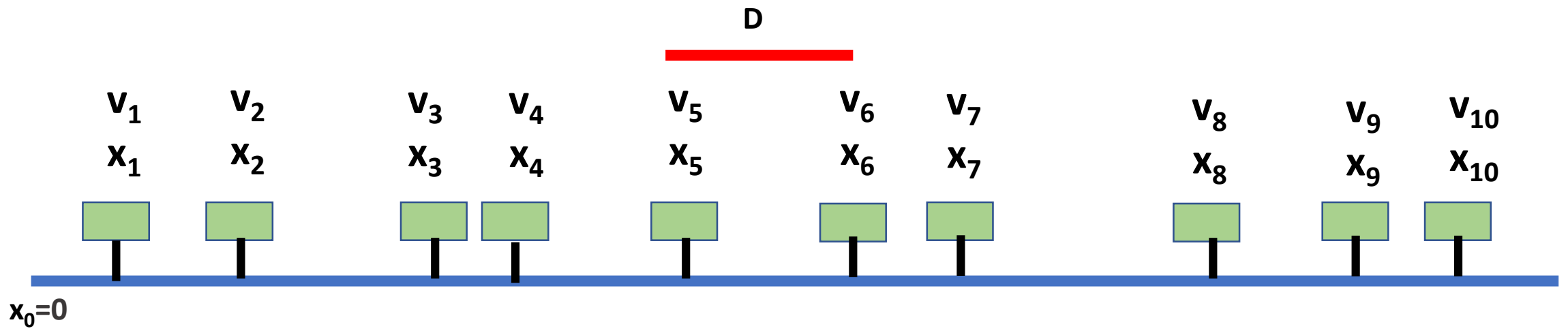
max

$(x_1, x_2, x_3, \dots, x_n)$: mile markers

$(v_1, v_2, v_3, \dots, v_n)$: Viewership, e.g., v_i = number of people that view billboard at x_i

D: distance parameters, can not place ads that are closer than D miles apart

Goal: is to maximize viewership for an acceptable campaign

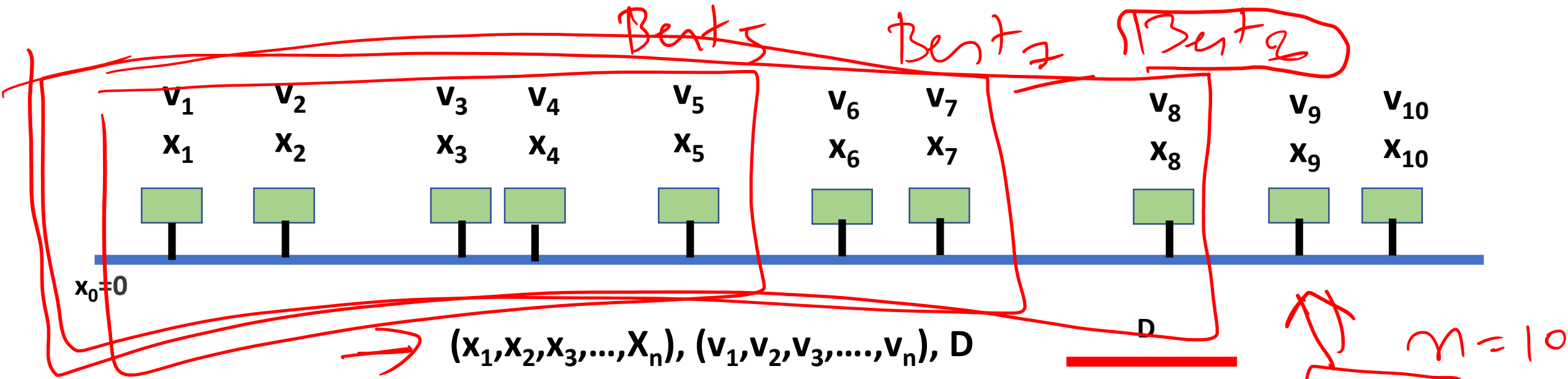


$(x_1, x_2, x_3, \dots, x_n)$: mile markers

$(v_1, v_2, v_3, \dots, v_n)$: Viewership, e.g., v_i = number of people that view billboard at x_i

D: distance parameters, can not place ads that are closer than D miles apart

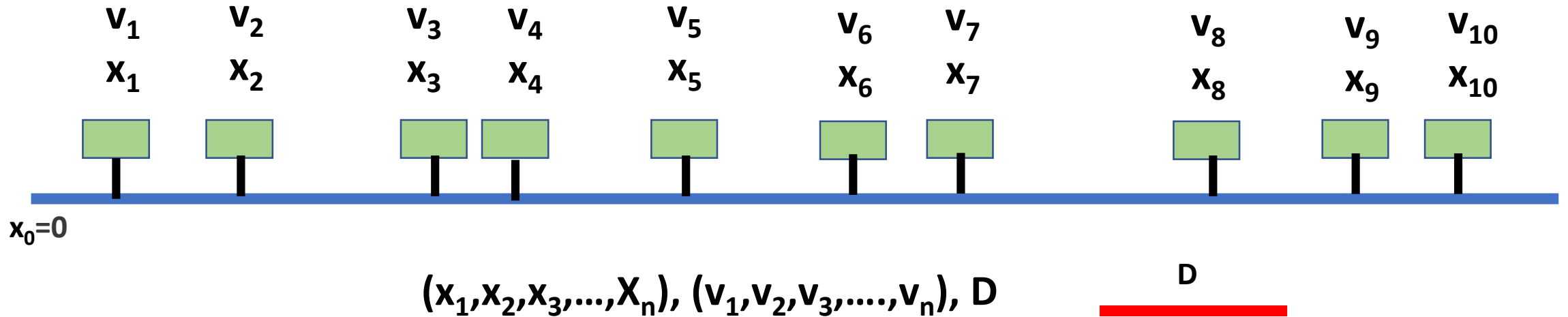
Goal: is to maximize viewership for an acceptable campaign



$Best_n$ = max viewership for an acceptable campaign that considers the first n billboards

$Best_j$ = max viewership for an acceptable campaign that considers the first j billboards

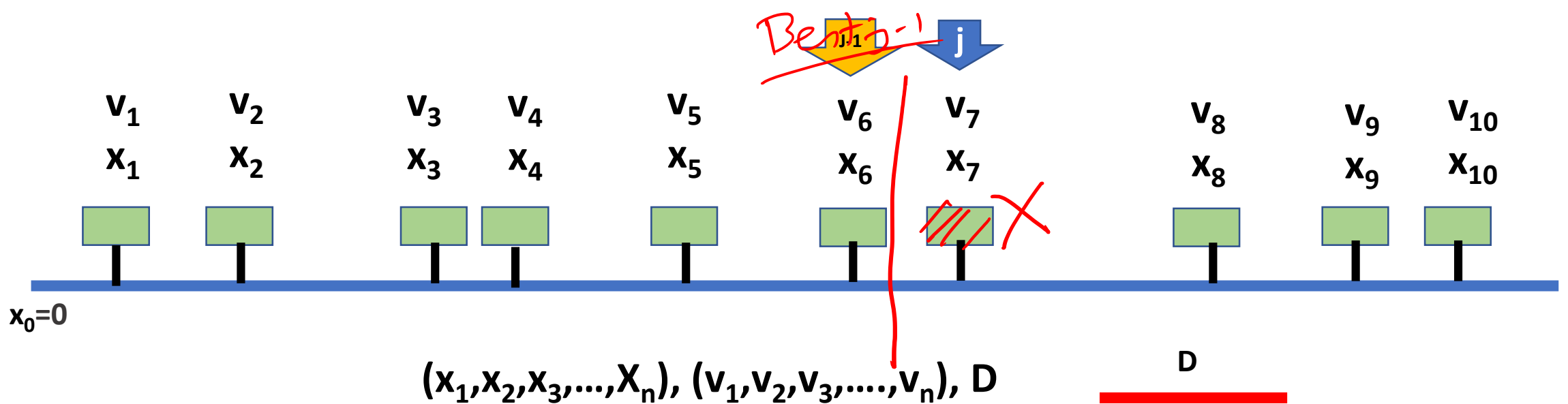
$j = 1, n$
 $j = 7$



$\text{Best}_n = \text{max viewership for an acceptable campaign that considers the first } n \text{ billboards}$

