CS166: Advanced Data Structures

Welcome!

Why study advanced data structures?

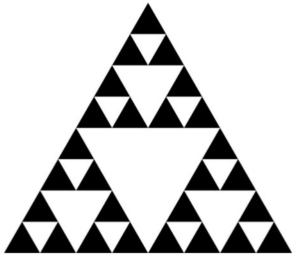
Why Study Advanced Data Structures?

- ***Expand your toolkit.***
  - We have amazing data structures for all sorts of practical problems. Dazzle interviewers and build awesome software with what you learn.
- ***Learn new problem-solving techniques.***
  - You’ll see some truly amazing techniques for solving problems. They have applications way beyond Theoryland.
- ***See the beauty of theoretical CS.***
  - This is where the line between “purely theoretical” and “deployed in production” gets blurry.

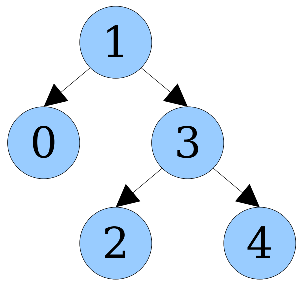
Where is CS166 situated in Stanford’s CS sequence?

Our (Transitive) Prerequisites

CS106B / CS107



```
struct Node {
    int value;
    Node* left;
    Node* right;
};
```




```
make && gdb ./a.out
```

CS103

$a_0 = 1 \qquad a_{n+1} = 2a_n + n$

Theorem: $a_n = 2^{n+1} - n - 1$.

Proof: By induction. As a base case, when $n = 0$, we have

$$2^{n+1} - n - 1 = 2^1 - 0 - 1 = 1 = a_0.$$

For the inductive step, assume that $a_k = 2^{k+1} - k - 1$. Then

$$\begin{aligned} a_{k+1} &= 2a_k + k \\ &= 2^{k+2} - 2k - 2 + k \\ &= 2^{(k+1)+1} - (k+1) - 1, \end{aligned}$$

as required. ■

CS109

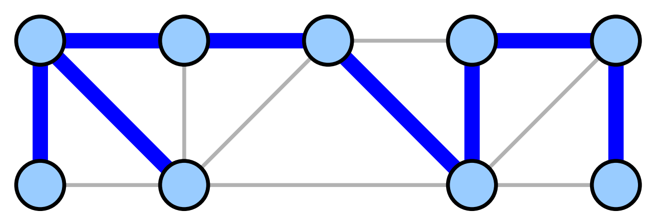
$$E\left[\sum_{i=1}^{n} X_i\right] = \sum_{i=1}^{n} E[X_i]$$

$$\Pr[X \geq c] \leq \frac{E[X]}{c}$$

CS161

$$T(n) = aT(n / b) + O(n^d)$$

$$\begin{aligned} n^2 \log n^2 &= O(n^3) \\ n^2 \log n^2 &= \Omega(n^2) \\ n^2 \log n^2 &= \Theta(n^2 \log n) \end{aligned}$$



Who are we?

Course Staff

Keith Schwarz (***htiek@cs.stanford.edu***)

An Doan
Weixin Yu

Ping us over EdStem with questions!

The Course Website

https://cs166.stanford.edu

Course Requirements

- We'll have six ***problem sets***.
  - Problem sets may be completed individually or in a pair. (Exception: PS0 must be done individually.)
  - They're a mix of written problems and C++ coding exercises.
  - You'll submit one copy of the problem set regardless of how many people worked on it.
  - Need to find a partner? Use EdStem, stop by office hours, or send us an email.
- We have a ***final exam*** during the normally-scheduled final exam time slot: Saturday, June 6, 3:30PM – 6:30PM.
- We'll require ***lecture participation*** through PollEV, starting next week.
  - This will build community, improve learning outcomes, and help me stay calibrated.
  - We'll allow folks to shift participation credit to the final exam via a form sent out in Week 4. Details to follow.

Problem Set 0

- Problem Set 0 goes out today.
  - It’s due next ***Tuesday*** at ***1:00PM*** Pacific time.
- It’s a concept refresher (C++, probability, proofs, algorithmic analysis, etc.)
- If you’re mostly comfortable with these problems and are just “working through some rust,” then you’re probably in the right place!
- If these questions are on topics that you haven’t encountered before, ping us and we can chat.

Let’s Get Started!

Range Minimum Queries

The RMQ Problem

- The ***Range Minimum Query problem*** (***RMQ*** for short) is the following:

  Given an array A and two indices $i \leq j$, what is the smallest element out of A[i], A[i + 1], …, A[j – 1], A[j]?

31	41	59	26	53	58	97	93

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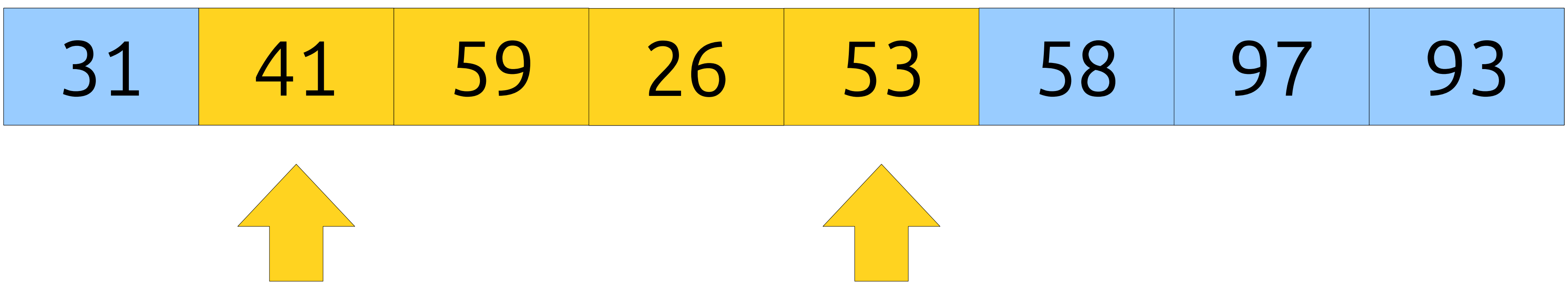

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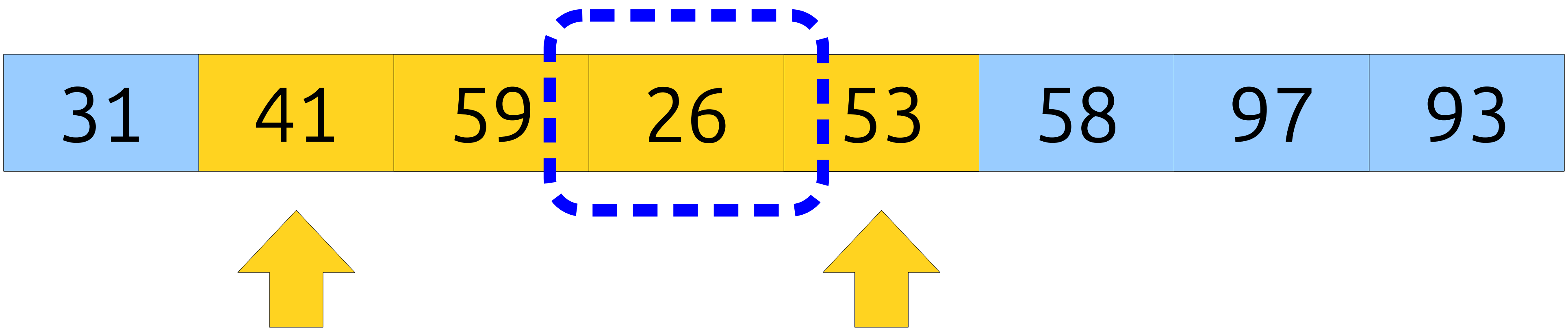

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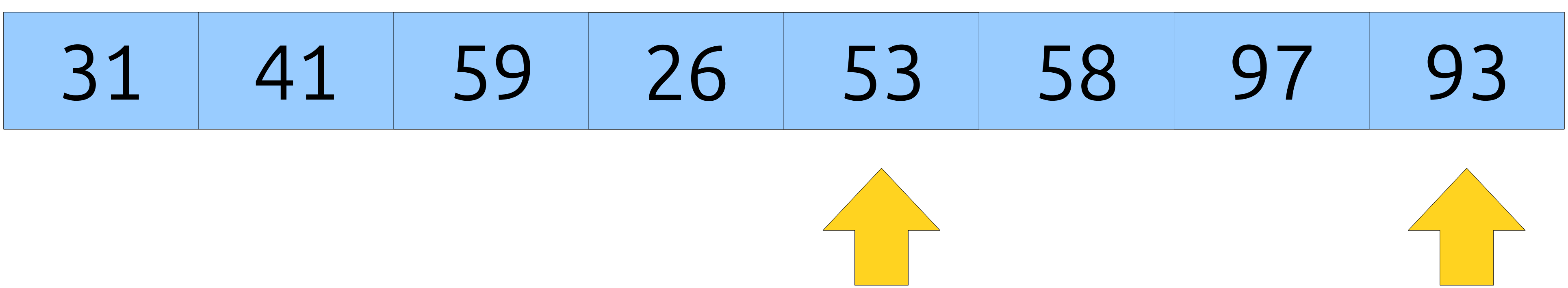

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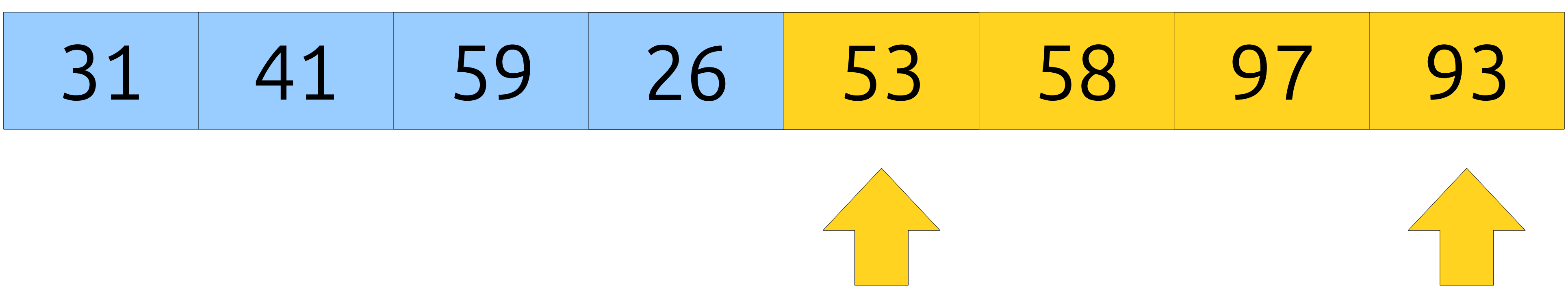

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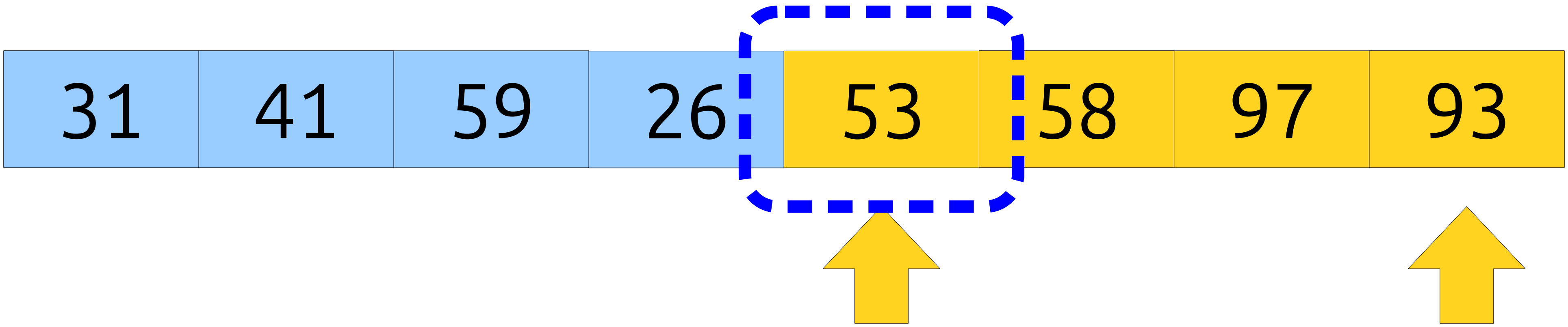

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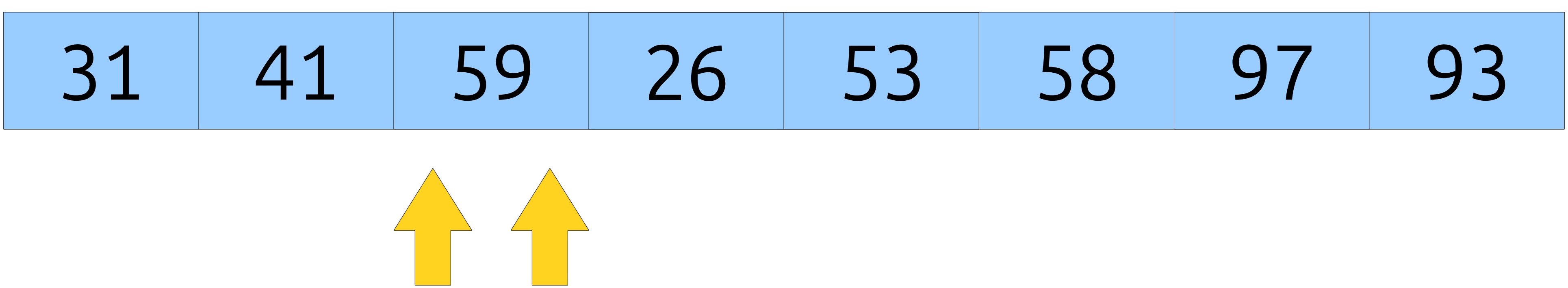

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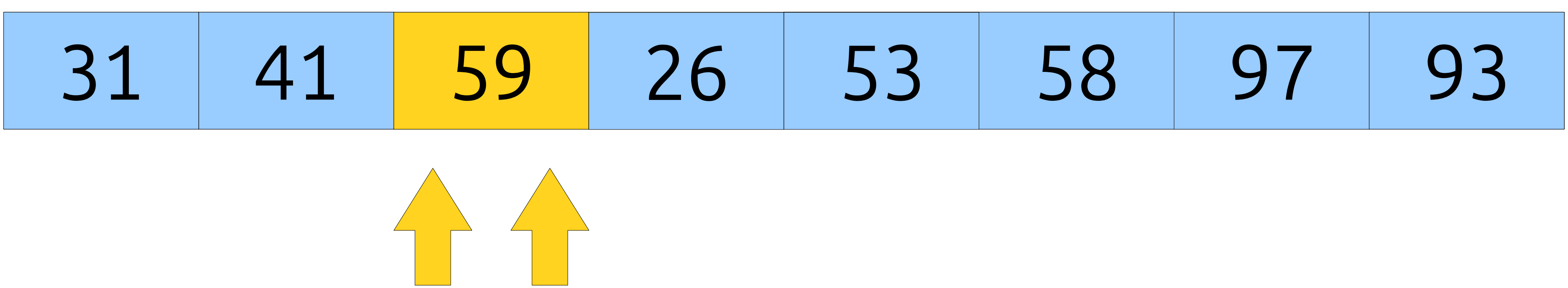

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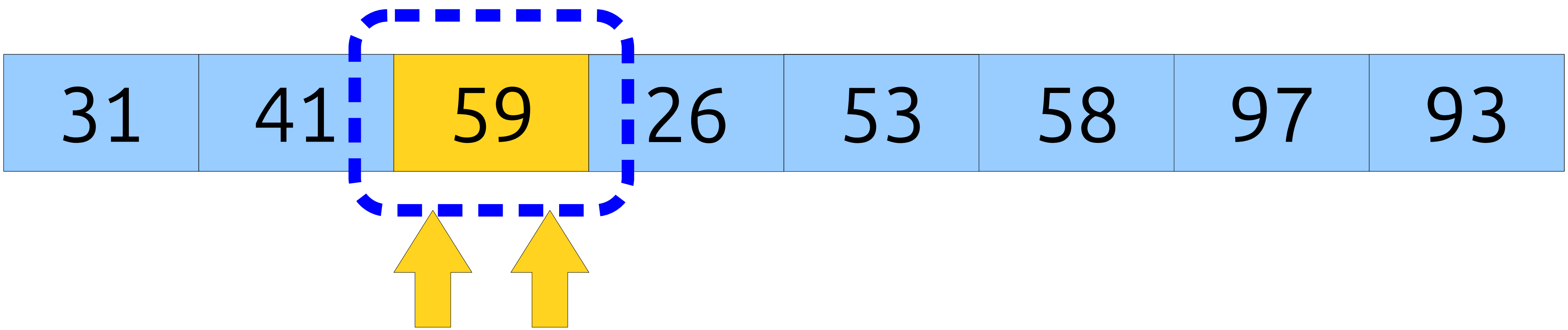

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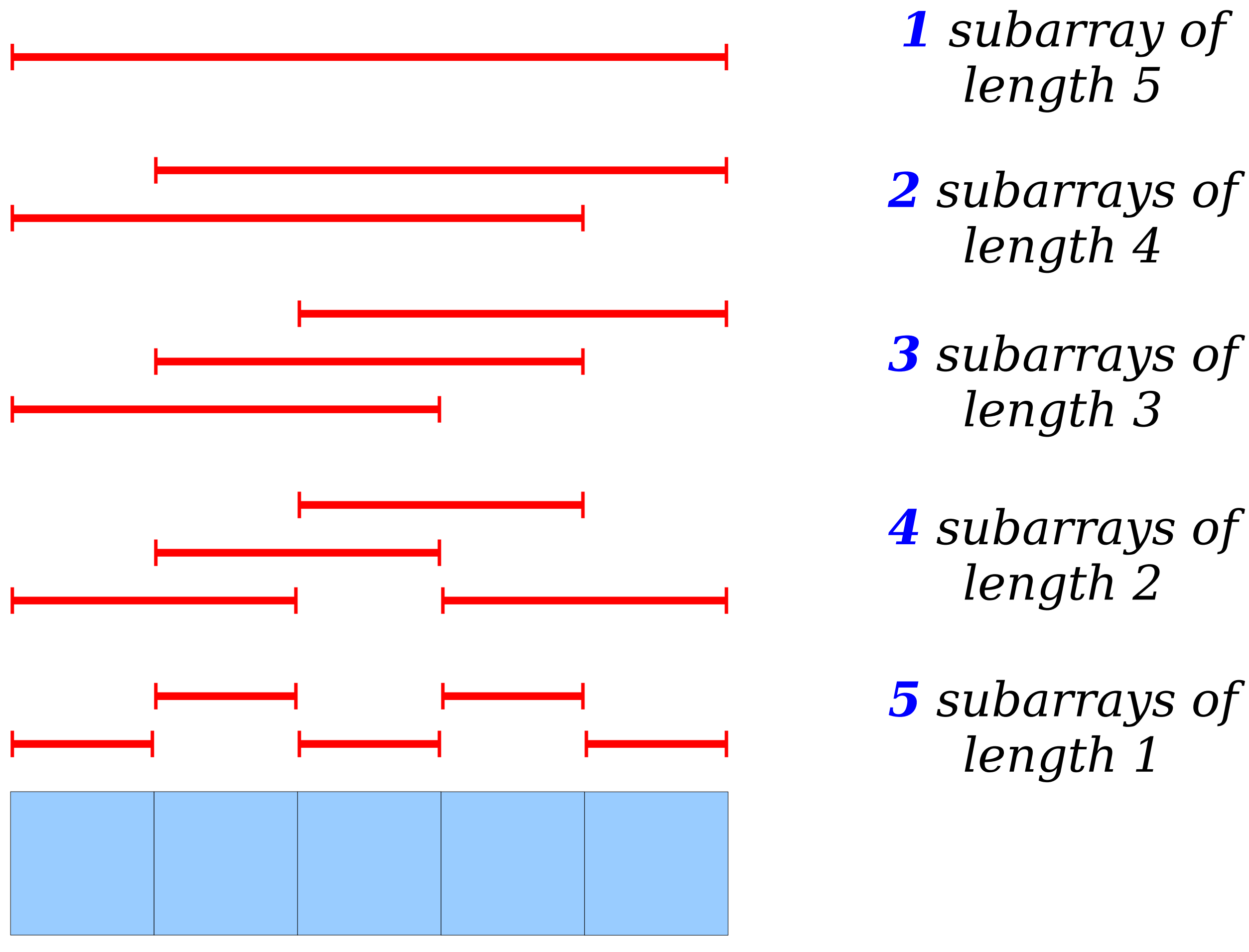
- Notation: We'll denote a range minimum query in array A between indices i and j as $\mathbf{RMQ_A}(\boldsymbol{i, j})$.
- For simplicity, let's assume 0-indexing.

A Trivial Solution

- There's a simple O(n)-time algorithm for evaluating $RMQ_A(i, j)$.
  - Just iterate across the elements between i and j, inclusive, and take the minimum.
- So… why is this problem at all algorithmically interesting?
- Suppose that the array A is fixed in advance and you're told that we're going to make multiple queries on it.
- Can we do better than the naïve algorithm?

An Observation

- In an array of length n, there are only $\Theta(n^2)$ distinct possible queries.
- Why?



A Different Approach

- There are only $\Theta(n^2)$ possible RMQs in an array of length n.
- If we precompute all of them, we can answer RMQ in time O(1) per query.