$\text{Best}_j = \text{max viewership for an acceptable campaign that considers the first } j \text{ billboards}$

~~#~~ $\text{Best}_j = \max \left\{ \begin{array}{l} \text{Best}_{j-1} \\ v_j + \text{Best}_{(\text{closest billboard that is at least } D \text{ away})} \end{array} \right.$

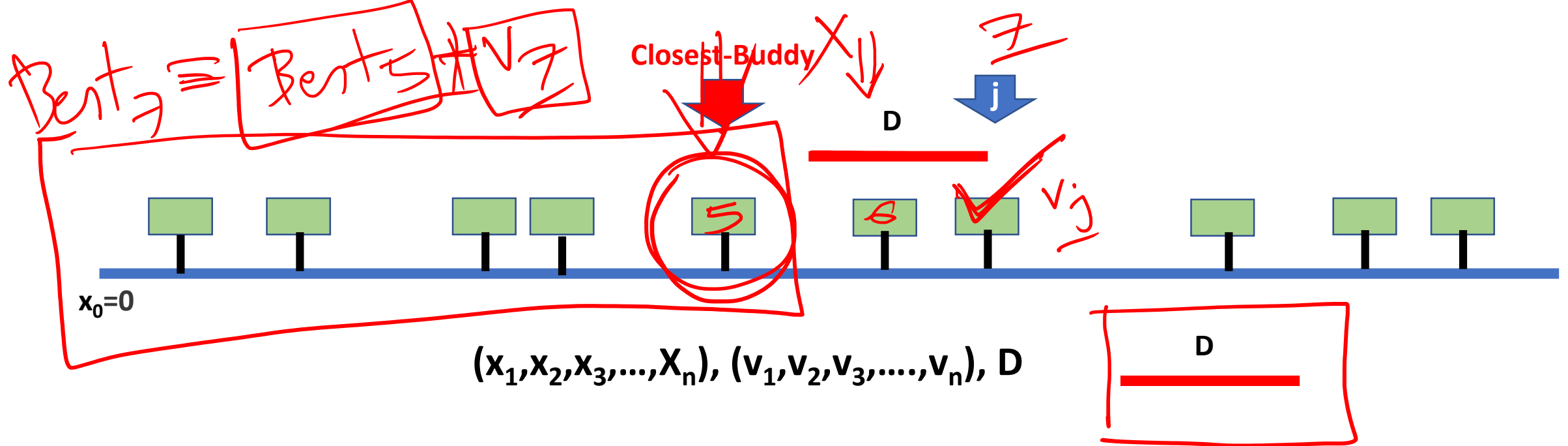


$\text{Best}_n = \text{max viewership for an acceptable campaign that considers the first } n \text{ billboards}$

$\text{Best}_j = \text{max viewership for an acceptable campaign that considers the first } j \text{ billboards}$

$$\text{Best}_j = \max \left\{ \begin{array}{l} \text{Best}_{j-1} \\ v_j + \text{Best}_{(\text{closest billboard that is at least } D \text{ away})} \end{array} \right.$$

$j=7$



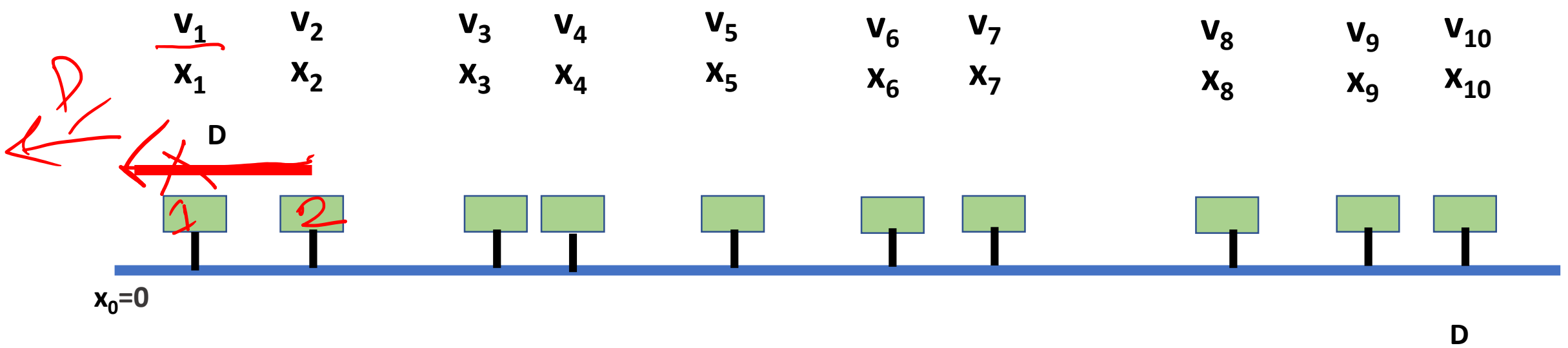
$Best_n$ = max viewership for an acceptable campaign that considers the first n billboards

$Best_j$ = max viewership for an acceptable campaign that considers the first j billboards

Handwritten: $Best_j = \max \left[Best_{j-1}, V_j + Best_{(\text{closest billboard that is at least } D \text{ away})} \right]$

Closest-Buddy

Handwritten: j



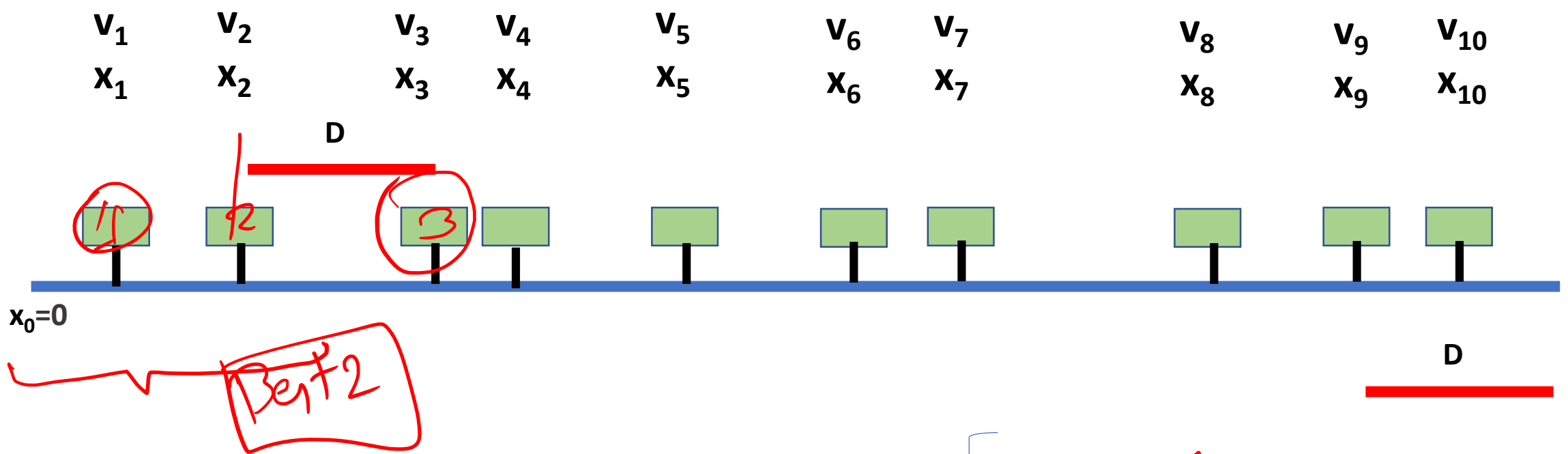
$$\text{Best}_1 = v_1$$

$$\text{Best}_2 = \text{Max} (\text{Best}_1, v_2 + \text{Best}_{\text{Closest-Buddy}})$$

$$\text{Best}_j = \max \left\{ \begin{array}{l} \text{Best}_{j-1} \\ v_j + \text{Best}_{(\text{closest billboard that is atleast } D \text{ away})} \end{array} \right.$$

$$(x_1, x_2, x_3, \dots, x_n), (v_1, v_2, v_3, \dots, v_n), D$$

Handwritten red annotations include a circle around $\text{Best}_{\text{Closest-Buddy}}$, a red arrow pointing to Best_{j-1} , and a red expression $\text{Max}(v_1, v_2)$.



$$\text{Best}_1 = v_1$$

$$\text{Best}_2 = \text{Max} (\text{Best}_1 , v_2 + \text{Best}_{\text{Closest-Buddy}})$$

$$\text{Best}_3 = \text{Max} (\text{Best}_2 , v_3 + \text{Best}_{\text{Closest-Buddy}})$$

$$= \text{Max}(v_2 , v_3 + \text{Best}_1)$$

$$\text{Best}_j = \max \left\{ \begin{array}{l} \text{Best}_{j-1} \\ v_j + \text{Best}_{(\text{closest billboard that is atleast } D \text{ away})} \end{array} \right.$$

$$(x_1, x_2, x_3, \dots, x_n), (v_1, v_2, v_3, \dots, v_n), D$$

Best ¹ Closest-Buddy for (3)
Best i

$$(x_3 - x_2) > 0$$

Best

$\text{Best}_j = \max$

$\left\{ \begin{array}{l} \text{Best}_{j-1} \\ v_j + \text{Best}_{\text{cl}(j)} \end{array} \right.$

$\text{Cl}(j) :=$ closest buddy that is at least D distance away

✓ $\text{Best}[0] = 0$

For $i=1$ to n

~~$\text{cl} = i-1$~~

~~while($\text{dist}(x[\text{cl}], x[i]) < D$) $\text{cl}--$;~~

~~$\text{Best}[i] = \max \{ \text{best}[i-1], v[i] + \text{best}[\text{cl}] \}$~~

Return $\text{best}[n]$

$i=6$

$j=5$

$d=4$ ✓

$x[5] - x[4]$
 $\theta(n^2)$

$\theta(n)$

$\theta(n)$

But, we can do better?

$\theta(n^2)$

$d=3$?

$d=2$ ✓



Pre-Computation to speed up DP Algorithm

Dynamic Programming

1. Has a **recursive solution** to the problem
2. Has **memory**
3. Pick the **correct order** for evaluating the smaller problems

$$\text{Best}_j = \max \left\{ \begin{array}{l} \text{Best}_{j-1} \\ v_j + \text{Best}_{\text{cl}(j)} \end{array} \right.$$

$\text{Cl}(j) :=$ closest buddy that is at least D distance away

$\text{Best}[0] = 0$

For $i=1$ to n

$\theta(n)$

$\text{cl} = i-1$

while($\text{dist}(x[\text{cl}], x[i]) < D$) $\text{cl}--$;

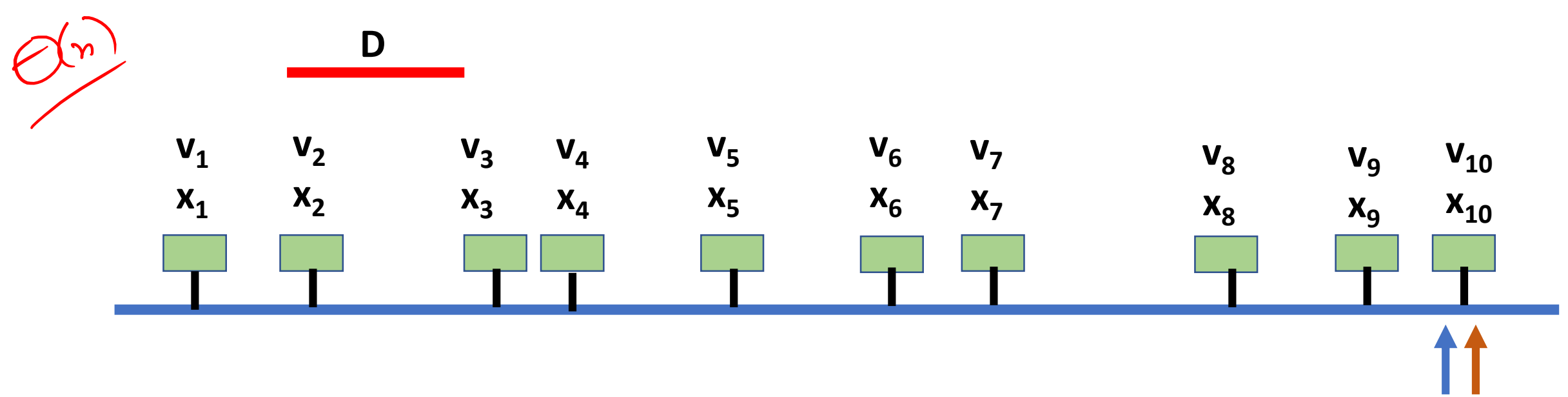
$\theta(n)$

$\theta(n^2)$

But, we can do better?

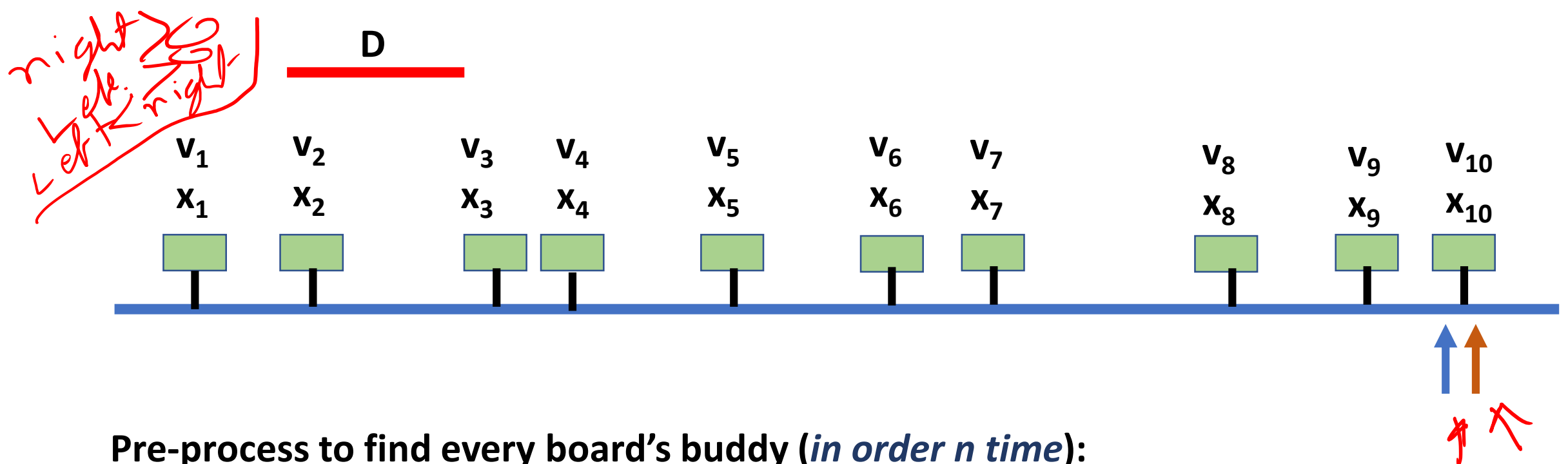
$\text{Best}[i] = \max \{ \text{best}[i-1], v[i] + \text{best}[\text{cl}] \}$