16	18	33	98
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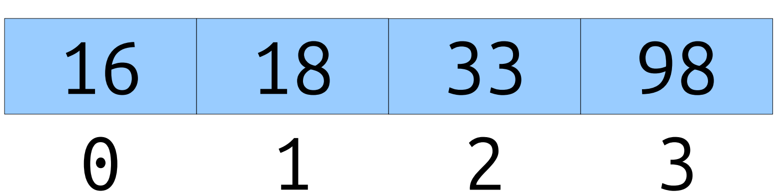

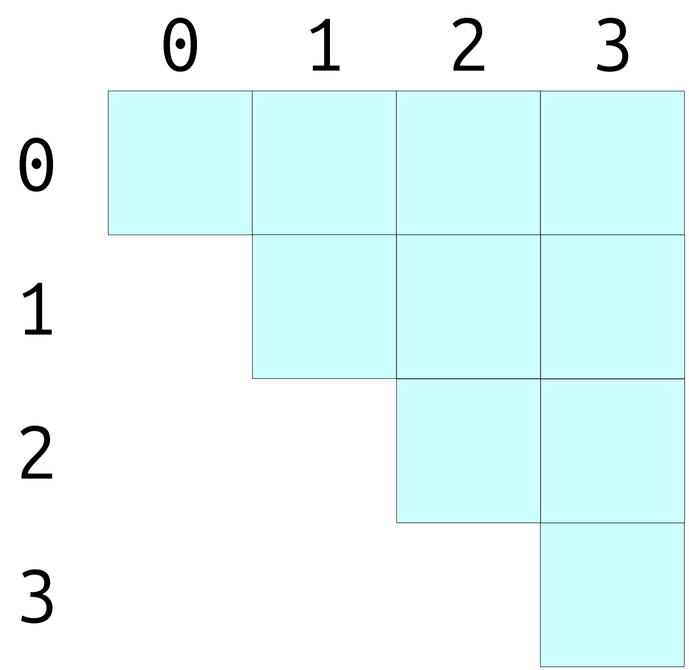

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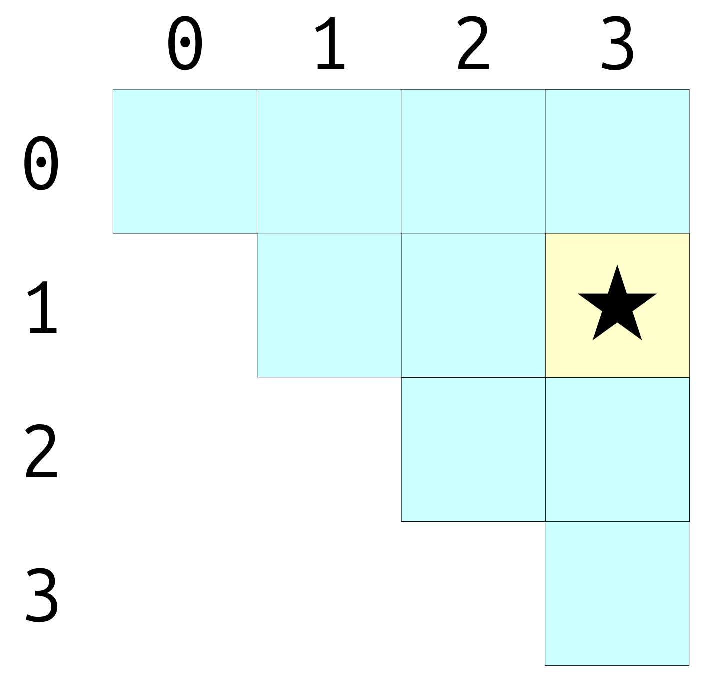

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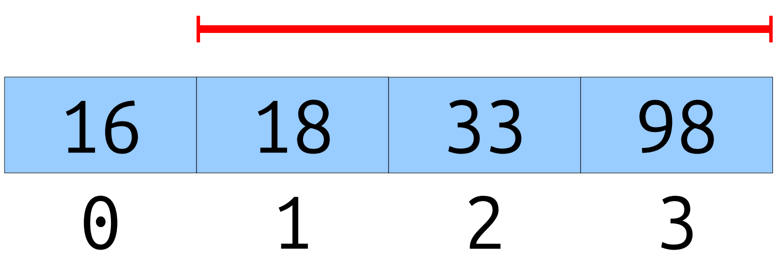

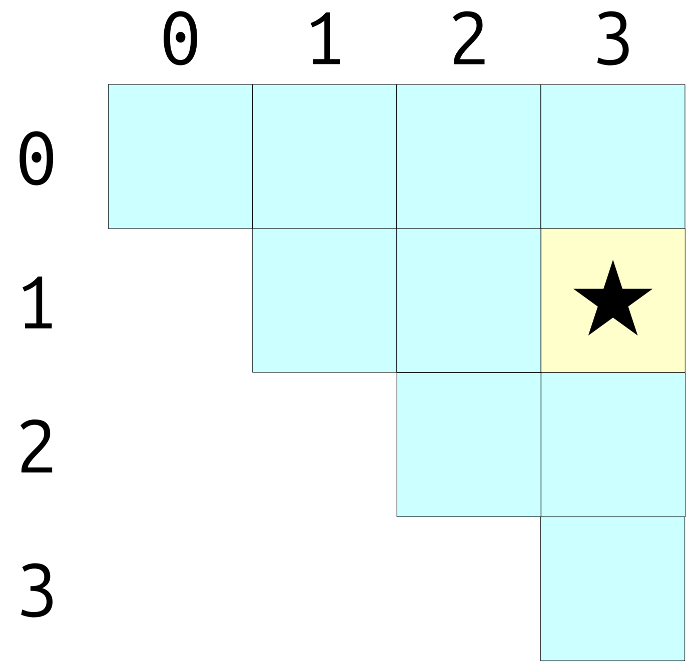

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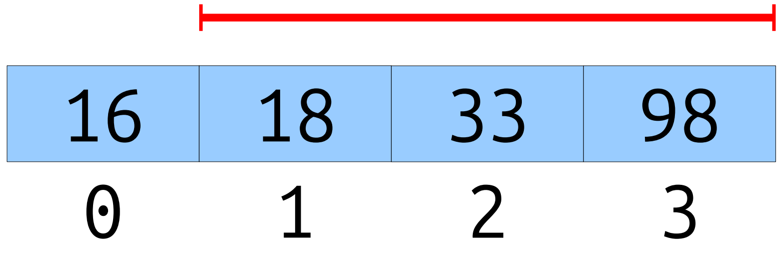

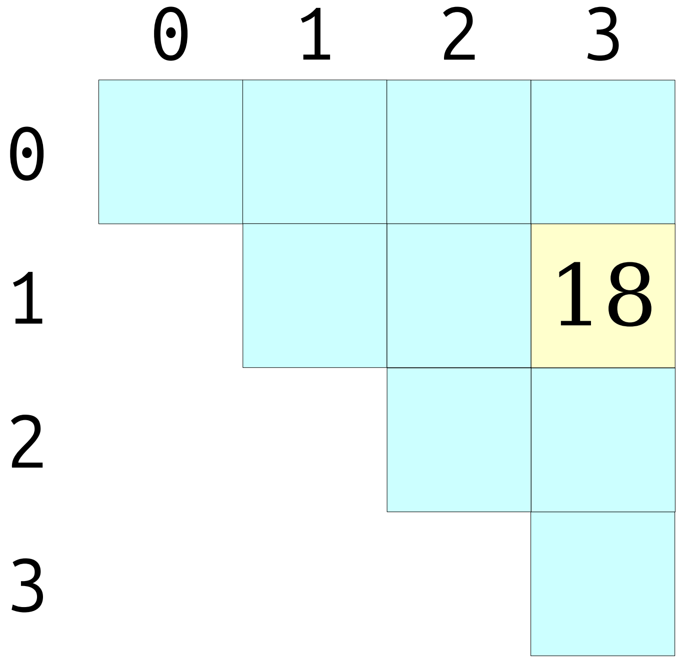

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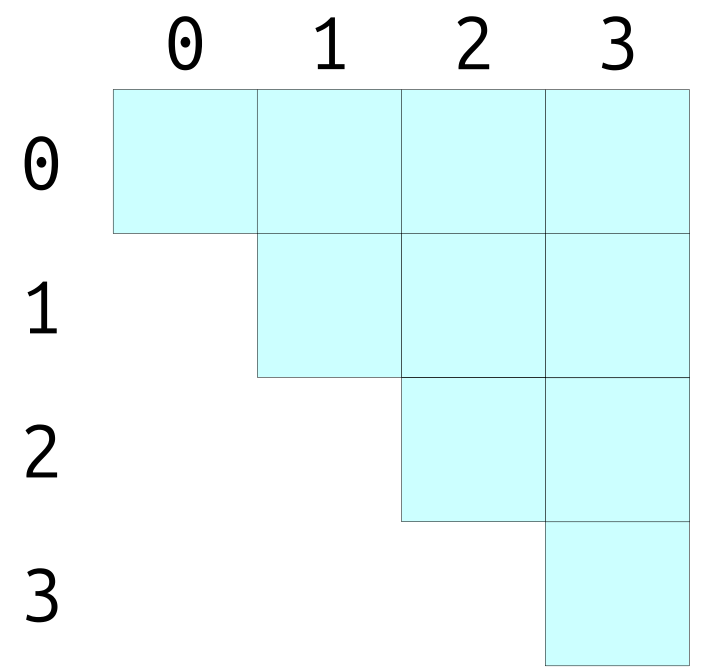
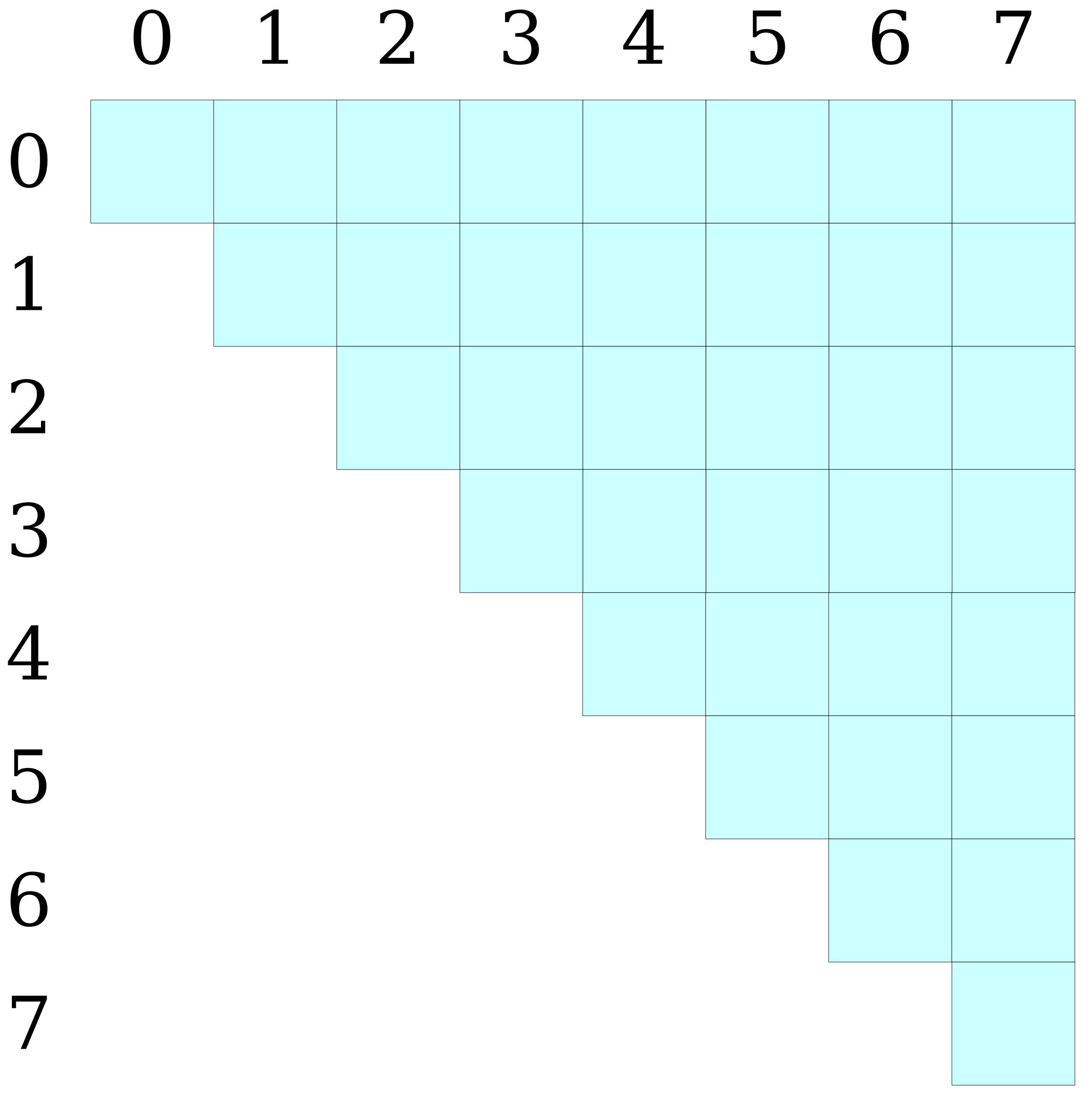


Building the Table

- One simple approach: for each entry in the table, iterate over the range in question and find the minimum value.
- How efficient is this?
  - Number of entries: $\Theta(n^2)$.
  - Time to evaluate each entry: $O(n)$.
  - Time required: $O(n^3)$.
- The runtime is $O(n^3)$ using this approach. Is it also $\Theta(n^3)$?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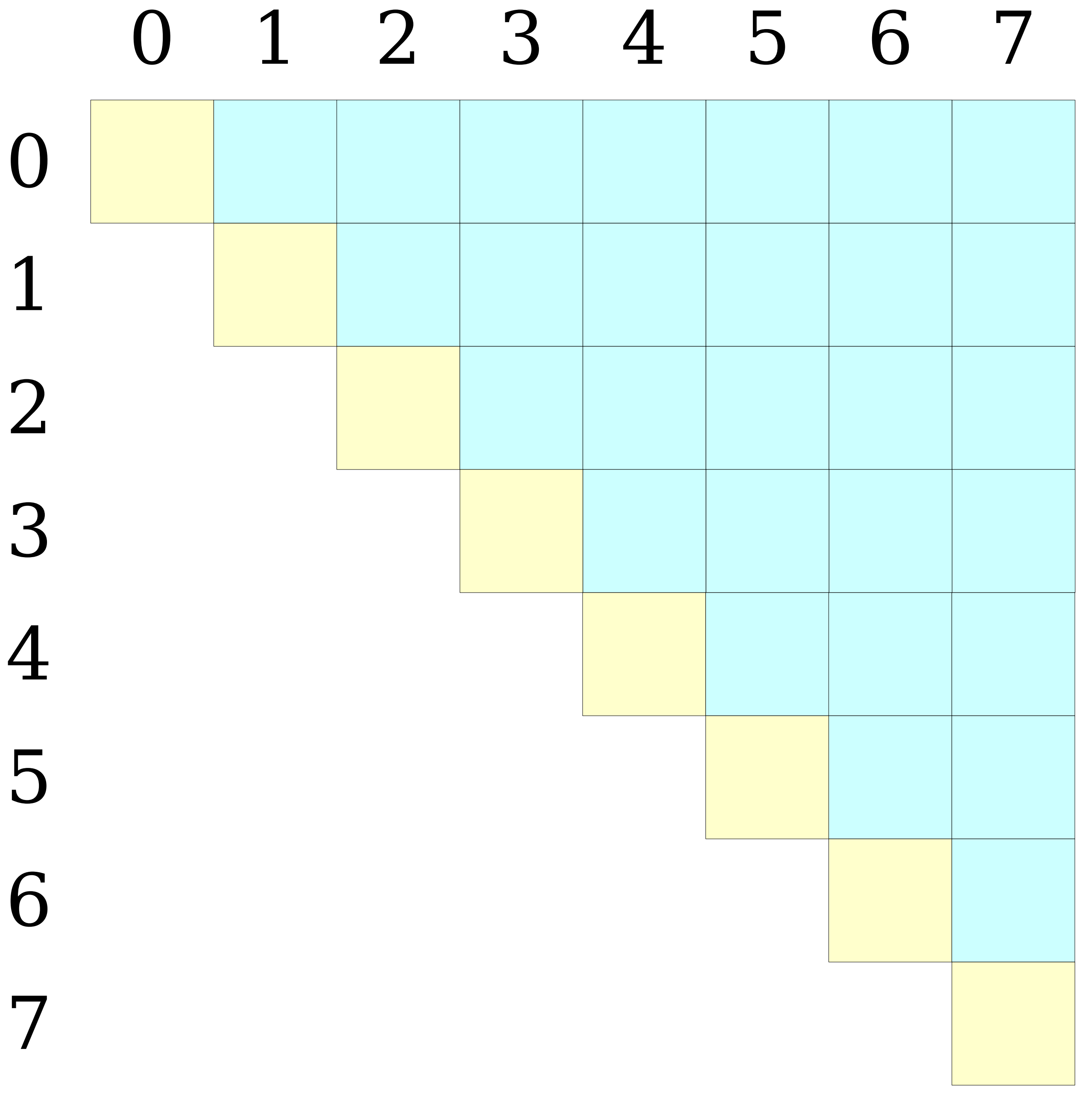
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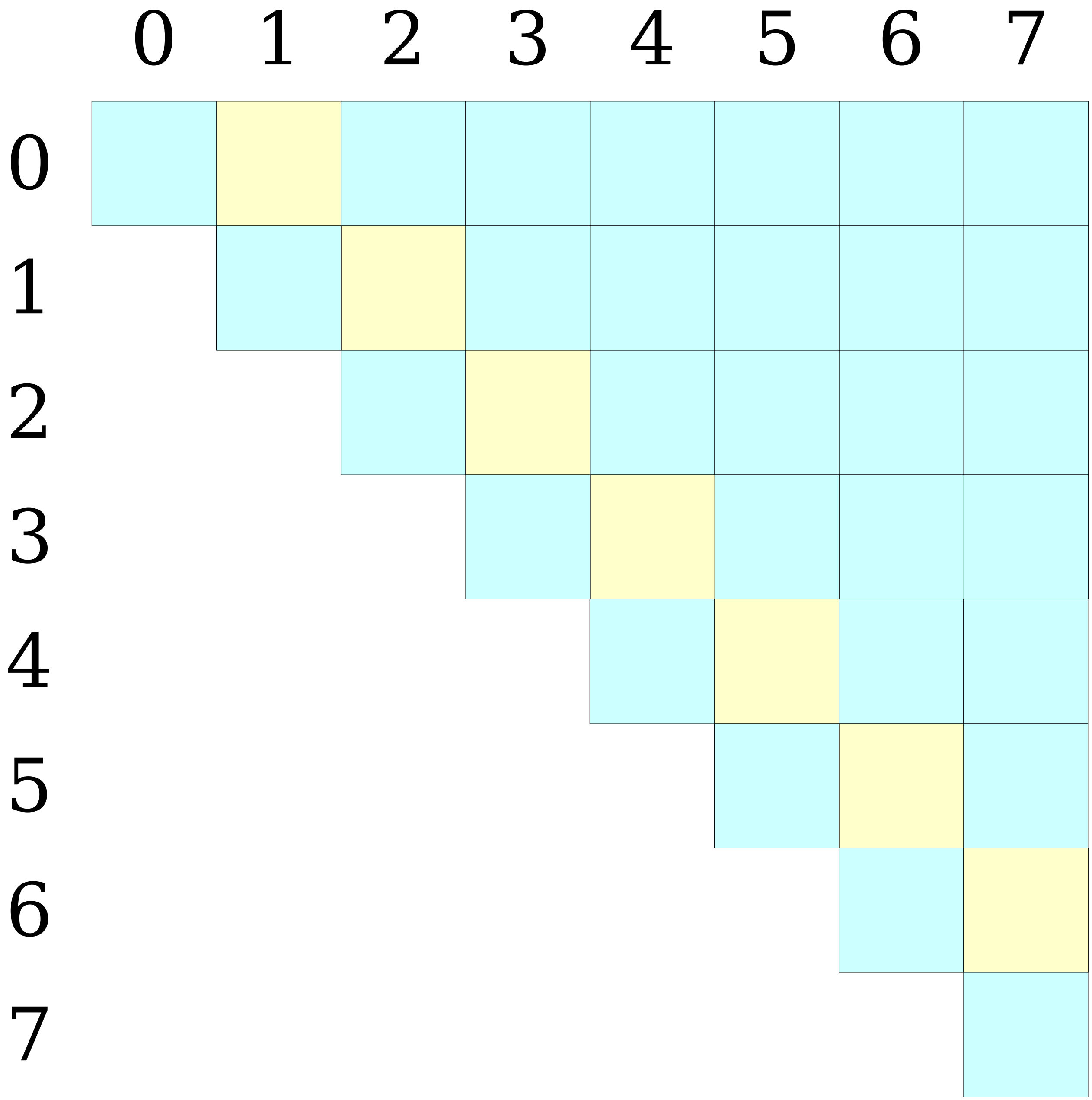
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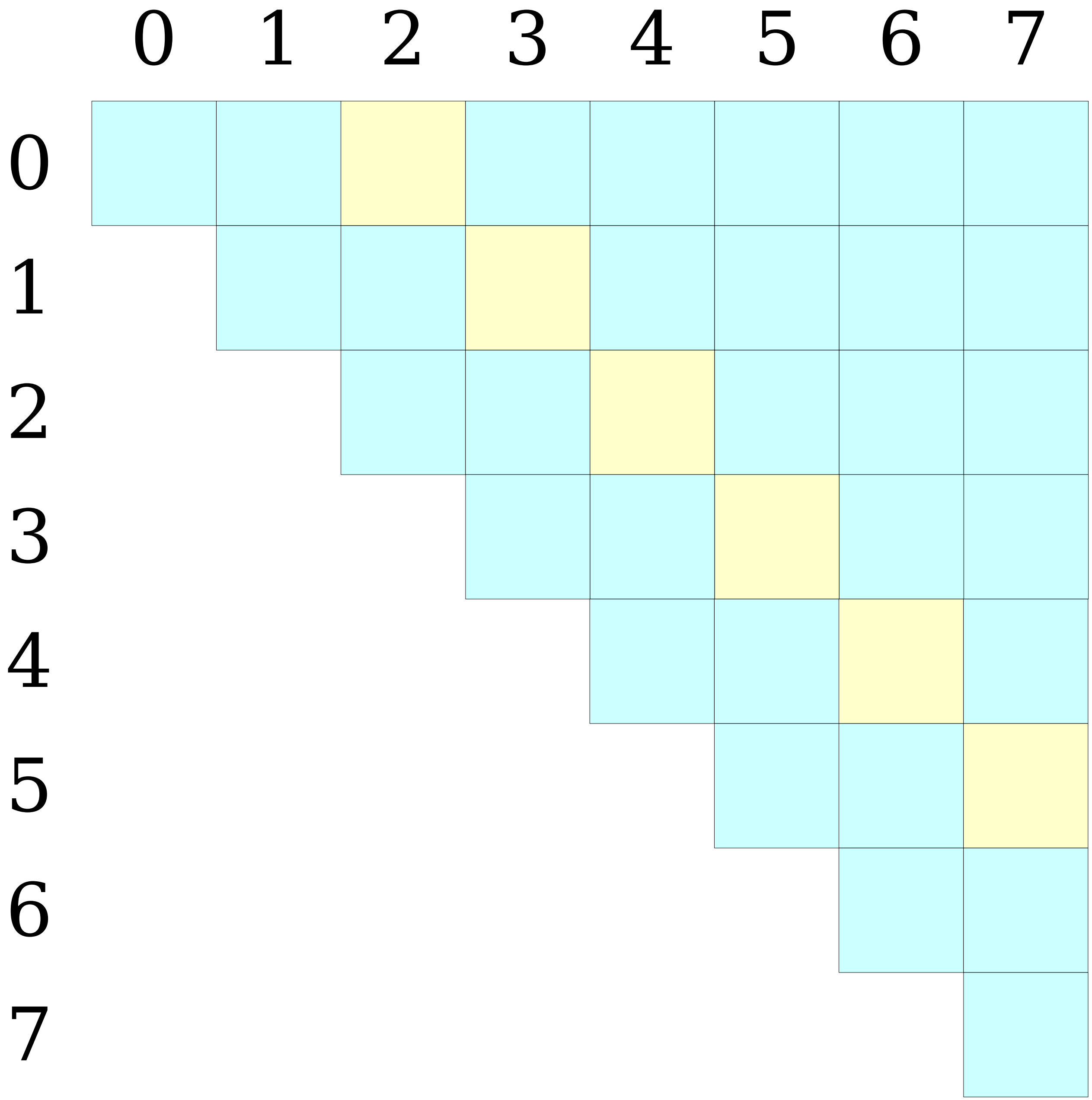
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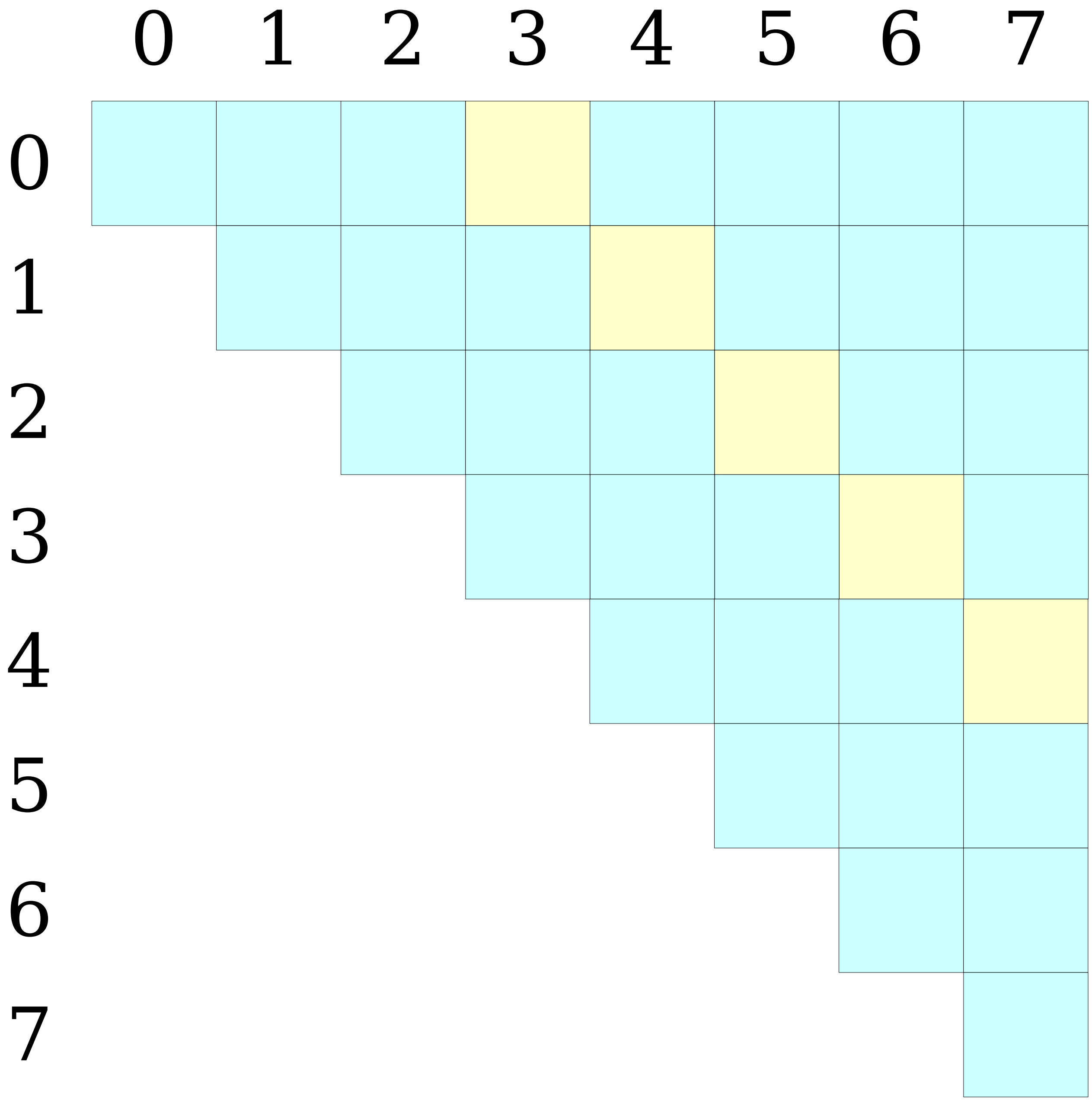
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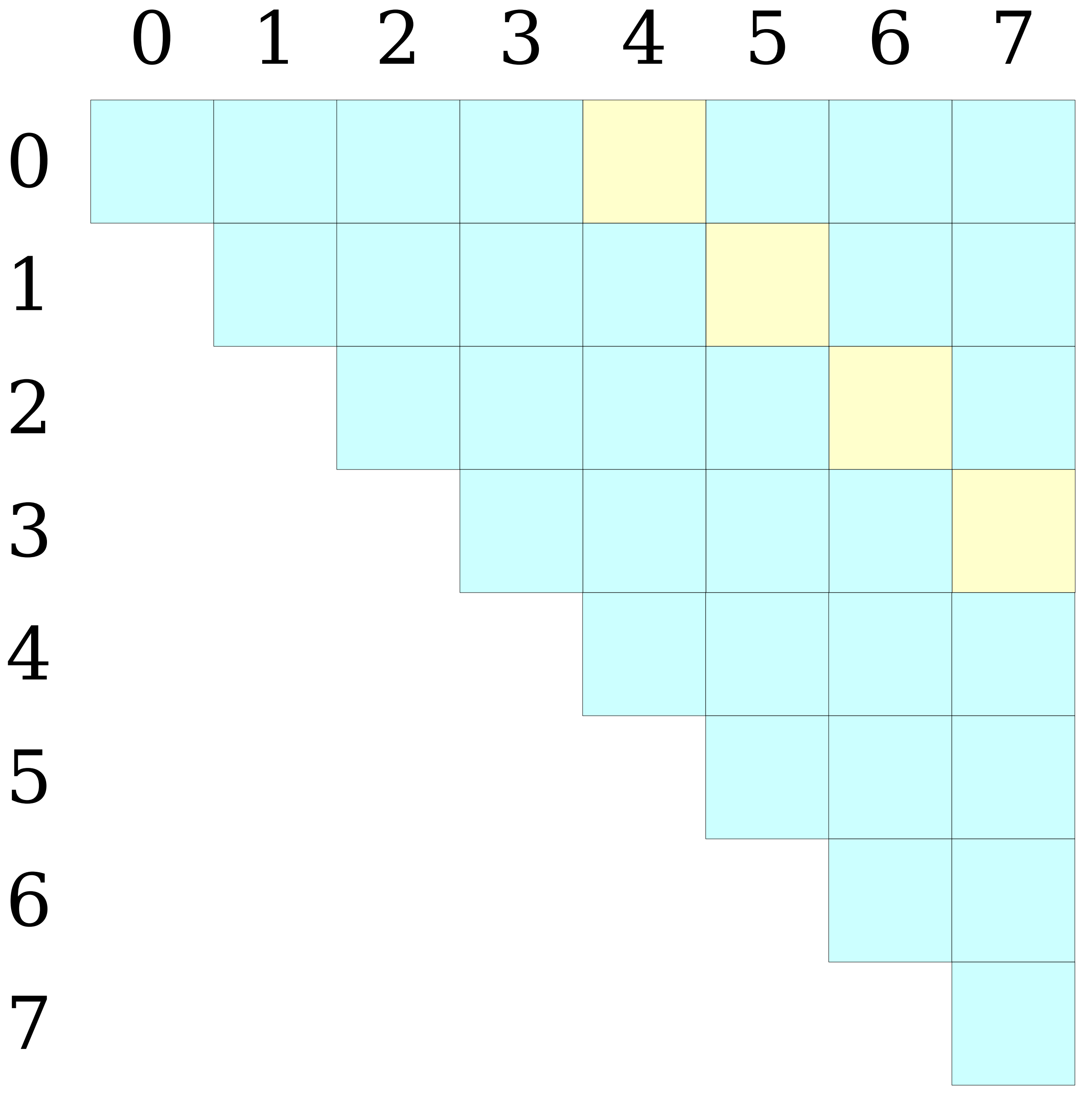
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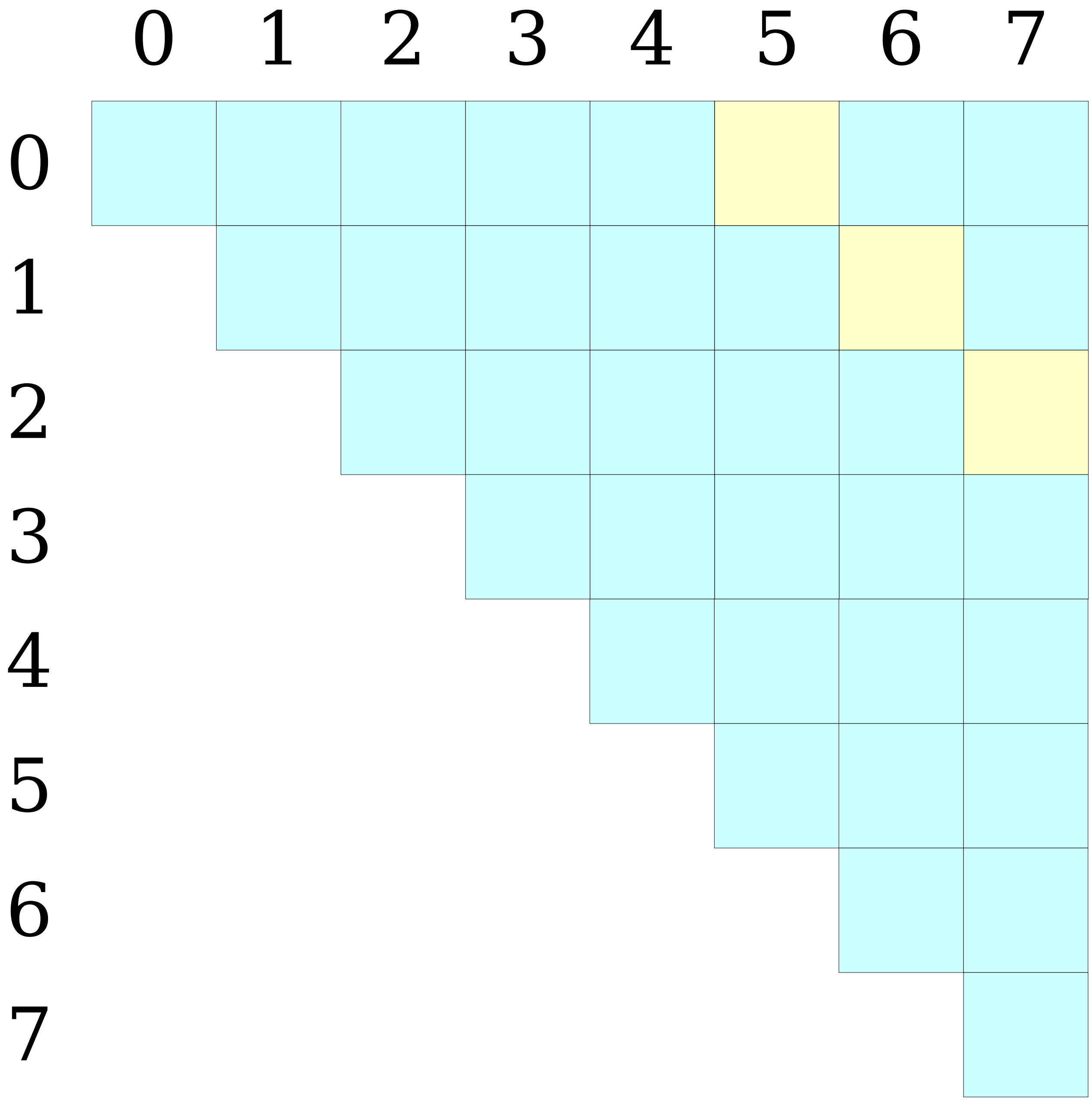
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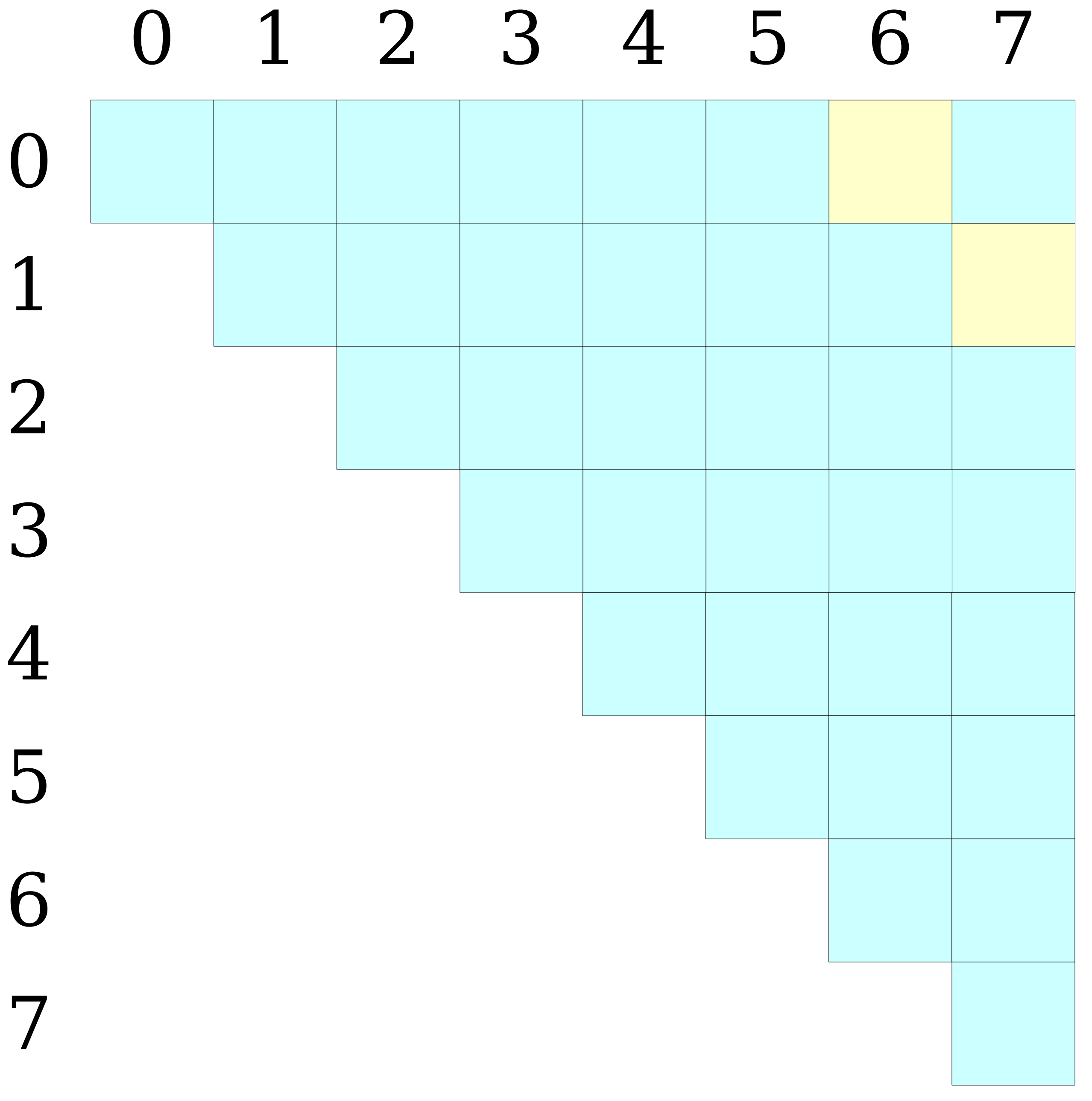
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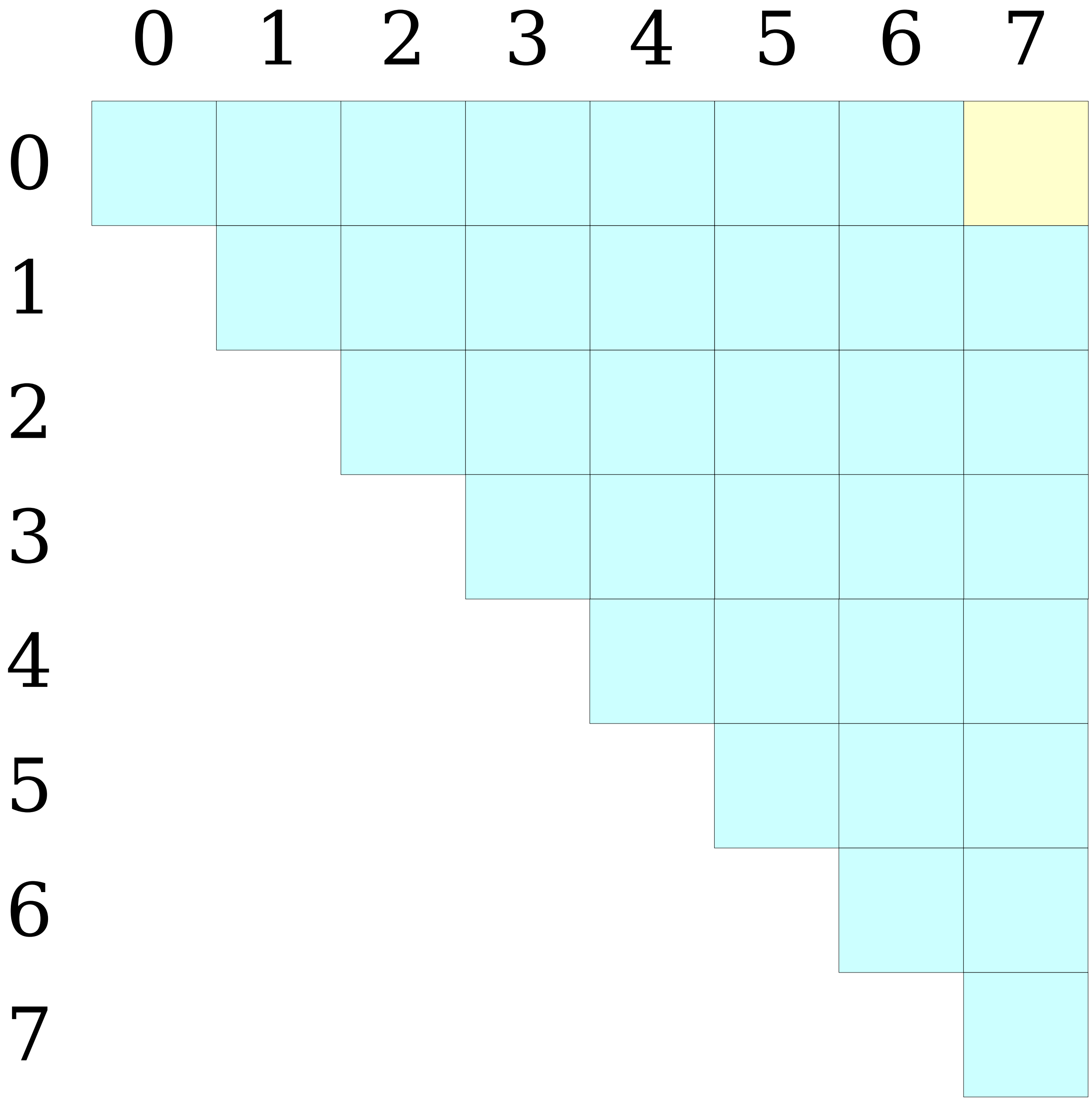
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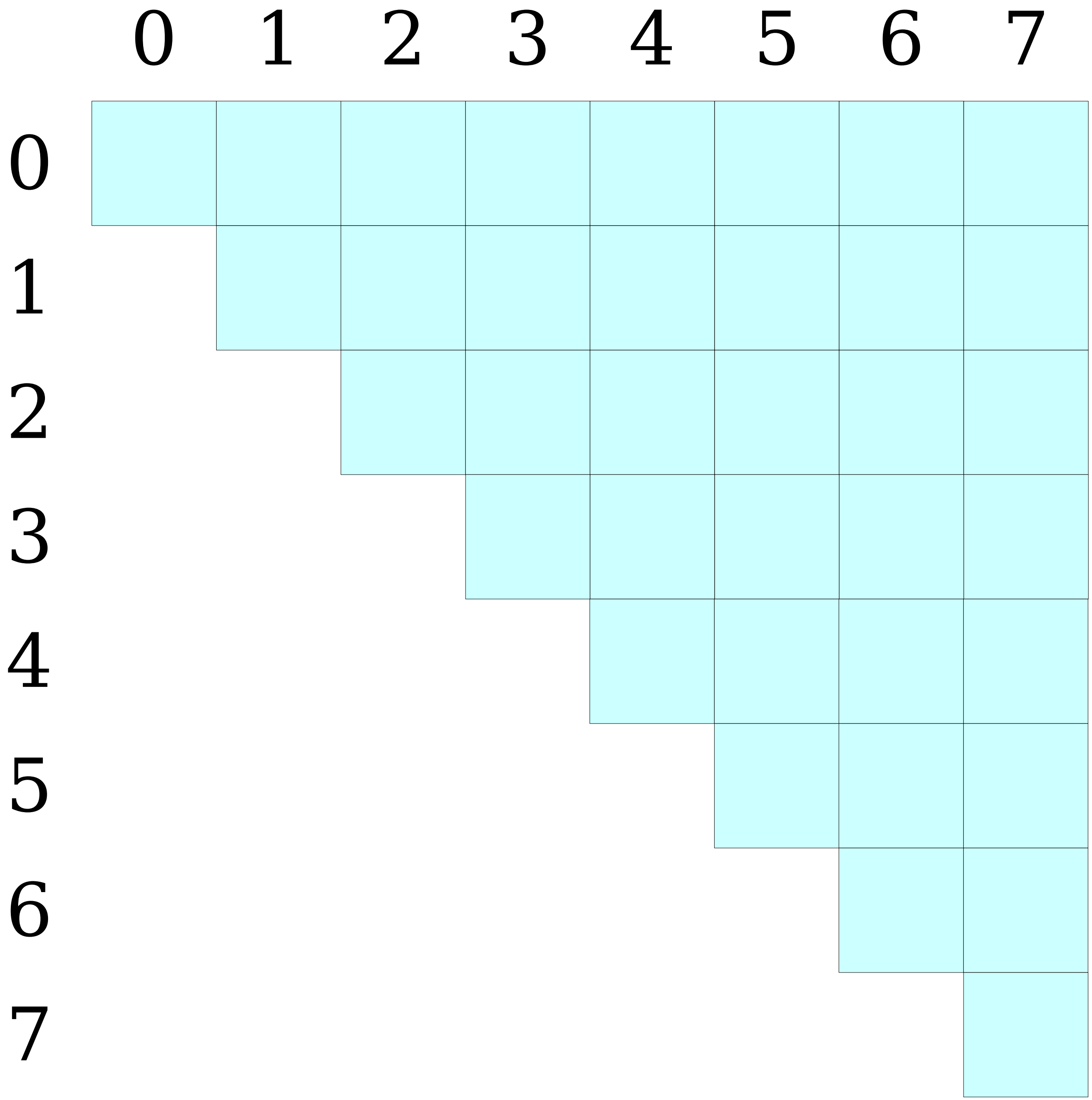
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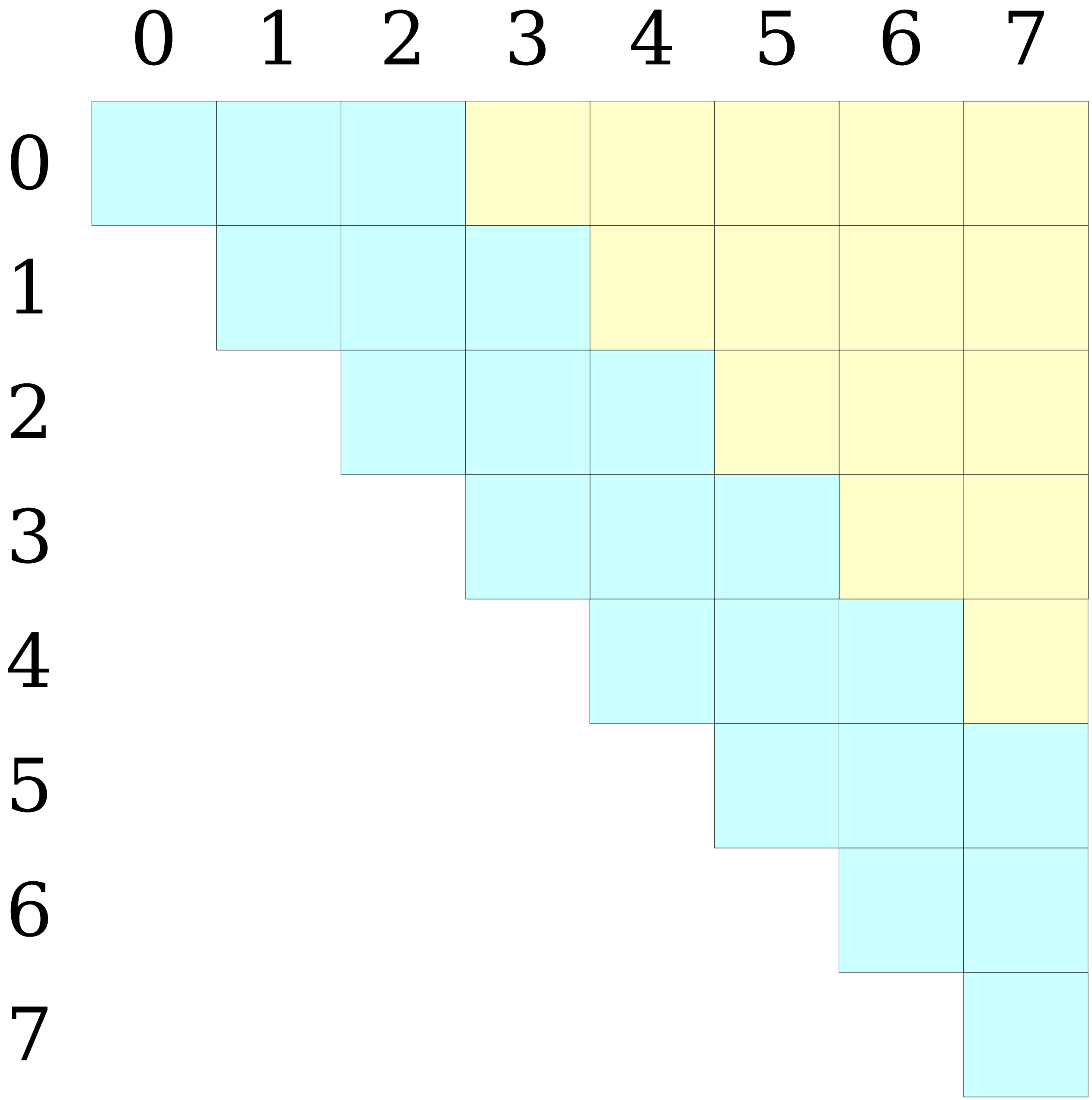
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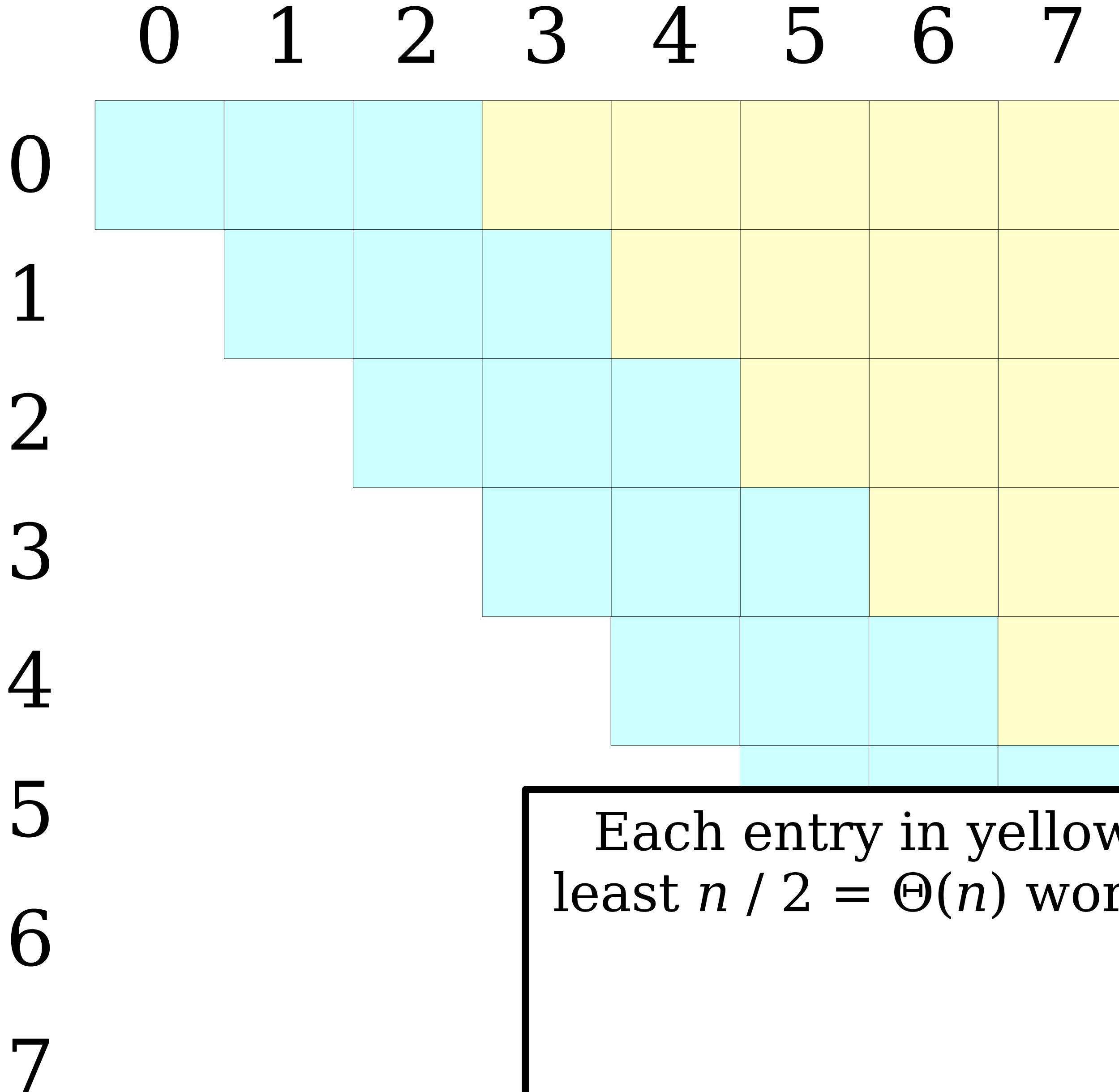
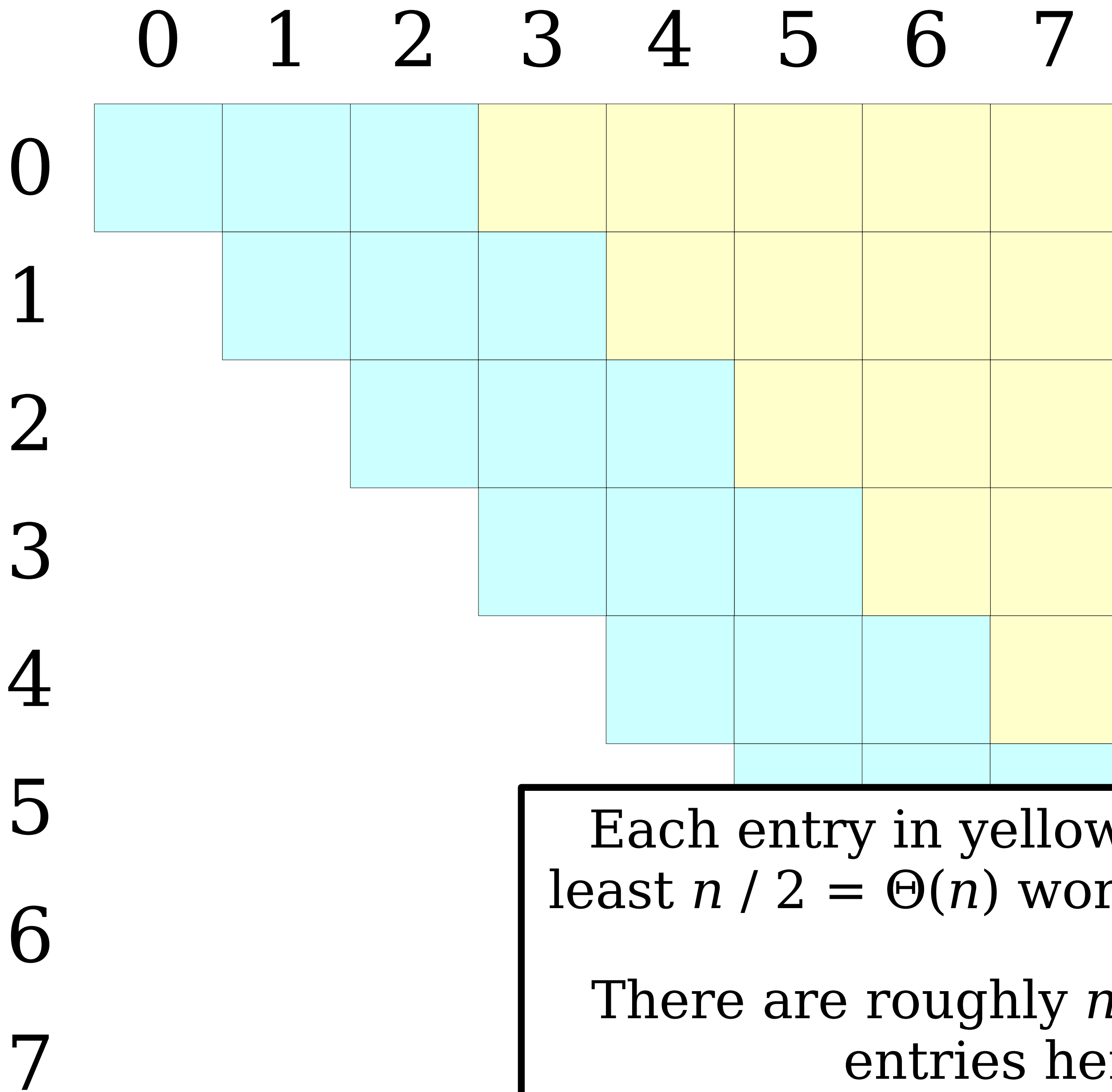