Return $\text{best}[n]$



Pre-process to find every board's buddy (*in order n time*):

right=n, left=n

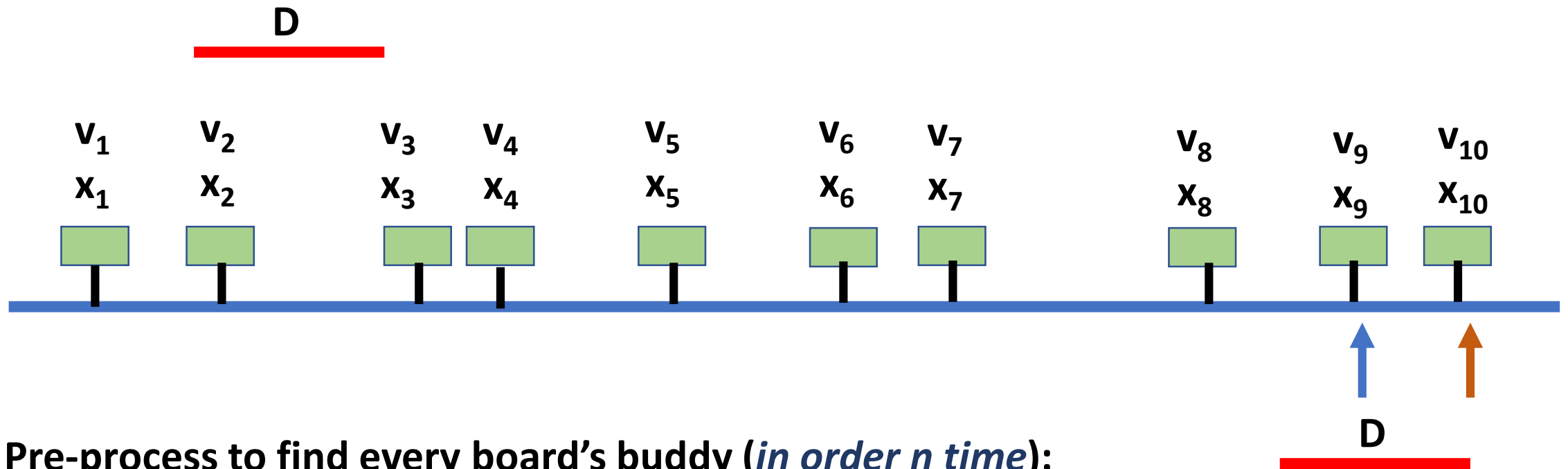


Pre-process to find every board's buddy (*in order n time*):

right=n, **left**=n

While **right** and **left** are valid:

move left until distance($x[\text{right}], x[\text{left}]$) > D

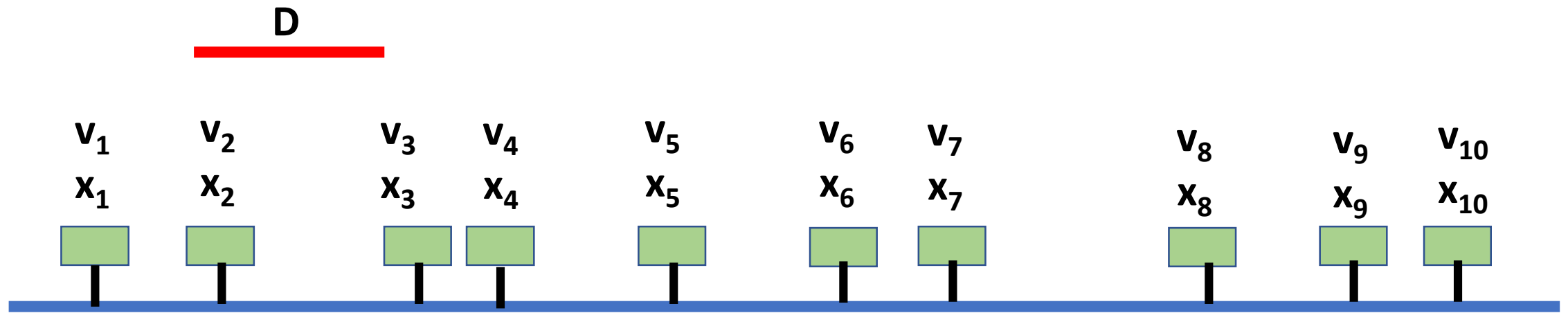


Pre-process to find every board's buddy (*in order n time*):

$right=n$, $left=n$

While $right$ and $left$ are valid:

move $left$ until distance($x[right], x[left]$) $> D$



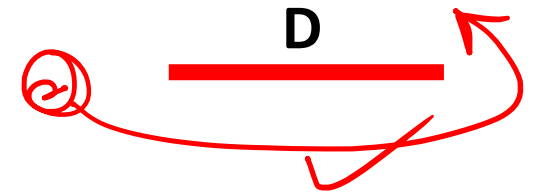
Pre-process to find every board's buddy (*in order n time*):

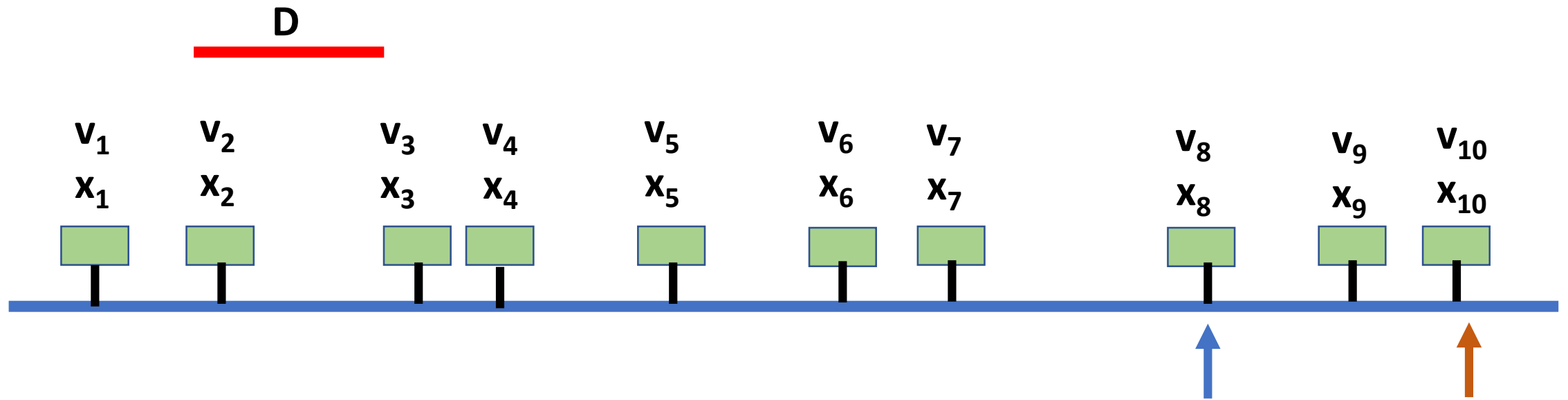
$right=n$, $left=n$

While $right$ and $left$ are valid:

move $left$ until $distance(x[right], x[left]) > D$

$buddy[right]=left$





Pre-process to find every board's buddy (*in order n time*):