Each entry in yellow requires at least $n / 2 = \Theta(n)$ work to evaluate.



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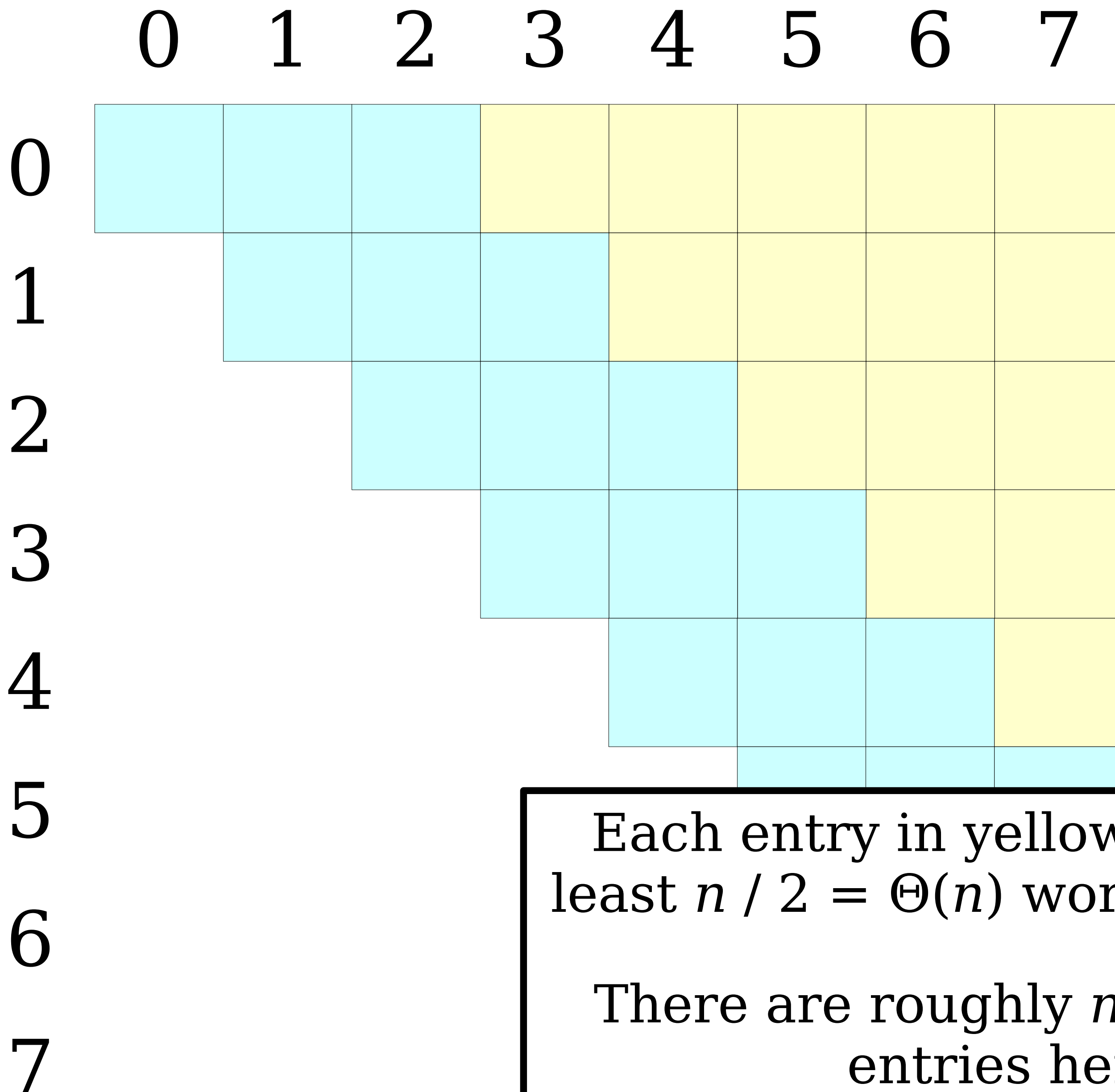
There are roughly n^2 / 8 = $\Theta(n^2)$ entries here.



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Total work required: $\Theta(n^3)$

A Different Approach

- Naïvely precomputing the table is inefficient.
- Can we do better?
- ***Claim:*** We can precompute all subarrays in time $\Theta(n^2)$ using dynamic programming.

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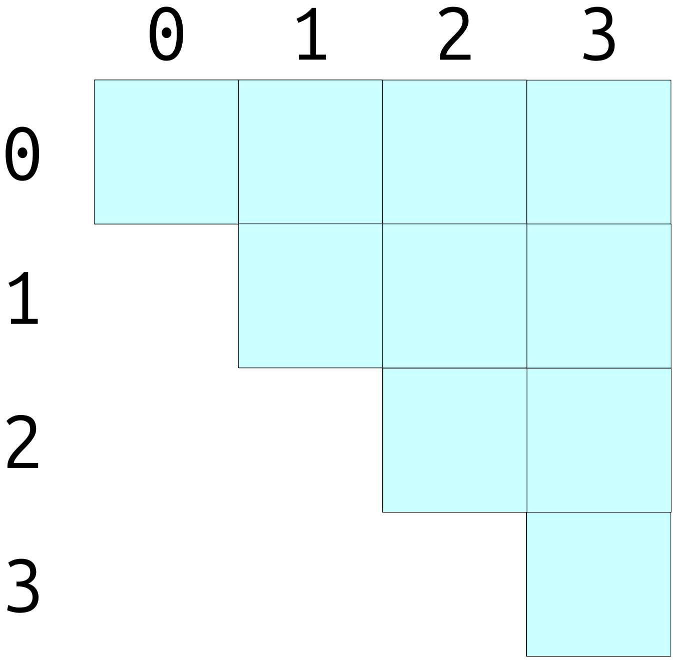

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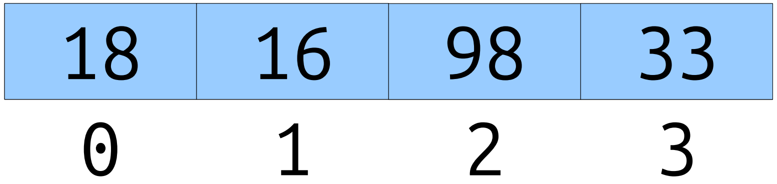

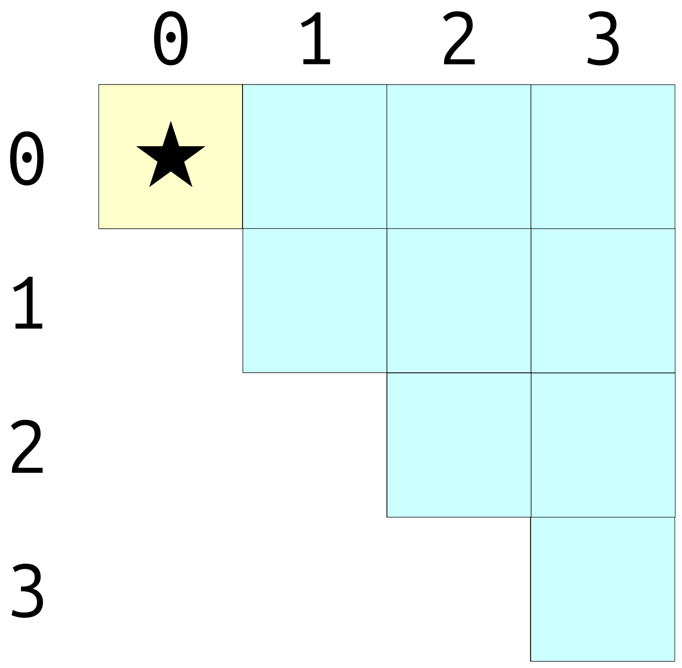

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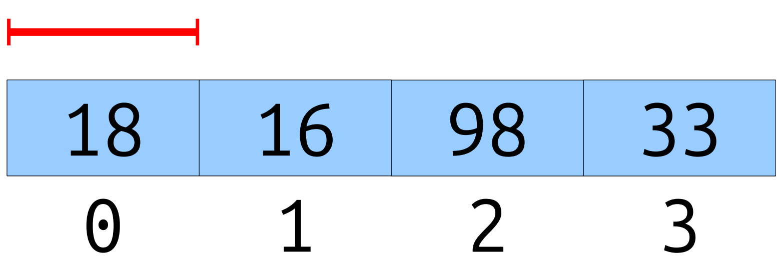

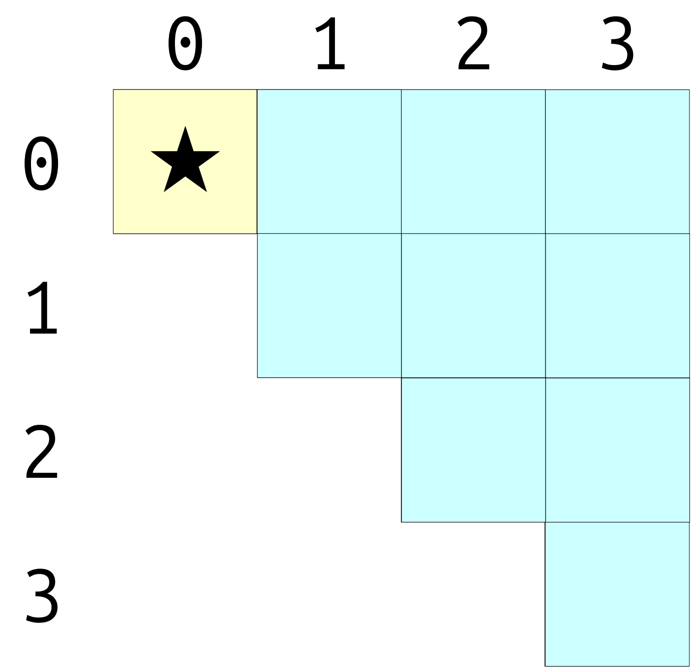

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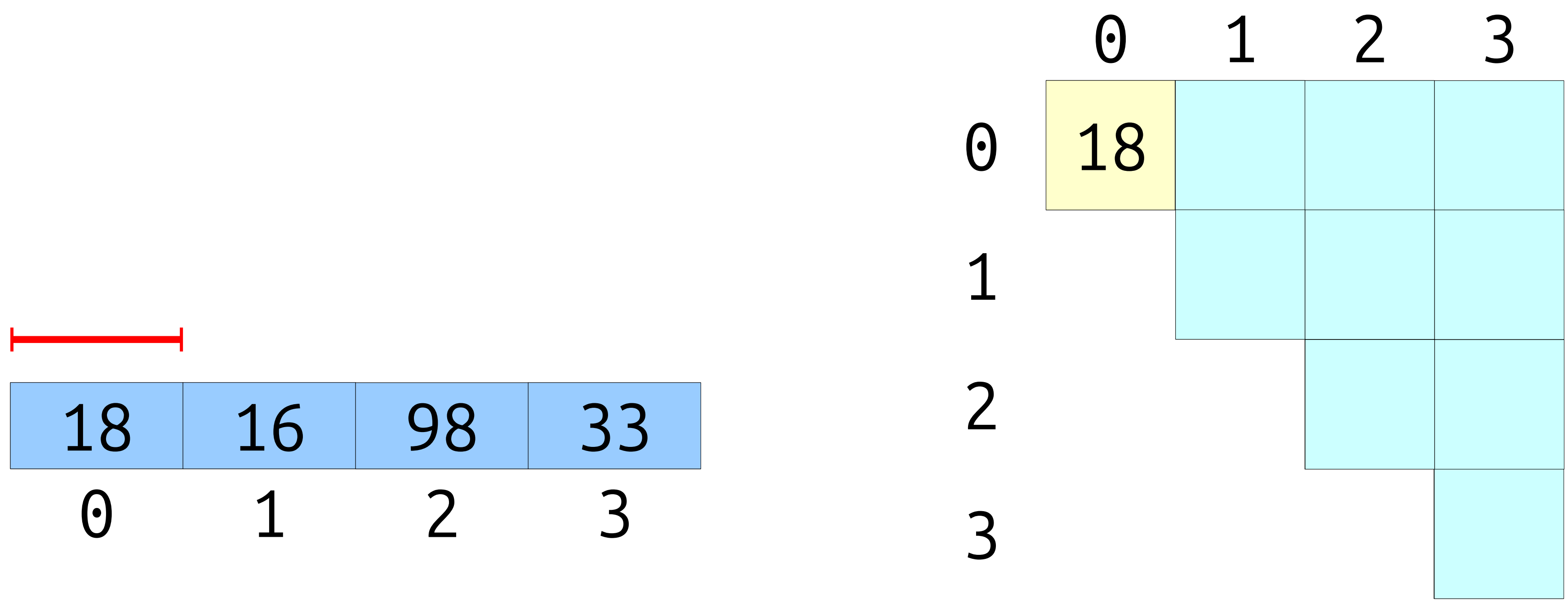

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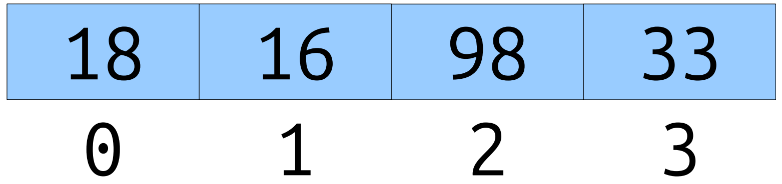

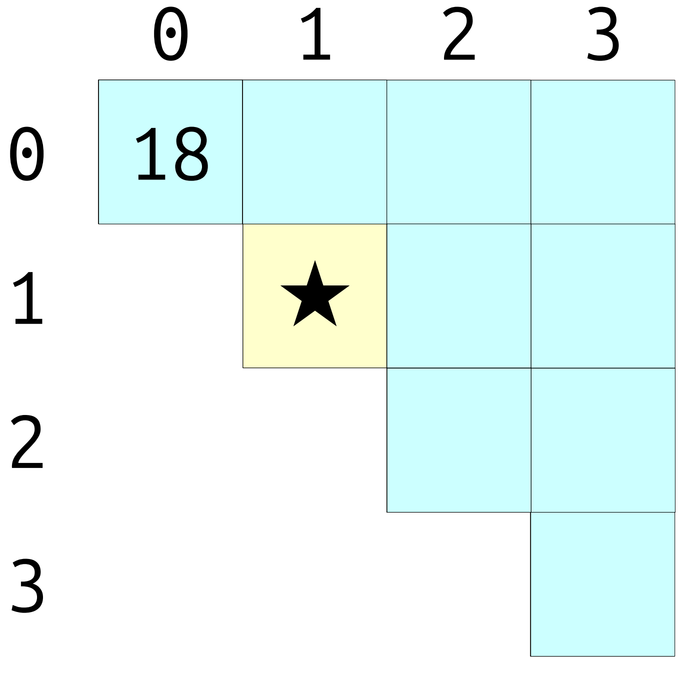

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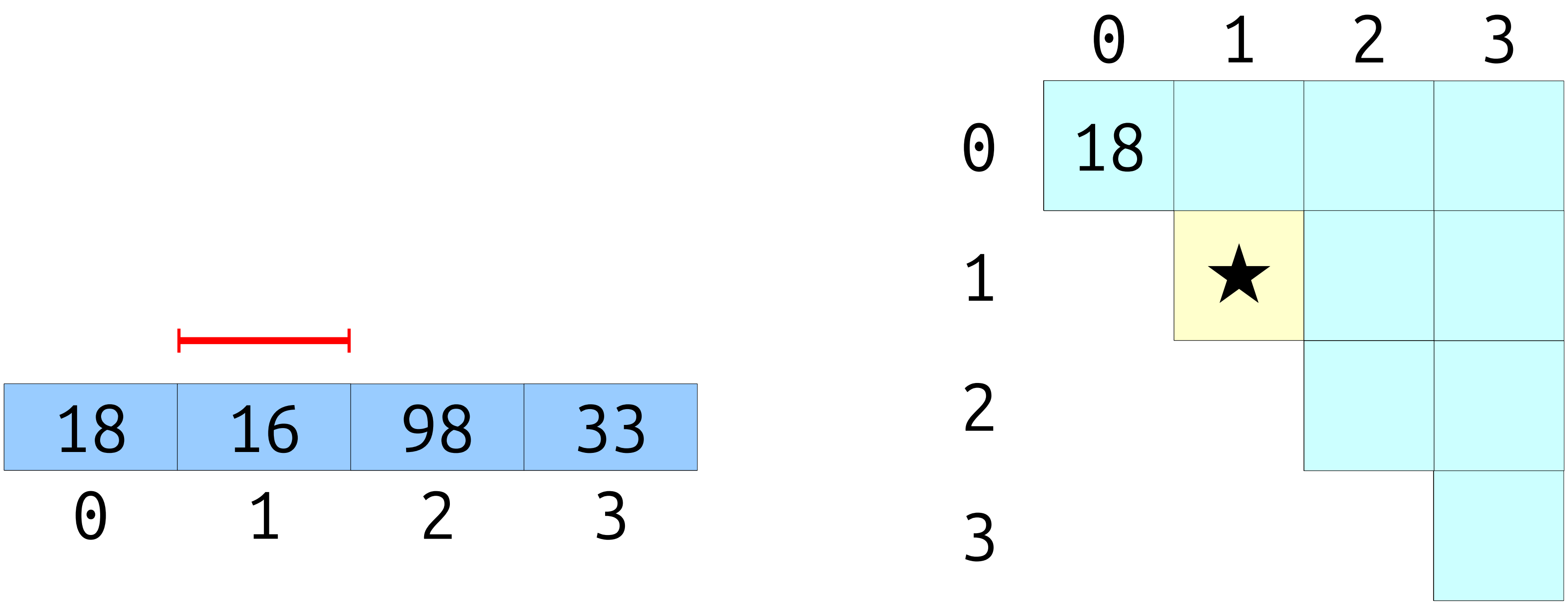

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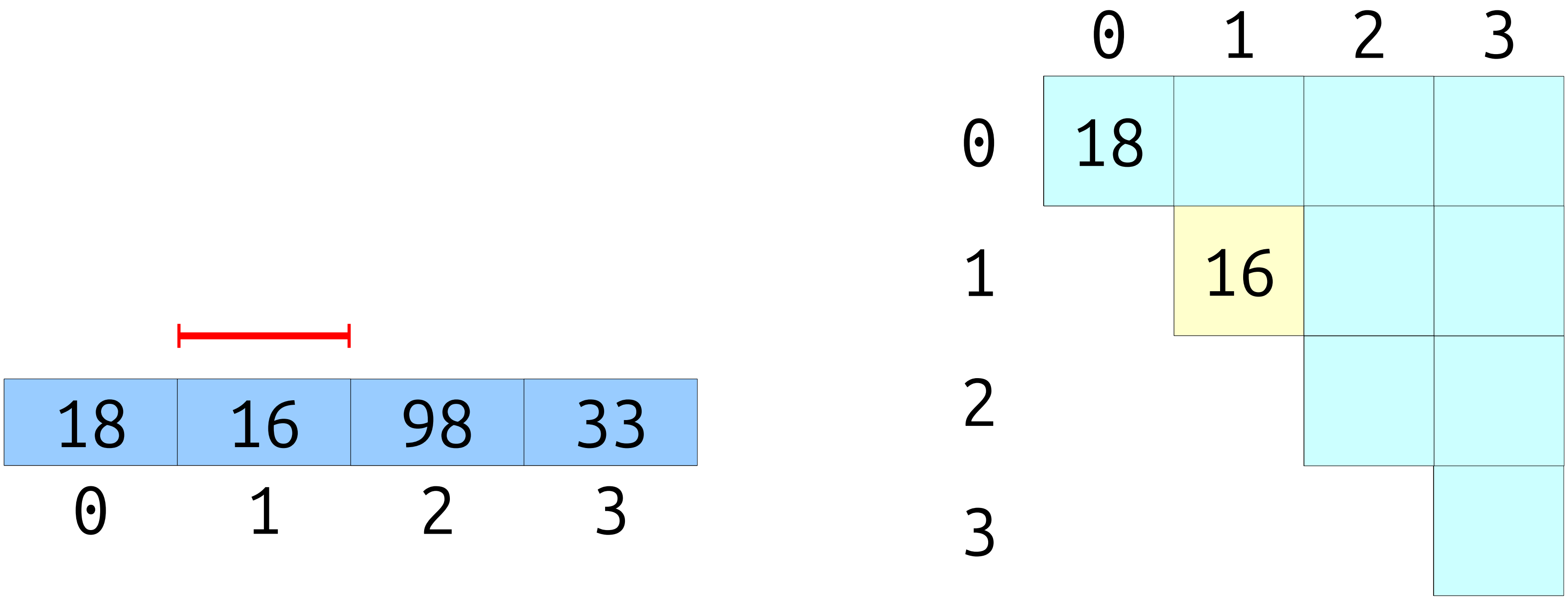

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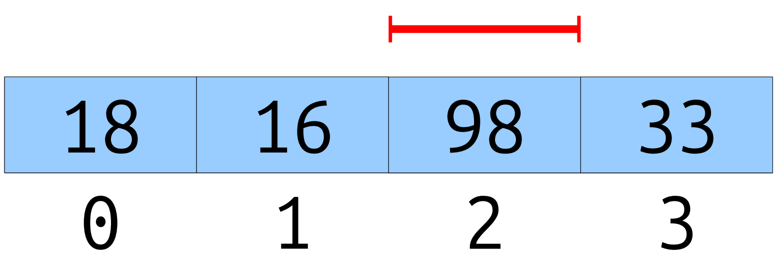

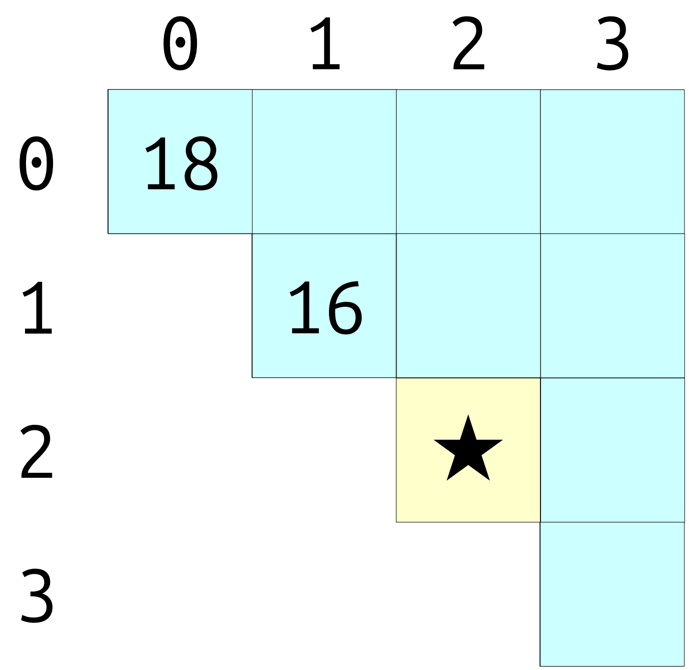

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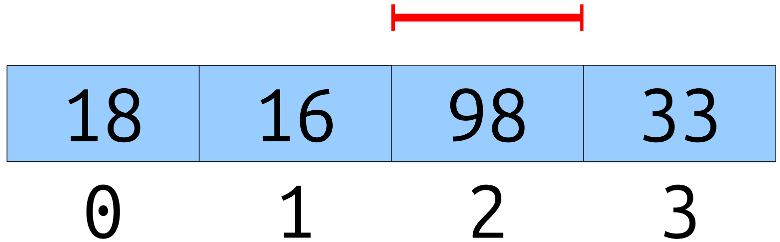

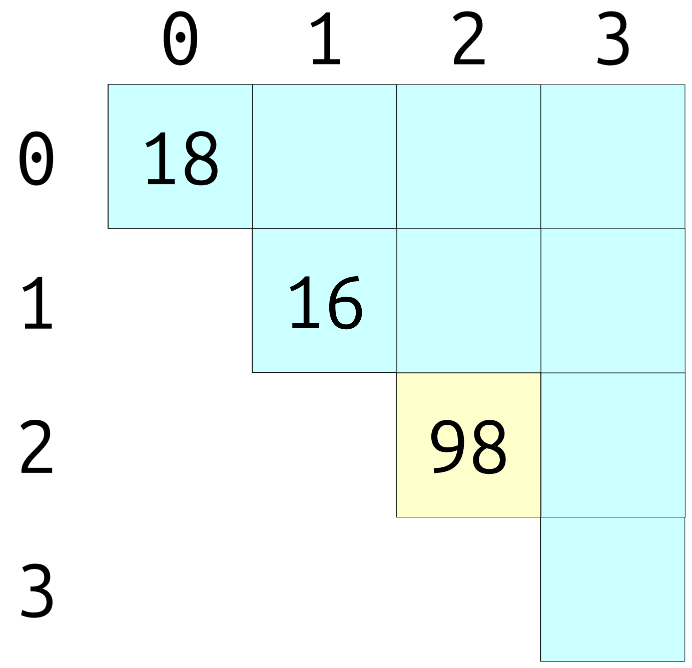

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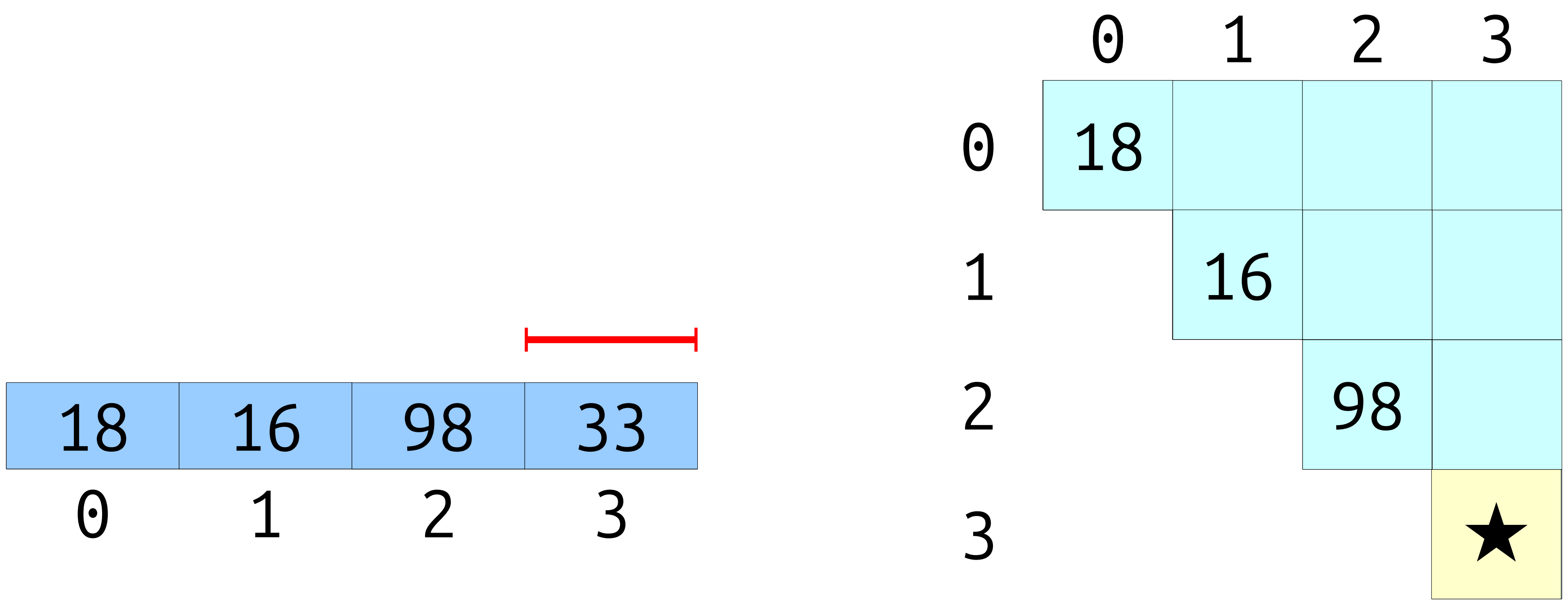

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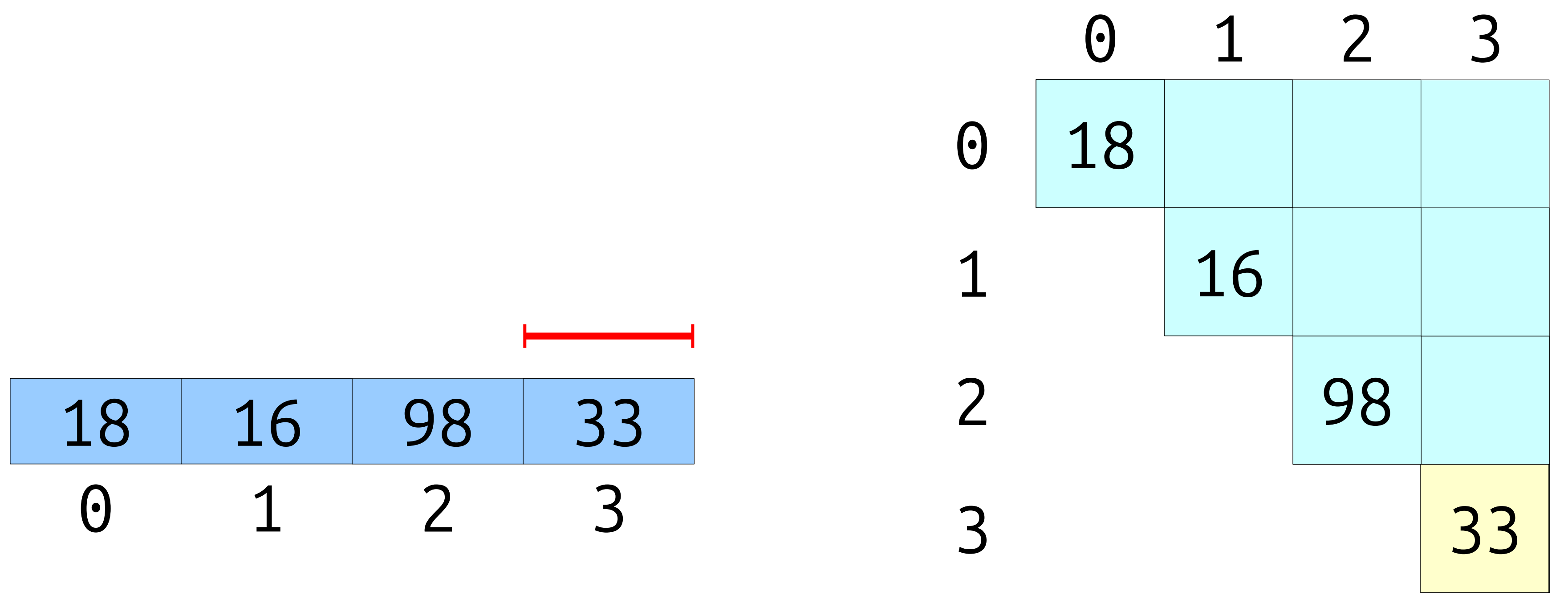