$right=n$, $left=n$

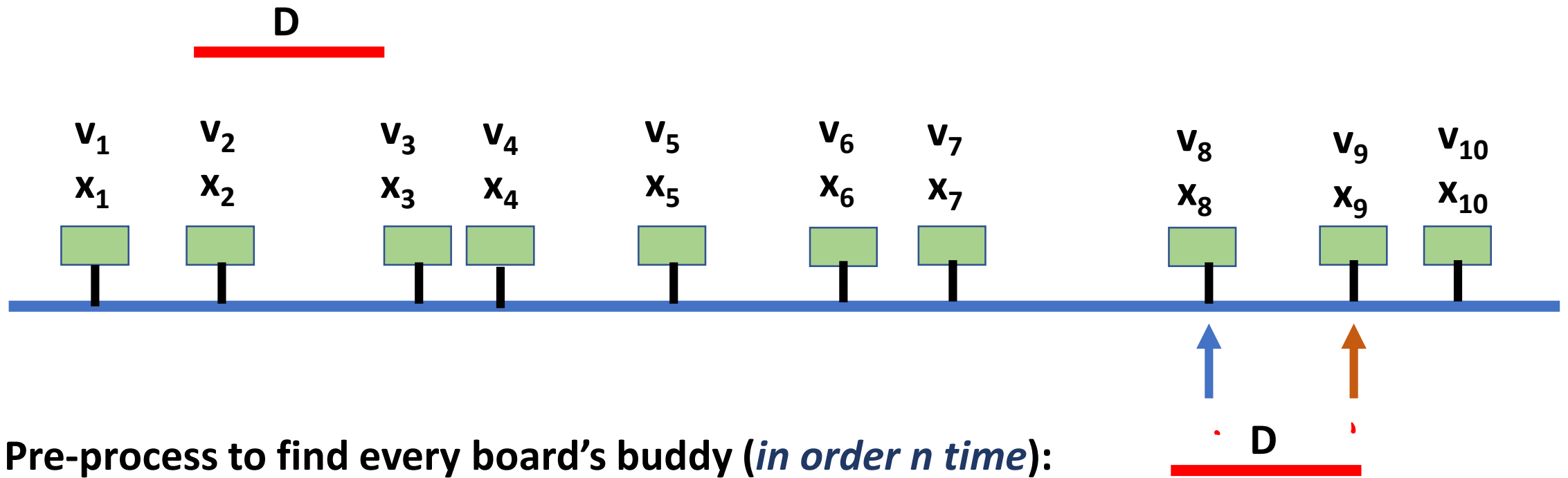
While $right$ and $left$ are valid:

 move $left$ until $distance(x[right], x[left]) > D$

$buddy[right]=left$

D

$buddy[10]=8$



Pre-process to find every board's buddy (*in order n time*):

$right = n$, $left = n$

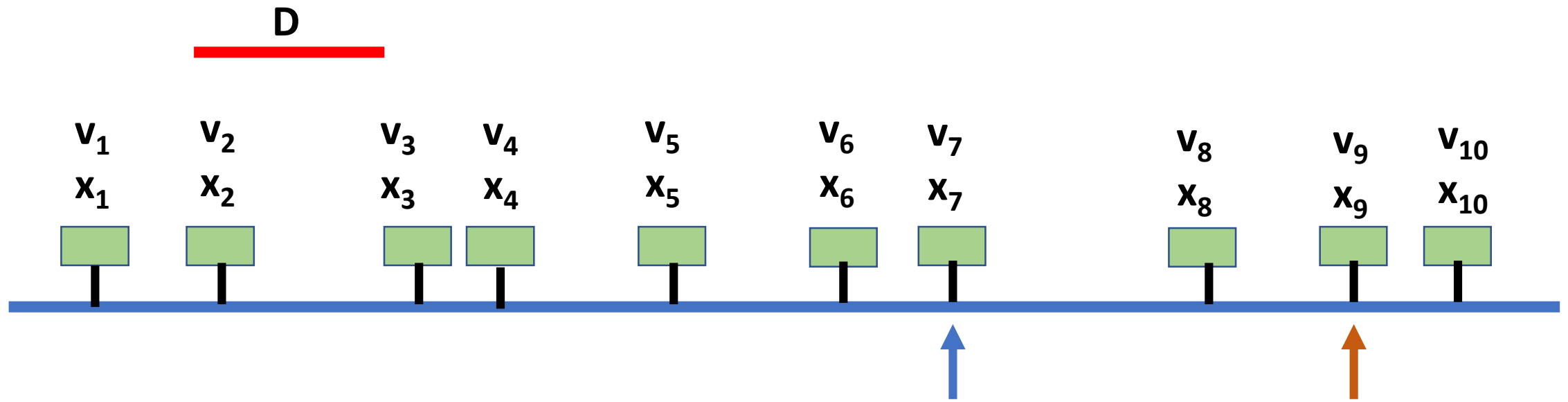
While $right$ and $left$ are valid:

move $left$ until $distance(x[right], x[left]) > D$

$buddy[right] = left$

move $right$ one position

$buddy[10] = 8$



Pre-process to find every board's buddy (*in order n time*):

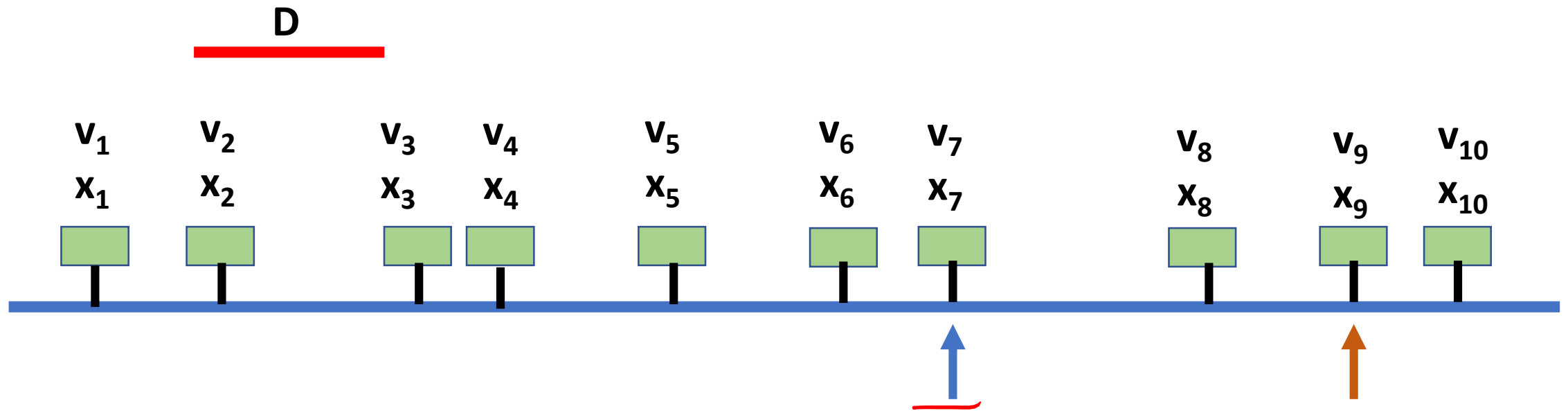
$right=n$, $left=n$

While $right$ and $left$ are valid:

- move $left$ until $distance(x[right], x[left]) > D$
- $buddy[right]=left$
- move $right$ one position



$buddy[10]=8$



Pre-process to find every board's buddy (*in order n time*):

$right=n$, $left=n$

While $right$ and $left$ are valid:

move $left$ until $distance(x[right], x[left]) > D$

$buddy[right]=left$

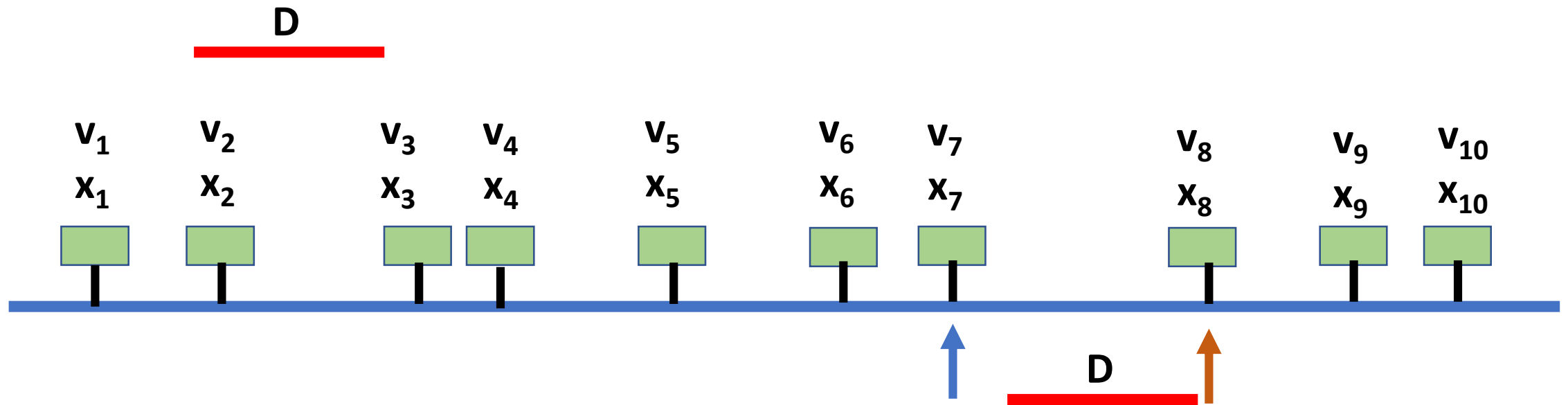
move $right$ one position



D

$buddy[10]=8$

$buddy[9]=7$



Pre-process to find every board's buddy (*in order n time*):

$right=n$, $left=n$

While $right$ and $left$ are valid:

move $left$ until $\text{distance}(x[\text{right}], x[\text{left}]) > D$

$\text{buddy}[\text{right}] = \text{left}$

move $right$ one position

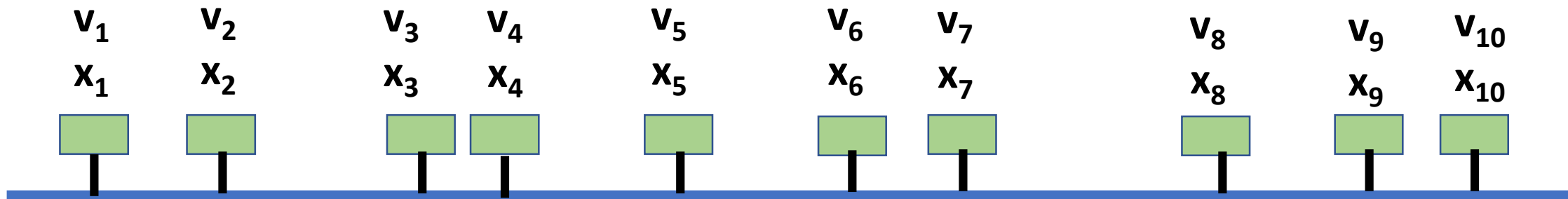
$\text{buddy}[10] = 8$

$\text{buddy}[9] = 7$

$\text{buddy}[8] = 7$

2n-1

D



Pre-process to find every board's buddy (*in order n time*):

right=n, **left**=n

While **right** and **left** are valid:

move **left** until $\text{distance}(x[\text{right}], x[\text{left}]) > D$

buddy[**right**]=**left**

move **right** one position

$O(n)$

buddy[10]=8

buddy[9]=7

buddy[8]=7

$$\text{Best}_j = \max \left\{ \begin{array}{l} \text{Best}_{j-1} \\ v_j + \text{Best}_{\text{cl}(j)} \end{array} \right.$$

$\text{Cl}(j) :=$ closest buddy that is at least D distance away
buddy : array

<preprocess buddies>

$\theta(n)$

Best[0]=0

For $i=1$ to n

$\theta(n)$

~~$\text{cl} = i - 1$~~

~~while ($\text{dist}(x[\text{cl}], x[i]) < D$) $\text{cl}--$;~~

Left, right

$\text{Best}[i] = \max \{ \text{best}[i-1], v[i] + \text{best}[\text{buddy}[i]] \}$

$\theta(1)$

Return best[n]

Runtime of the algorithm: $\theta(n)$

DNA Testing

- A DNA sequence is a series of nucleotides (ACGT).

One compares DNA for:

- Maternity/paternity testing
- Finding how similar a newly found gene is to existing known genes
- Find what breeds are in your dog through DNA testing
- Finding longest common set of nucleotides.



Longest Common Subsequence

Application: comparison of two Sequence

$X = \{A B C B D A B\}$, $Y = \{B D C A B A\}$

Longest Common Subsequence:

→ X= A B C D E F G H I J

→ Y= E C D G I

Which set of common symbols or characters are coming in sequence.

Longest Common Subsequence

Application: comparison of two Sequence

$X = \{A B C B D A B\}$, $Y = \{B D C A B A\}$

Longest Common Subsequence:

X= A B C D E F G H I J

Y= E C D G I

Which set of common symbols or characters are coming in sequence.

Longest Common Subsequence

Application: comparison of two Sequence

$$X = \{ \text{ABCBDAB} \}, Y = \{ \text{BDCABA} \}$$

Longest Common Subsequence:

X= ~~A~~ ~~B~~ ~~C~~ ~~D~~ E ~~F~~ ~~G~~ ~~H~~ ~~I~~ ~~J~~
 Y= E ~~C~~ ~~D~~ ~~G~~ ~~I~~

Which set of common symbols or characters are coming in sequence.

Longest Common Subsequence

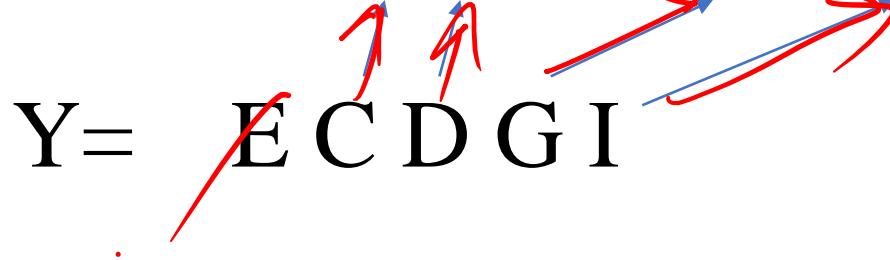
Application: comparison of two Sequence

$X = \{A B C B D A B\}$, $Y = \{B D C A B A\}$

Longest Common Subsequence:

X= A B C D E F G H I J

Y= ~~E~~ C D G I



Which set of common symbols or characters are coming in sequence.

Longest Common Subsequence

$\longleftrightarrow \overset{n}{\text{---}} \longleftrightarrow$
X= ABCDEFGHIJ

Y= ECDGI

$\longleftrightarrow \overset{m}{\text{---}} \longleftrightarrow$

Brute-force algorithm

Find out all subsequence of X and Y, and match them.

Number of subsequence of a n length sequence : 2^n

③ Suppose: {A B C}

Subsequences: {}, {A}, {B}, {C}, {A B}, {A C}, {B C}, {A B C}

Brute-force algorithm run-time $\theta(2^n 2^m)$

2^n
 2^m
 2

Longest Common Subsequence

Define the sub-problems

Base Case:

If one or both strings are {}, then the solution is clearly 0

$\overset{\textcolor{red}{n}}{\longleftrightarrow}$
 $X = \text{A B C B}$
 $Y = \text{B D C A B}$
 $\overset{\textcolor{red}{m}}{\longleftrightarrow}$

$Z = \{\}$

$X = \text{A B C B}$

$\text{sub}_n = \{\}$

0

Longest Common Subsequence (LCS)

Define the sub-problems

Base Case:

If one or both strings are {}, then the solution is clearly 0

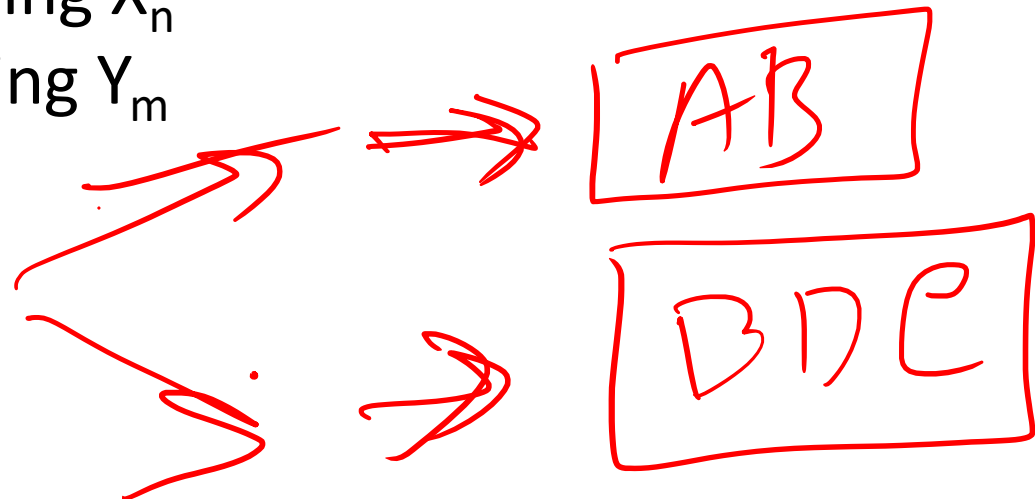
Let LCS (i, j) be the sub-problem of LCS(X_n, Y_m) where:

- X_i is the first i characters of string X_n
- Y_j is the first j characters of string Y_m

$X = \underline{A}BCB$
 $Y = BDCAB$

n
 m

LCS(2, 3)



Longest Common Subsequence

Define the sub-problems

Base Case:

If one or both strings are {}, then the solution is clearly 0

Let $LCS(i, j)$ be the **sub-problem** of $LCS(X_n, Y_m)$ where:

- X_i is the first i characters of string X_n
- Y_j is the first j characters of string Y_m

$LCS(4, 5)$

$X = \overbrace{A B C B}^n$
 $Y = \overbrace{B D C A B}^m$

$LCS(4, 5)$

A B C B
↓ ↓ ↓ ↓
B D C A

Longest Common Subsequence

Key observation

If last two characters match, then we can use LCS of sub-problem and simply add the last two matching characters to it.

If $X[i] == Y[j]$

$$\text{LCS}(X_i, Y_j) = \text{LCS}(X_{i-1}, Y_{j-1}) + 1$$

But if last characters do not match?

$$\text{LCS}(X_{i-1}, Y_j) \longleftrightarrow \text{LCS}(X_i, Y_{j-1})$$

X=ABC

Y=BDC

X=ABCB

Y=BD

X=ABCB

Y=BDCA

X[4]=Y[5]

$$\text{LCS}(X_4, Y_5) = \text{LCS}(X_3, Y_4) + 1$$

LCS(X, Y)

~~X=ABCB~~

~~Y=BDC~~

Longest Common Subsequence

Key observation

If last two characters match, then we can use LCS of sub-problem and simply add the last two matching characters to it.

$LCS(3,4) + 1$
 $Max(LCS(3,3), LCS(2,4)) + 1$
 $X = ABCB$
 $Y = BDCAB$

⇒ If $X[i] == Y[j]$

$$LCS(X_i, Y_j) = LCS(X_{i-1}, Y_{j-1}) + 1$$

Max

$LCS(X_{i-1}, Y_j), LCS(X_i, Y_{j-1})$

$$X[4] = Y[5]$$

$$LCS(X_4, Y_5) = LCS(X_3, Y_4) + 1$$

But if last characters do not match?

⇒ $LCS(X_i, Y_j) = \max(LCS(X_{i-1}, Y_j), LCS(X_i, Y_{j-1}))$

$X = ABC$

$Y = BDC$

$X = ABCB$

$Y = BD$

$X = ABCB$

$Y = BDC$

Longest Common Subsequence (LCS)

Memory

$C[i,j]$ two-dimensional array that stores $LCS(X_i, Y_j)$

$$C[i,j] = \begin{cases} \underline{C[i-1,j-1] + 1} & \text{if } \underline{X[i]=Y[j]} \\ \text{Max}(\underline{C[i-1,j]}, \underline{C[i,j-1]}) & \text{otherwise} \end{cases}$$

Base Case:

We start with $i=j=0$ (empty substrings of x and y)

If any of the length is 0, X_0, Y_0 , their LCS is empty

LCS Example

- ▶ We'll see how LCS algorithm works on the following example:

▶ $X = \text{ABCB}$

▶ $Y = \text{BDCAB}$

- ▶ What is the Longest Common Subsequence of X and Y?

▶ $\text{LCS}(X, Y) = \text{BCB}$

▶ $X = \text{A} \mathbf{B} \quad \mathbf{C} \quad \mathbf{B}$

▶ $Y = \quad \mathbf{B} \mathbf{D} \mathbf{C} \mathbf{A} \mathbf{B}$

$\Theta(2^4 \cdot 2^5)$

LCS Example (0)

ABCB
BDCAB

		j	0	1	2	3	4	5
			Y _j	B	D	C	A	B
i								
0	X _i							
1	A							
2	B							
3	C							
4	B							

C

- $X = \text{ABCB}; m = |X| = \underline{4}$
- $Y = \text{BDCAB}; n = |Y| = \underline{5}$
- Allocate array $c[5,4]$

Longest Common Subsequence

Memory

$C[i,j]$ two-dimensional array that stores $\text{LCS}(X_i, Y_j)$

$$C[i,j] = \begin{cases} C[i-1,j-1] + 1 & \text{if } X[i]=Y[j] \\ \text{Max}(C[i-1,j], C[i,j-1]) & \text{otherwise} \end{cases}$$

Base Case:

We start with $i=j=0$ (empty substrings of x and y)

If any of the length is 0, X_0, Y_0 , their LCS is empty

LCS Example (1)

length = 0

ABCB

BDCAB

		j	0	1	2	3	4	5
			Yj	B	D	C	A	B
i	Xi	0	0	0	0	0	0	0
1	A	0						
2	B	0						
3	C	0						
4	B	0						

for i = 1 to m

c[i,0] = 0

for j = 1 to n

c[0,j] = 0

LCS Example (1)

ABCB

BDCAB

		j	0	1	2	3	4	5
			Y _j	B	D	C	A	B
i								
0	X _i		0	0	0	0	0	0
1	A		0					
2	B		0					
3	C		0					
4	B		0					

for i = 1 to m c[i,0] = 0
 for j = 1 to n c[0,j] = 0

LCS Example (2)

ABCB
BDCAB

		j					
		0	1	2	3	4	5
i		Y _j	B	D	C	A	B
0	X _i	0	0	0	0	0	0
1	A	0	0				
2	B	0					
3	C	0					
4	B	0					

if ($X[i] == Y[j]$)
 $c[i,j] = c[i-1,j-1] + 1$
 else $c[i,j] = \max(\underline{c[i-1,j]}, \underline{c[i,j-1]})$

LCS Example (3)

ABCB
BDCAB

		j	0	1	2	3	4	5
			Y _j	B	D	C	A	B
i	X _i							
0			0	0	0	0	0	0
1	A		0	0	0	0		
2	B		0					
3	C		0					
4	B		0					

if (X[i] == Y[j])

c[i,j] = c[i-1,j-1] + 1

else c[i,j] = max(c[i-1,j], c[i,j-1])

LCS Example (4)

ABCB
BDCAB

		j	0	1	2	3	4	5
			Y _j	B	D	C	A	B
i	X _i							
0			0	0	0	0	0	0
1	A		0	0	0	0	1	
2	B		0					
3	C		0					
4	B		0					

i = 1
j = 4

i = 0
j = 3

if (X[i] == Y[j])

c[i,j] = c[i-1,j-1] + 1

else c[i,j] = max(c[i-1,j], c[i,j-1])