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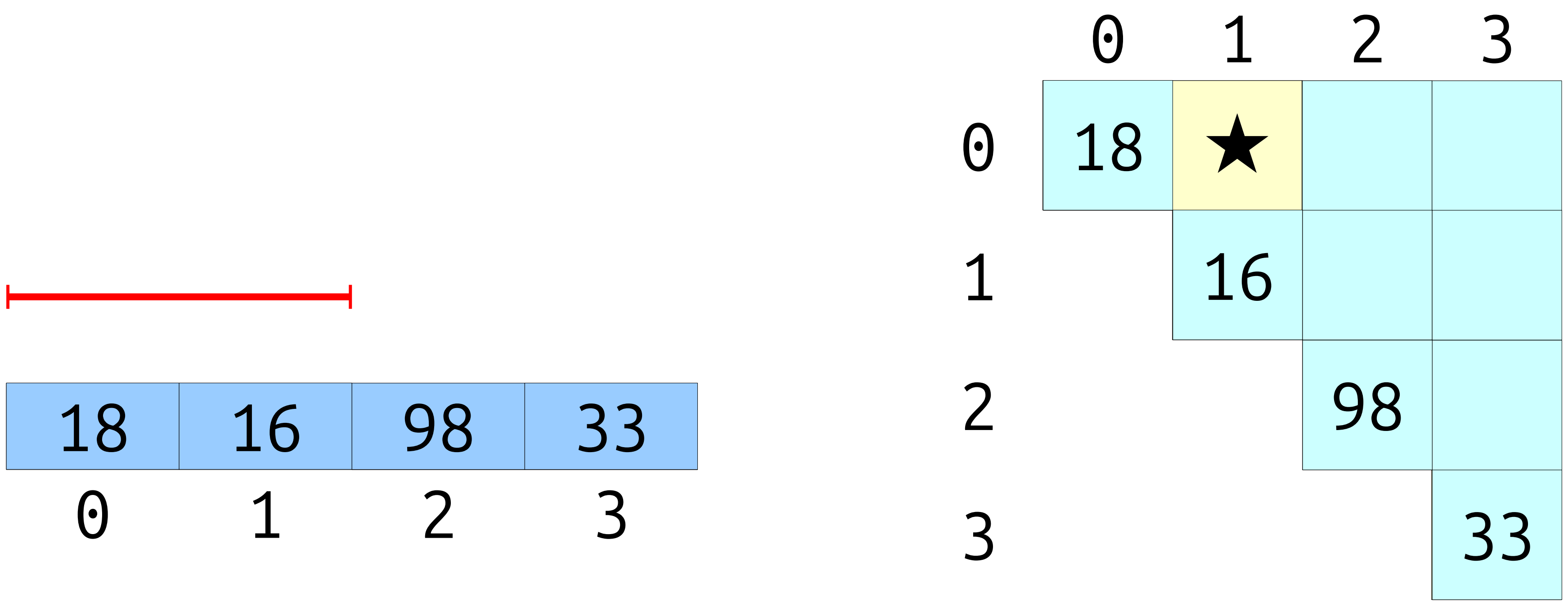

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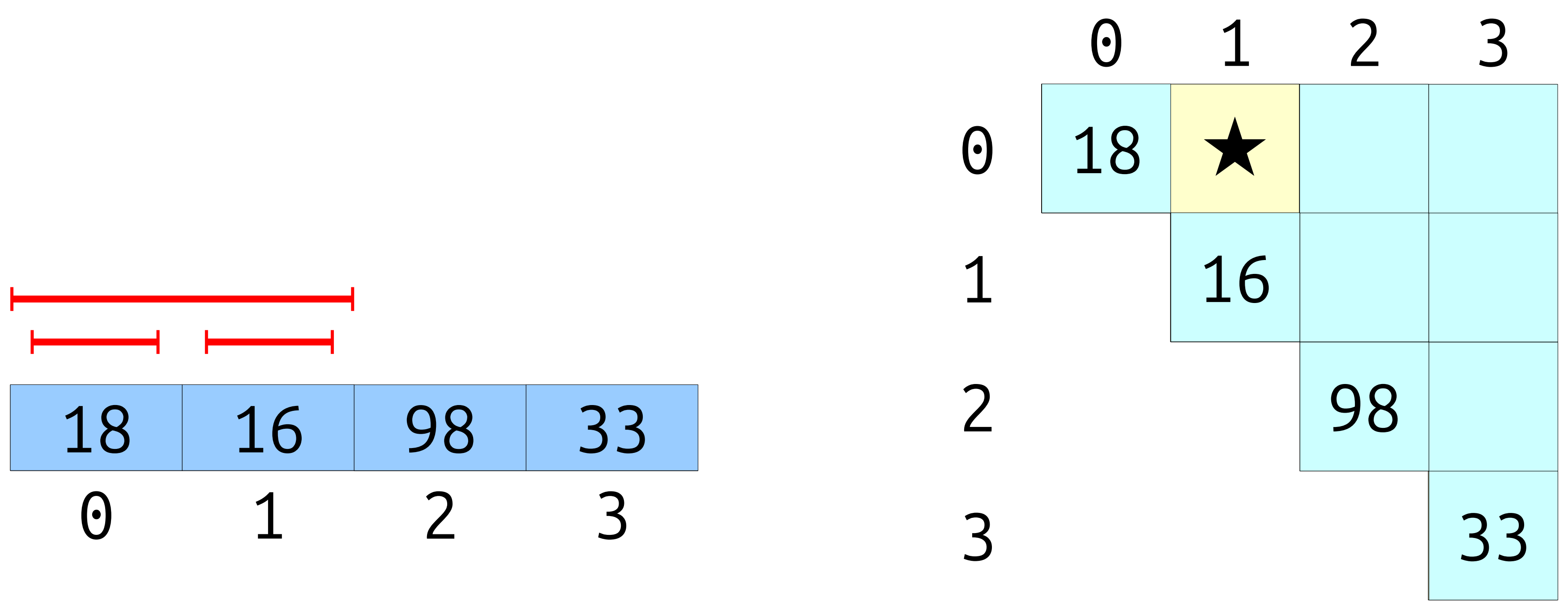

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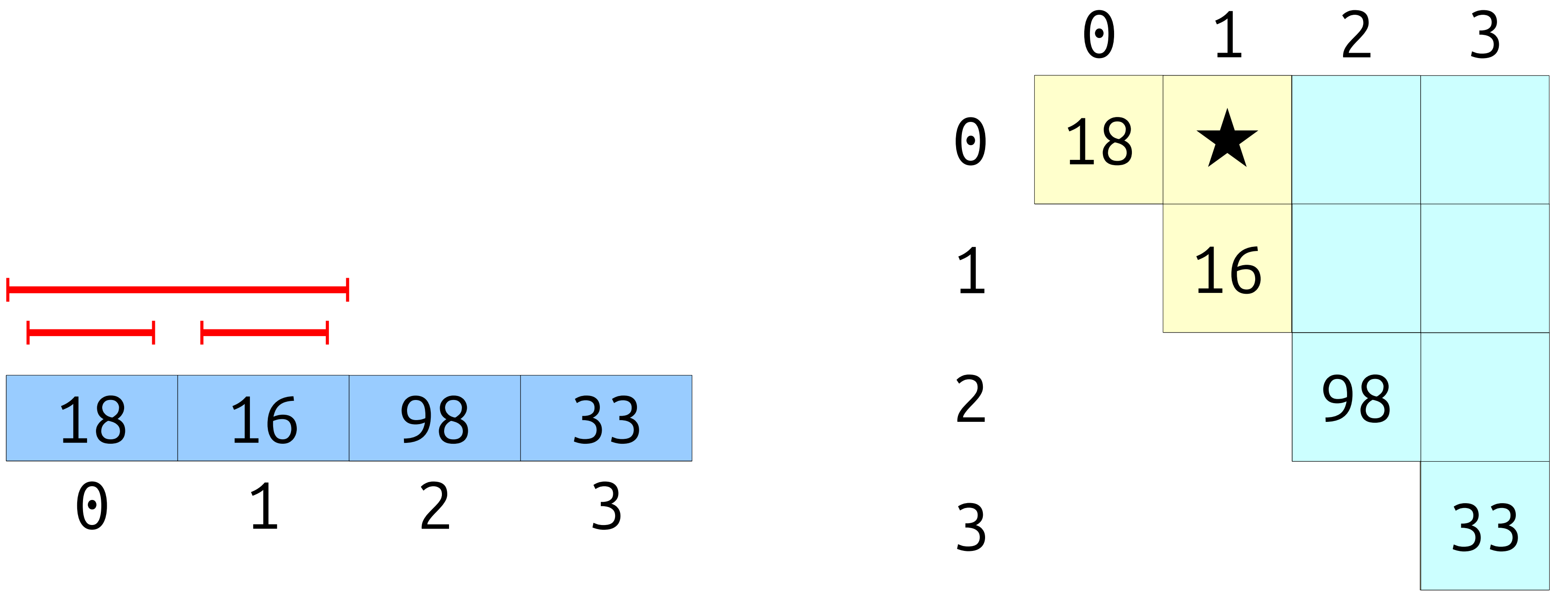

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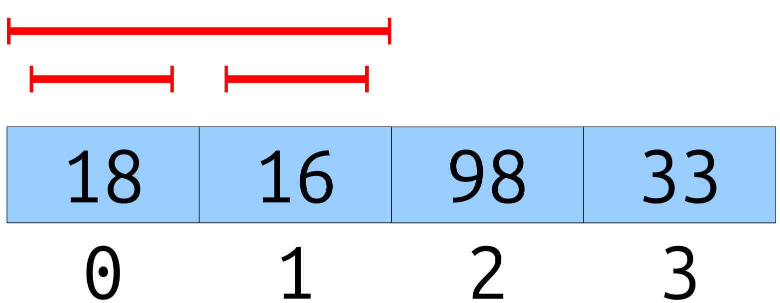

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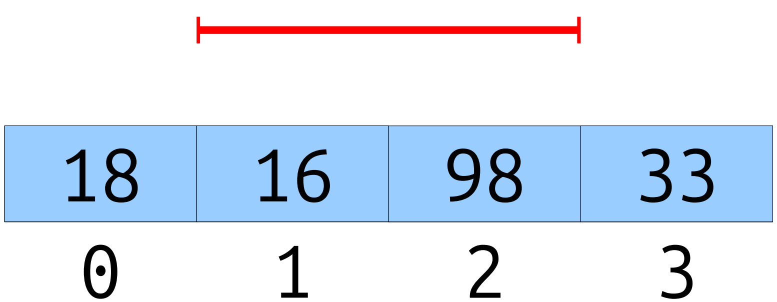

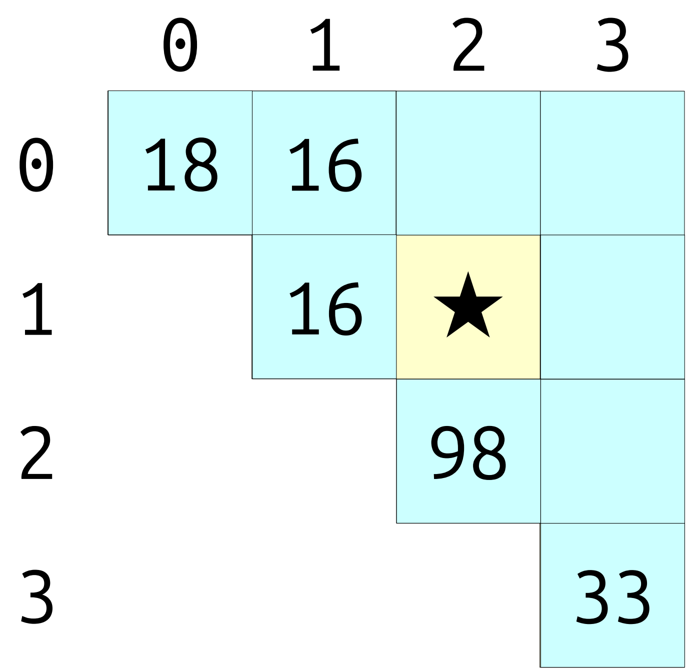

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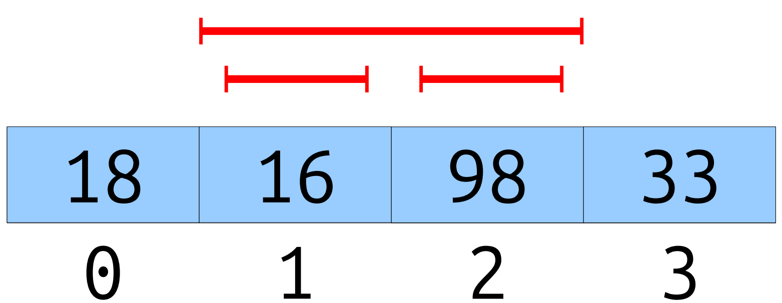

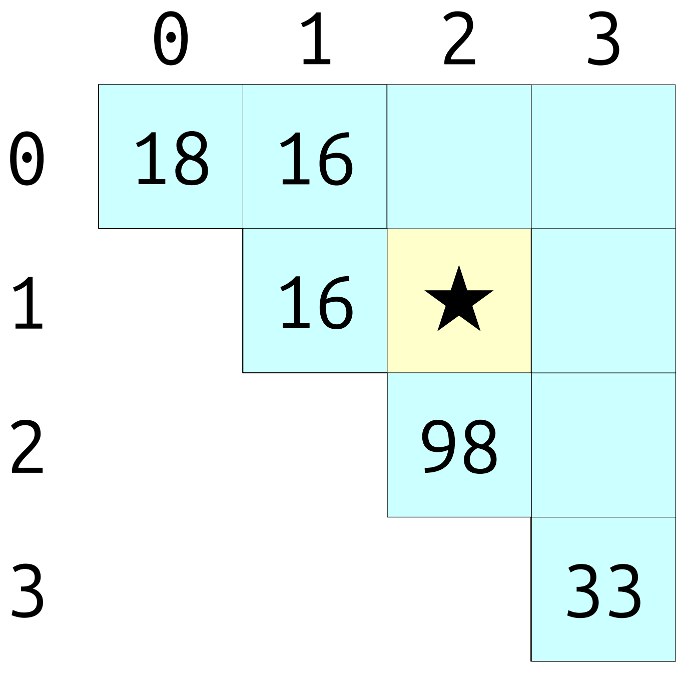

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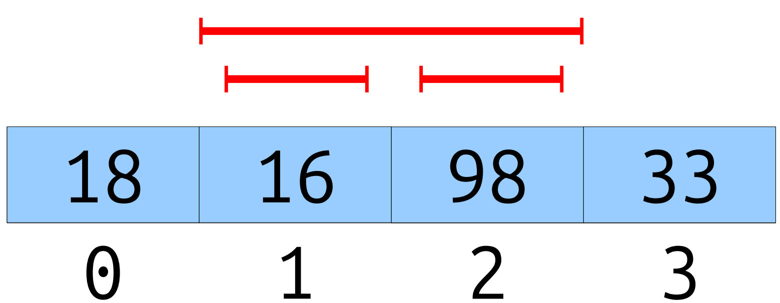

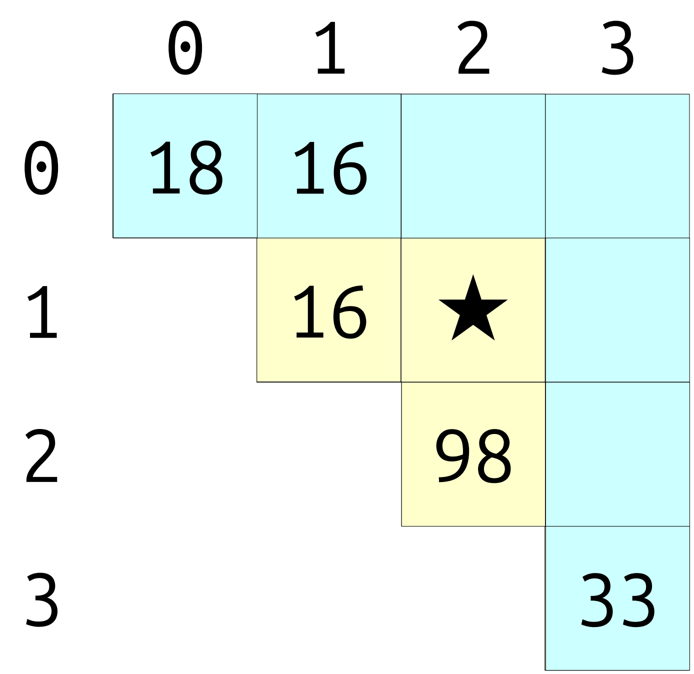

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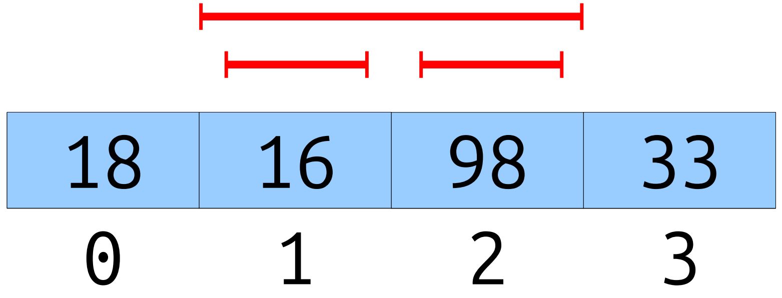

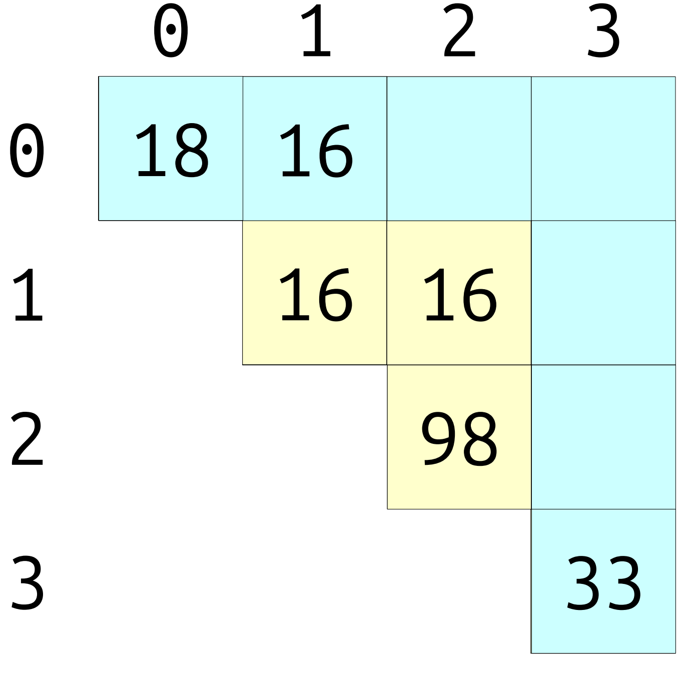

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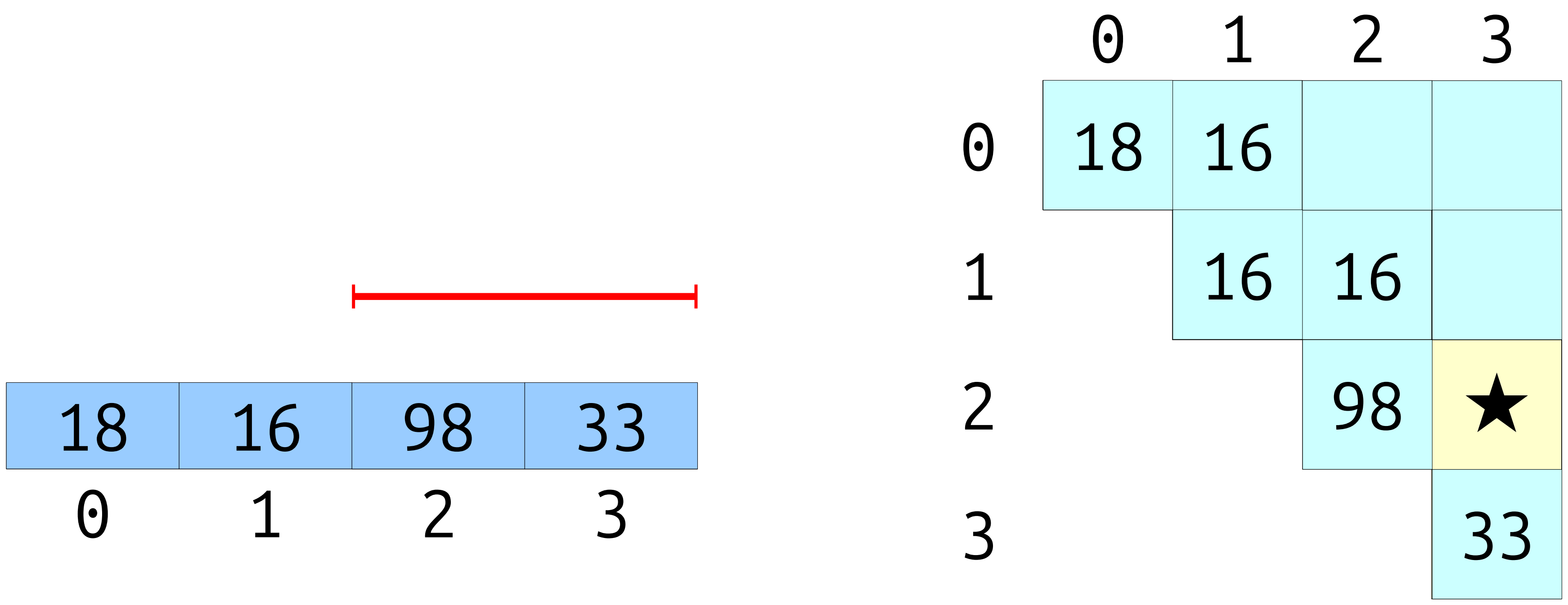

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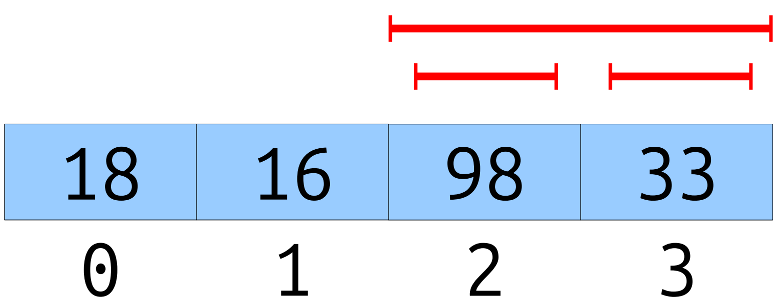

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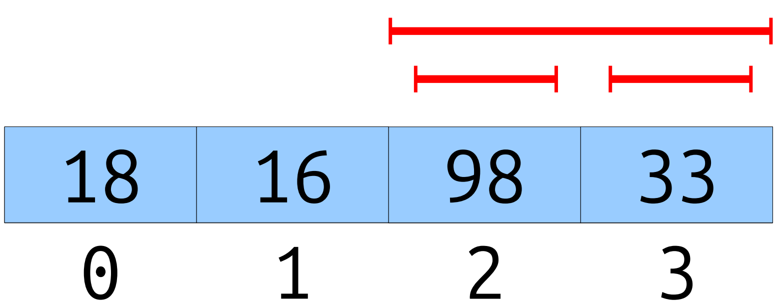

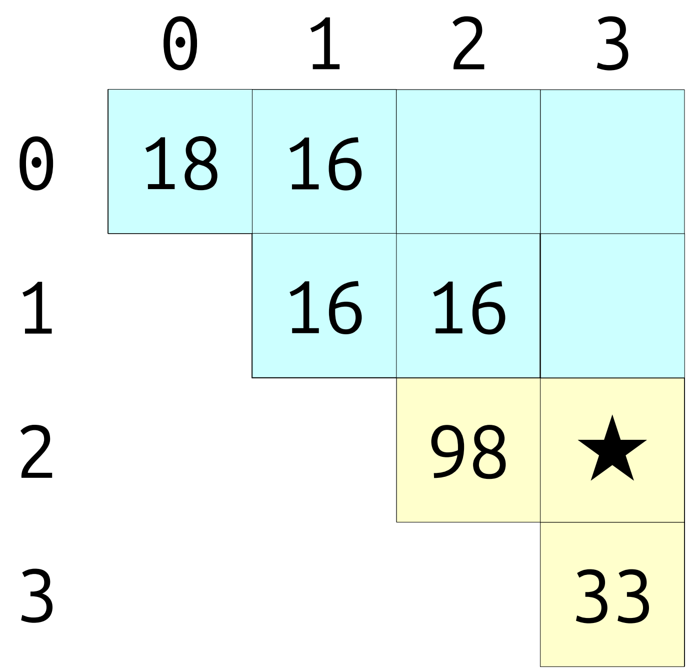

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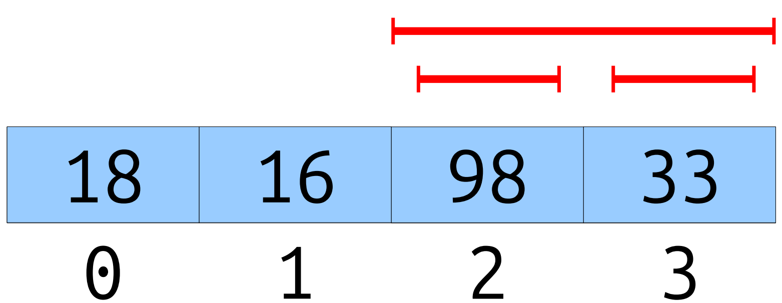

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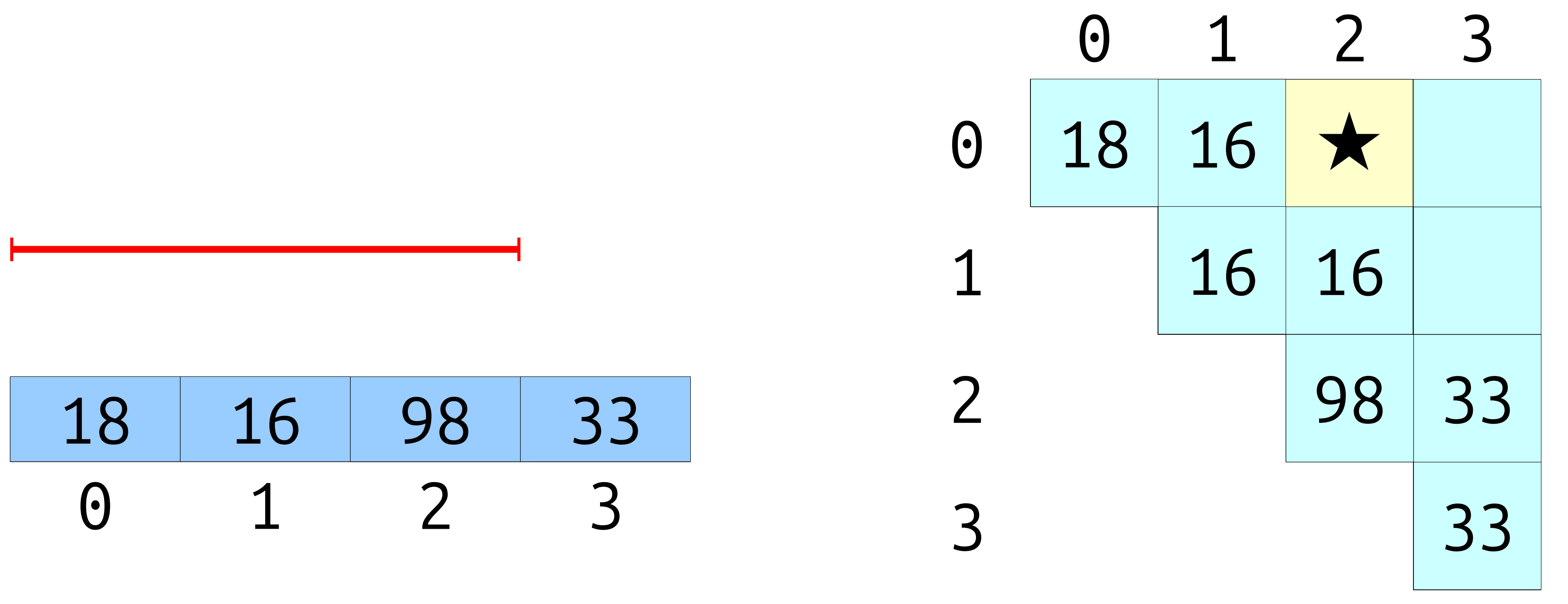

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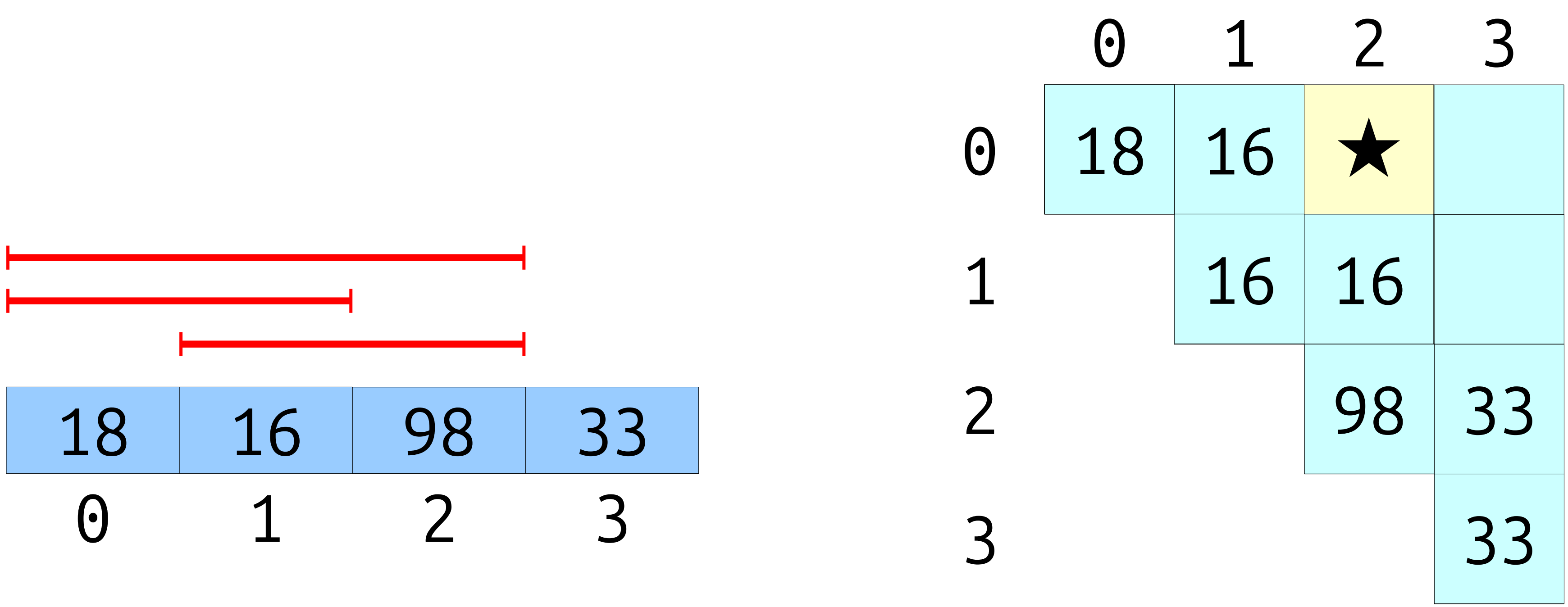

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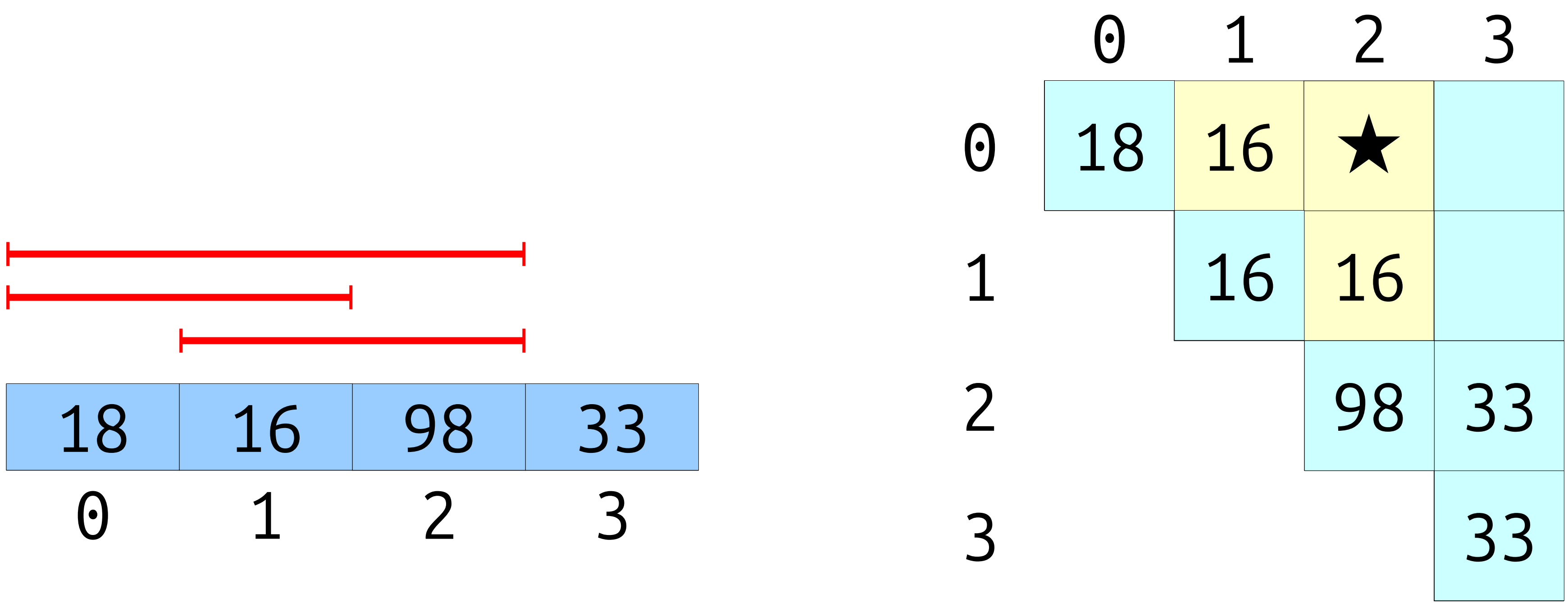

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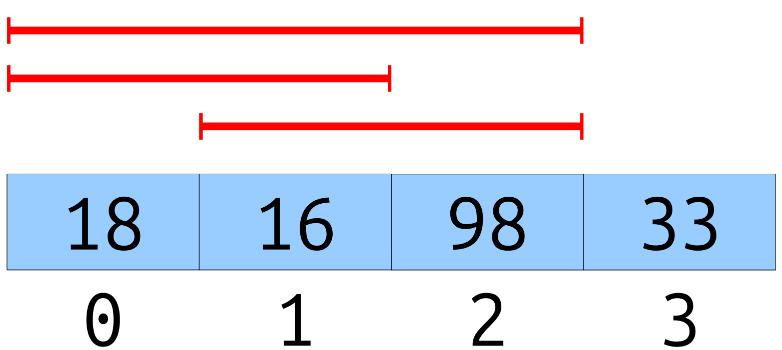

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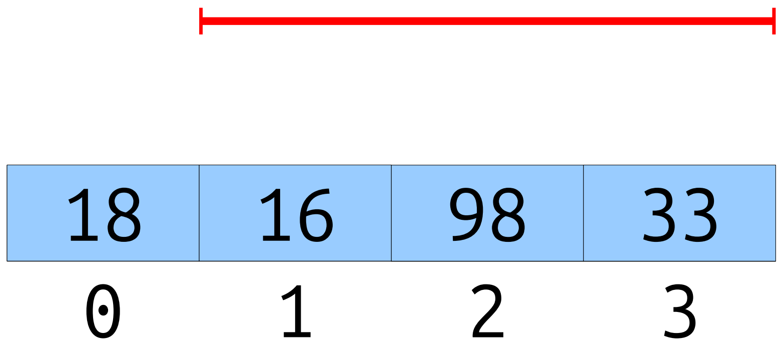

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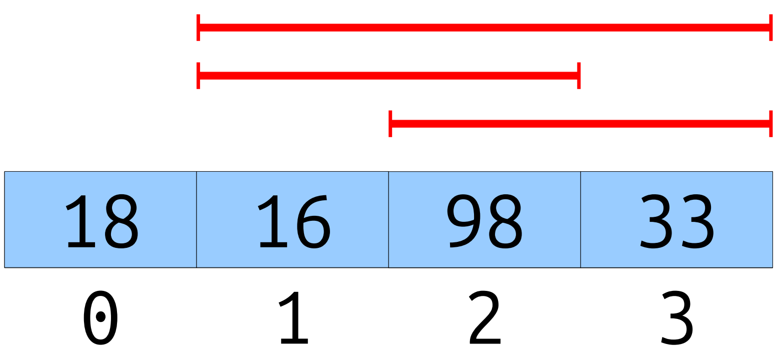

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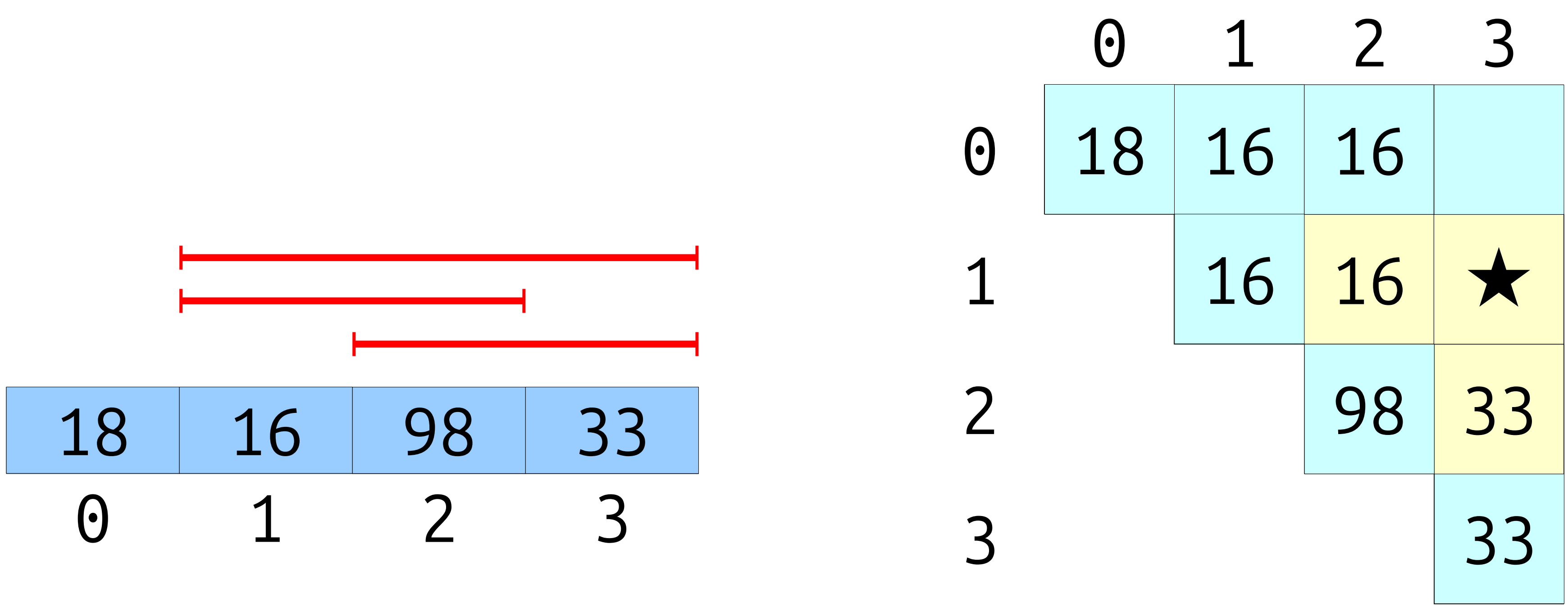

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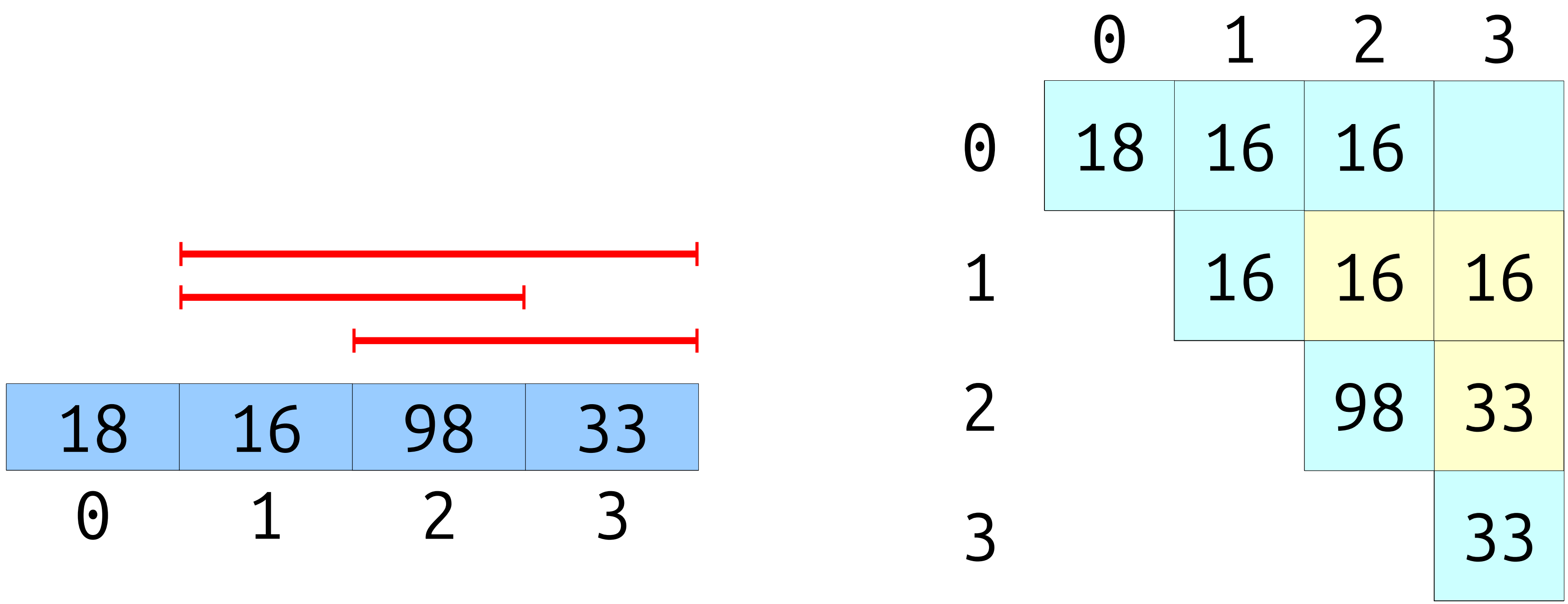

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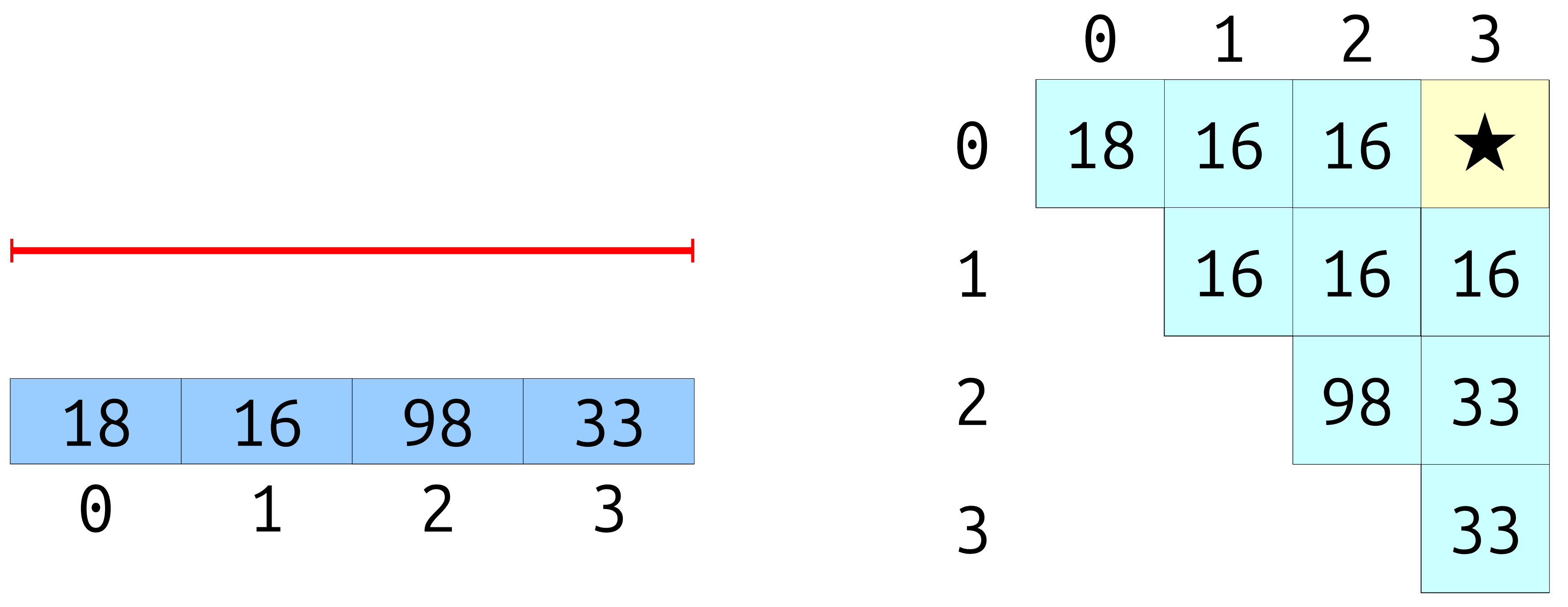