LCS Example (5)

ABCB
BDCA

		j	0	1	2	3	4	5
			Y _j	B	D	C	A	B
i	X _i							
0			0	0	0	0	0	0
1	A		0	0	0	0	1	
2	B		0					
3	C		0					
4	B		0					

if (X[i] == Y[j])

$c[i,j] = c[i-1,j-1] + 1$

→ else $c[i,j] = \max(c[i-1,j], c[i,j-1])$

LCS Example (5)

ABCB

BDCAB

		j	0	1	2	3	4	5
			Y _j	B	D	C	A	B
i	X _i							
0			0	0	0	0	0	0
1	A		0	0	0	0	1	1
2	B		0					
3	C		0					
4	B		0					

if (X[i] == Y[j])

c[i,j] = c[i-1,j-1] + 1

else c[i,j] = max(c[i-1,j], c[i,j-1])

LCS Example (6)

ABCB

BDCAB

		j	0	1	2	3	4	5
		Yj		B	D	C	A	B
i	Xi							
0		0	0	0	0	0	0	0
1	A	0	0	0	0	1	1	
2	B	0						
3	C	0						
4	B	0						

if (X[i] == Y[j])

c[i,j] = c[i-1,j-1] + 1

else c[i,j] = max(c[i-1,j], c[i,j-1])

LCS Example (6)

ABCB

BDCAB

		j	0	1	2	3	4	5
		Yj		B	D	C	A	B
i	Xi							
0			0	0	0	0	0	0
1	A		0	0	0	0	1	1
2	B		0	1				
3	C		0					
4	B		0					

if ($X[i] == Y[j]$)

$c[i,j] = c[i-1,j-1] + 1$

else $c[i,j] = \max(c[i-1,j], c[i,j-1])$

LCS Example (7)

ABCB
BD CAB

		j	0	1	2	3	4	5
		Yj	B	D	C	A	B	
i	Xi							
0			0	0	0	0	0	
1	A		0	0	0	1	1	
2	B		0	1	1	1		
3	C		0					
4	B		0					

if ($X[i] == Y[j]$)
 $c[i,j] = c[i-1,j-1] + 1$
 else $c[i,j] = \max(c[i-1,j], c[i,j-1])$

LCS Example (7)

ABCB
BD CAB

		j	0	1	2	3	4	5
		Yj	B	D	C	A	B	
i	Xi							
0			0	0	0	0	0	0
1	A		0	0	0	0	1	1
2	B		0	1	1	1		
3	C		0					
4	B		0					

if ($X[i] == Y[j]$)
 $c[i,j] = c[i-1,j-1] + 1$
 else $c[i,j] = \max(c[i-1,j], c[i,j-1])$

LCS Example (7)

ABCB
BD CAB

		j	0	1	2	3	4	5
		Yj	B	D	C	A	B	
i	Xi							
0			0	0	0	0	0	0
1	A		0	0	0	0	1	1
2	B		0	1	1	1		
3	C		0					
4	B		0					

if ($X[i] == Y[j]$)
 $c[i,j] = c[i-1,j-1] + 1$
 else $c[i,j] = \max(c[i-1,j], c[i,j-1])$

LCS Example (8)

ABCB

BDCAB

		j	0	1	2	3	4	5
		Yj	B	D	C	A	B	
i	Xi							
0		0	0	0	0	0	0	
1	A	0	0	0	0	1	1	
2	B	0	1	1	1	1		
3	C	0						
4	B	0						

$i = 2$
 $j = 5$
 $c[1, 4]$
 $\boxed{1+1}$
 $= 2$

if ($X[i] == Y[j]$)

$c[i,j] = c[i-1,j-1] + 1$

else $c[i,j] = \max(c[i-1,j], c[i,j-1])$

LCS Example (8)

ABCB
BD CAB

		j	0	1	2	3	4	5
			Yj	B	D	C	A	B
i	Xi							
0			0	0	0	0	0	0
1	A		0	0	0	0	1	1
2	B		0	1	1	1	1	2
3	C		0					
4	B		0					

if ($X[i] == Y[j]$)

$c[i,j] = c[i-1,j-1] + 1$

else $c[i,j] = \max(c[i-1,j], c[i,j-1])$

LCS Example (10)

ABCB

BD CAB

		j	0	1	2	3	4	5
		Yj		B	D	C	A	B
i	Xi							
0			0	0	0	0	0	0
1	A		0	0	0	0	1	1
2	B		0	1	1	1	1	2
3	C		0	1	1			
4	B		0					

if ($X[i] == Y[j]$)

$c[i,j] = c[i-1,j-1] + 1$

else $c[i,j] = \max(c[i-1,j], c[i,j-1])$

LCS Example (11)

ABCB

BDCAB

		j	0	1	2	3	4	5
			Yj	B	D	C	A	B
i	Xi							
0			0	0	0	0	0	0
1	A		0	0	0	0	1	1
2	B		0	1	1	1	1	2
3	C		0	1	1	2		
4	B		0					

if ($X[i] == Y[j]$)

$c[i,j] = c[i-1,j-1] + 1$

else $c[i,j] = \max(c[i-1,j], c[i,j-1])$

LCS Example (12)

ABCB

BDCAB

		j	0	1	2	3	4	5
		Yj		B	D	C	A	B
i	Xi							
0			0	0	0	0	0	0
1	A		0	0	0	0	1	1
2	B		0	1	1	1	1	2
3	C		0	1	1	2	2	2
4	B		0					

1, 1, 2, 2, 3

if (X[i] == Y[j])

c[i,j] = c[i-1,j-1] + 1

else c[i,j] = max(c[i-1,j], c[i,j-1])

LCS Example (13)

ABCB

BDCAB

		j					
		0	1	2	3	4	5
i	Yj		B	D	C	A	B
0	Xi	0	0	0	0	0	0
1	A	0	0	0	0	1	1
2	B	0	1	1	1	1	2
3	C	0	1	1	2	2	2
4	B	0	1				

if ($X[i] == Y[j]$)

$c[i,j] = c[i-1,j-1] + 1$

else $c[i,j] = \max(c[i-1,j], c[i,j-1])$

LCS Example (14)

ABCB
BD CAB

		j	0	1	2	3	4	5
			Y _j	B	D	C	A	B
i	X _i							
0			0	0	0	0	0	0
1	A		0	0	0	0	1	1
2	B		0	1	1	1	1	2
3	C		0	1	1	2	2	2
4	B		0	1	1	2	2	

if ($X[i] == Y[j]$)
 $c[i,j] = c[i-1,j-1] + 1$
 else $c[i,j] = \max(c[i-1,j], c[i,j-1])$

LCS Example (15)

ABCB
BD CAB

		j	0	1	2	3	4	5
		Yj	B	D	C	A	B	
i	Xi							
0			0	0	0	0	0	
1	A		0	0	0	1	1	
2	B		0	1	1	1	2	
3	C		0	1	2	2	2	
4	B		0	1	2	2	3	

if ($X[i] == Y[j]$)
 $c[i,j] = c[i-1,j-1] + 1$
 else $c[i,j] = \max(c[i-1,j], c[i,j-1])$

LCS Length Algorithm

LCS-Length(X,Y)

m = length(X) // get the # of symbols in X

n = length(Y) // get the # of symbols in Y

for i = 1 to m c[i,0] = 0 // special case: Y₀

for j = 1 to n c[0,j] = 0 // special case: X₀

for i = 1 to m // for all X_i

for j = 1 to n // for all Y_j

if (X[i] == Y[j])

c[i,j] = c[i-1,j-1] + 1

else

c[i,j] = max(c[i-1,j], c[i,j-1])

return c[m,n] // return LCS length for X and Y

$\Theta(n^2)$

$\Theta(1)$

$\Theta(1)$

$\Theta(1)$

$\Theta(1)$

$\Theta(n)$

$\Theta(n)$

$\Theta(1)$