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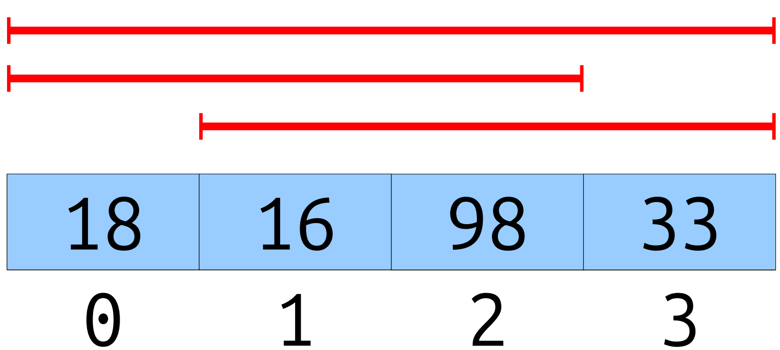

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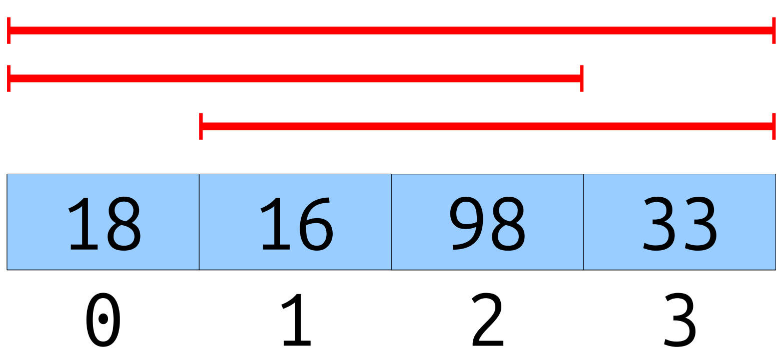

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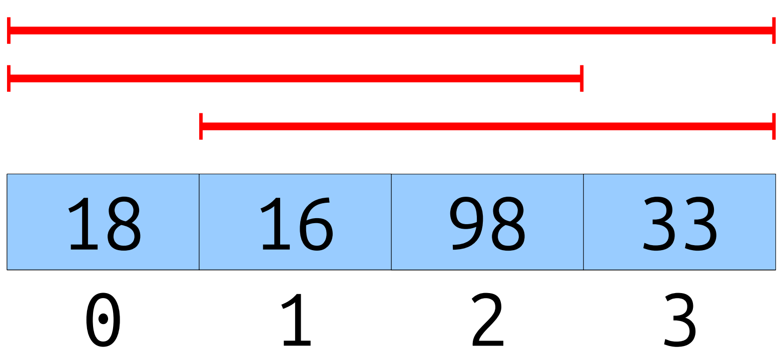

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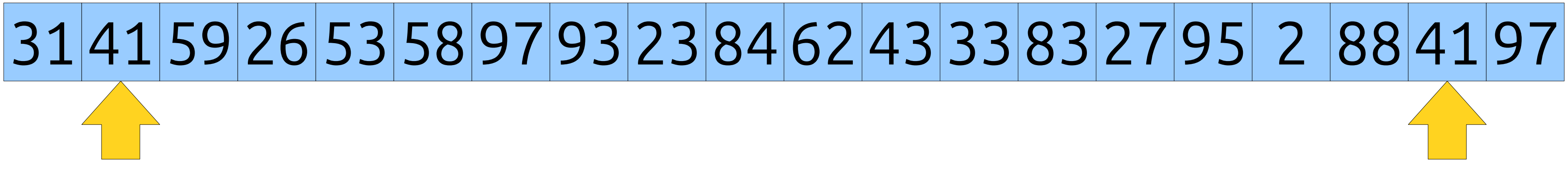
Some Notation

- We'll say that an RMQ data structure has time complexity **$\langle p(n), q(n) \rangle$** if
  - preprocessing takes time at most $p(n)$ and
  - queries take time at most $q(n)$.
- We now have two RMQ data structures:
  - $\langle O(1), O(n) \rangle$ with no preprocessing.
  - $\langle O(n^2), O(1) \rangle$ with full preprocessing.
- These are two extremes on a curve of tradeoffs: no preprocessing versus full preprocessing.
- ***Question:*** *Is there a "golden mean" between these extremes?*

Another Approach: ***Block Decomposition***

31	41	59	26	53	58	97	93	23	84	62	43	33	83	27	95	2	88	41	97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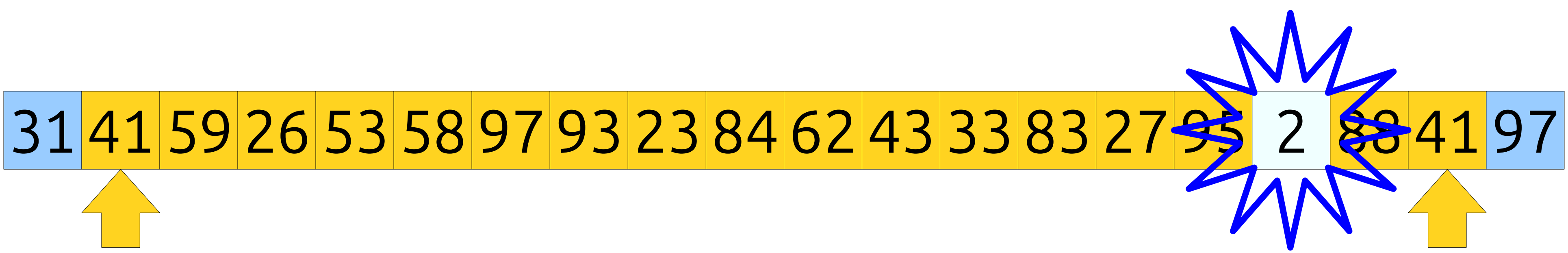
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A Block-Based Approach

- Split the input into O(n / b) blocks of some "block size" b.

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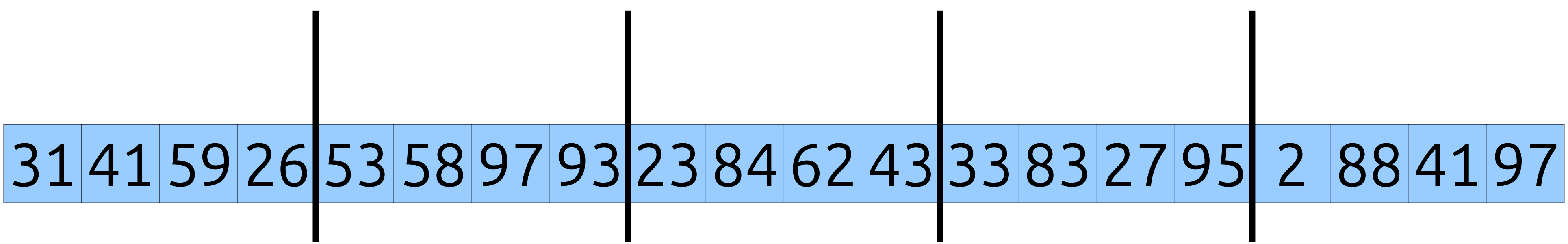

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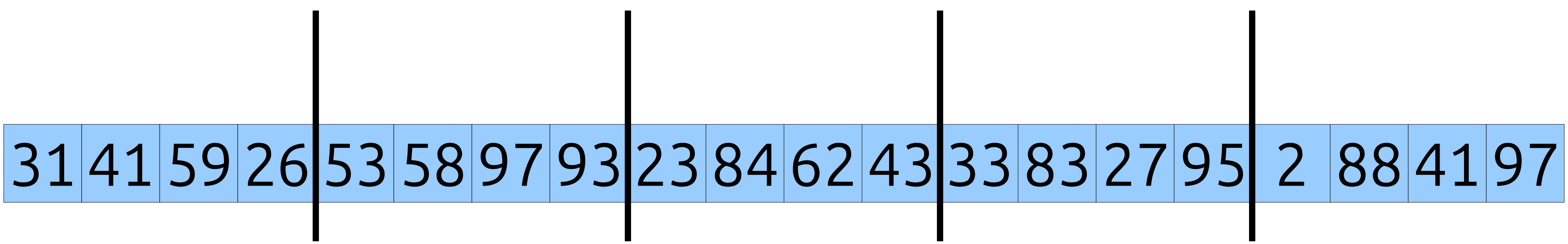
  - Here, b = 4.



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- Split the input into O(n / b) blocks of some "block size" b.
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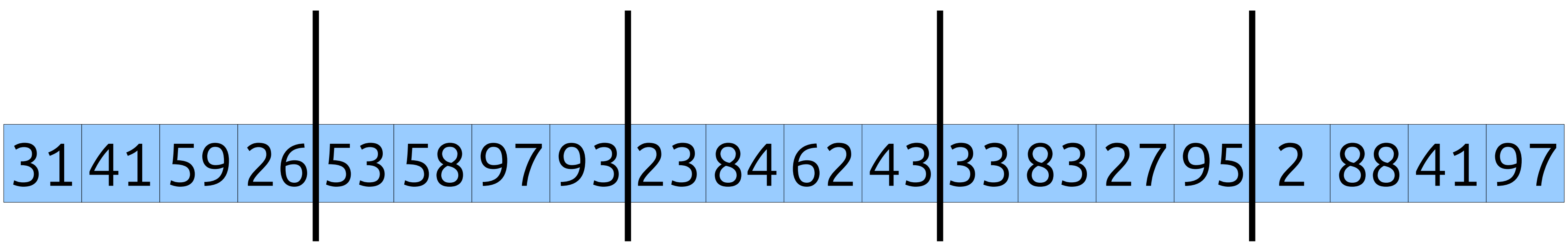

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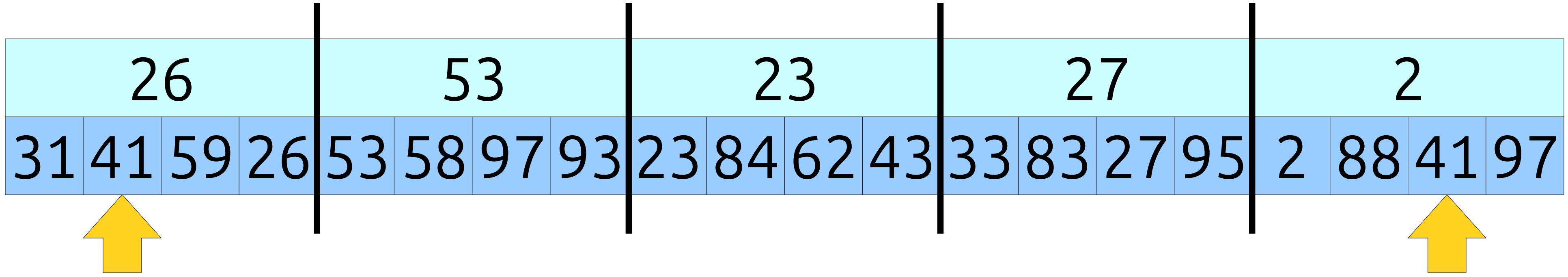

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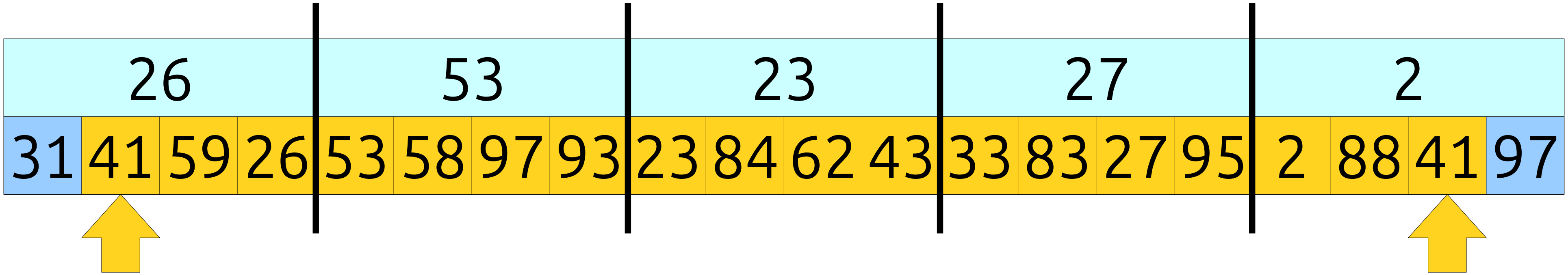

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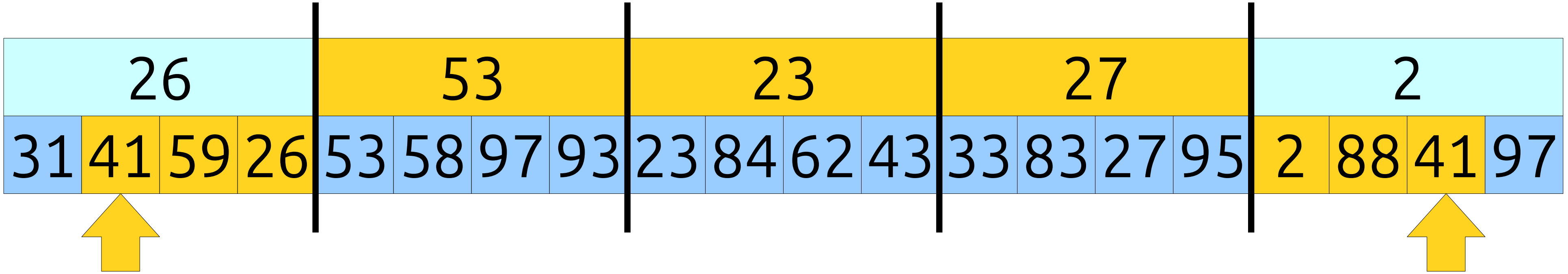

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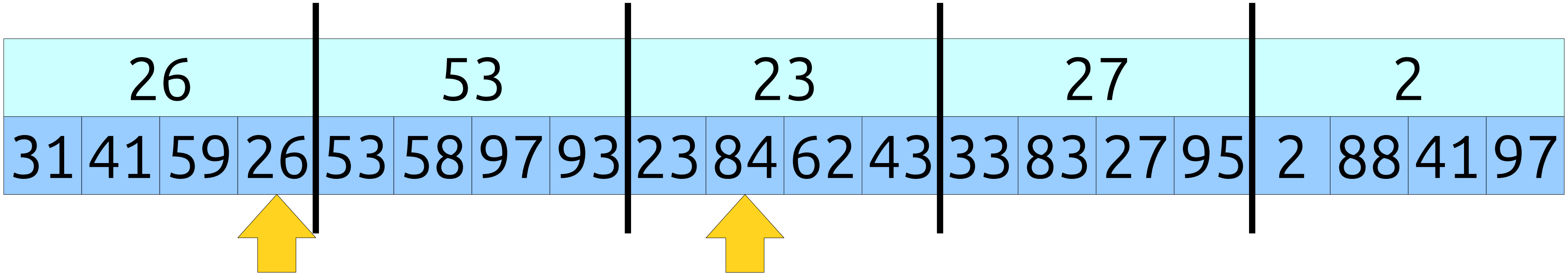
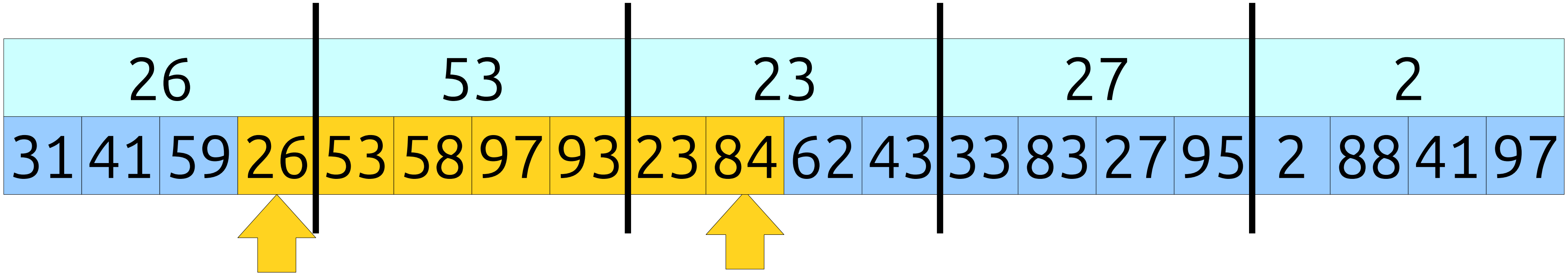


A Block-Based Approach

- Split the input into O(n / b) blocks of some "block size" b.
  - Here, b = 4.
- Compute the minimum value in each block.



A Block-Based Approach

- Split the input into $O(n / b)$ blocks of some "block size" b.
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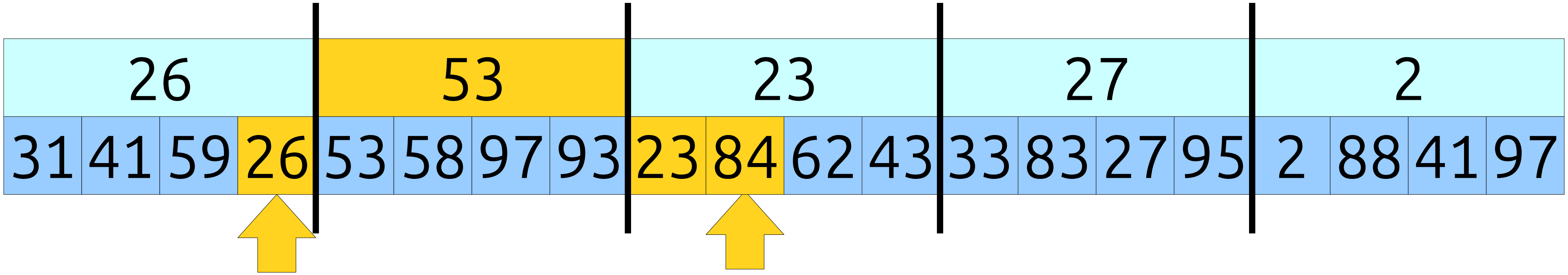


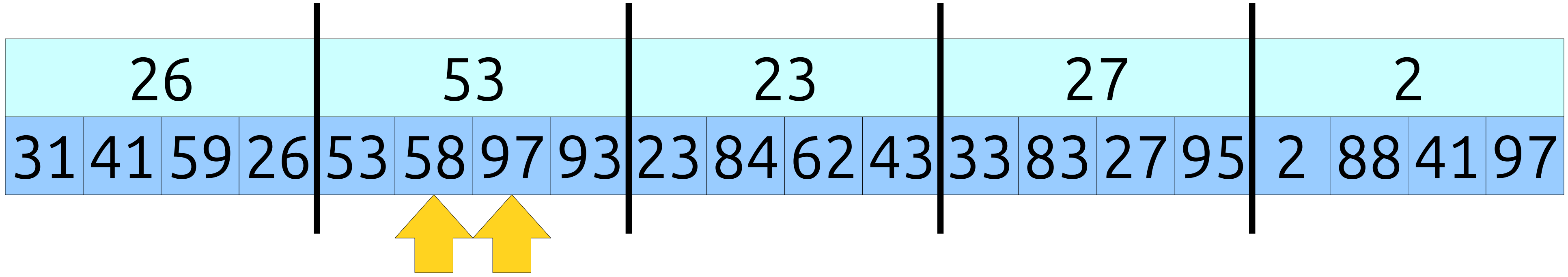
A Block-Based Approach

- Split the input into O(n / b) blocks of some "block size" b.
  - Here, b = 4.
- Compute the minimum value in each block.

26				53				23				27				2			
31	41	59	26	53	58	97	93	23	84	62	43	33	83	27	95	2	88	41	97

A Block-Based Approach

- Split the input into O(n / b) blocks of some "block size" b.
  - Here, b = 4.
- Compute the minimum value in each block.



A Block-Based Approach

- Split the input into O(n / b) blocks of some “block size” b.
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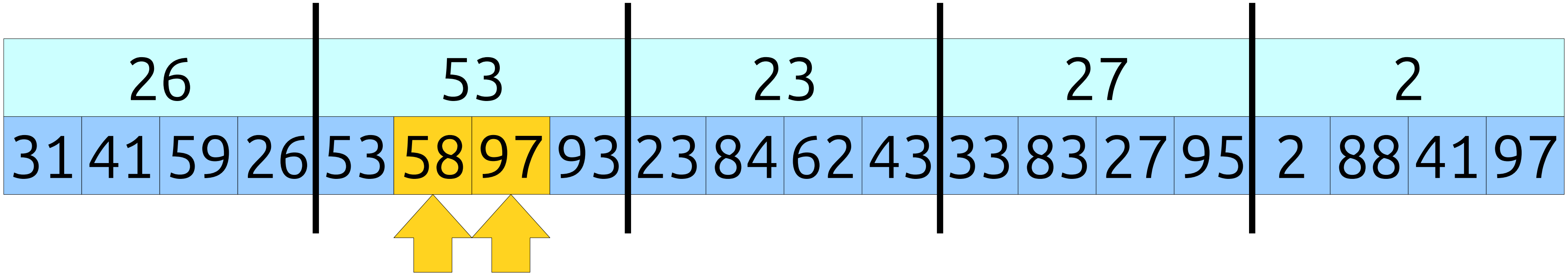
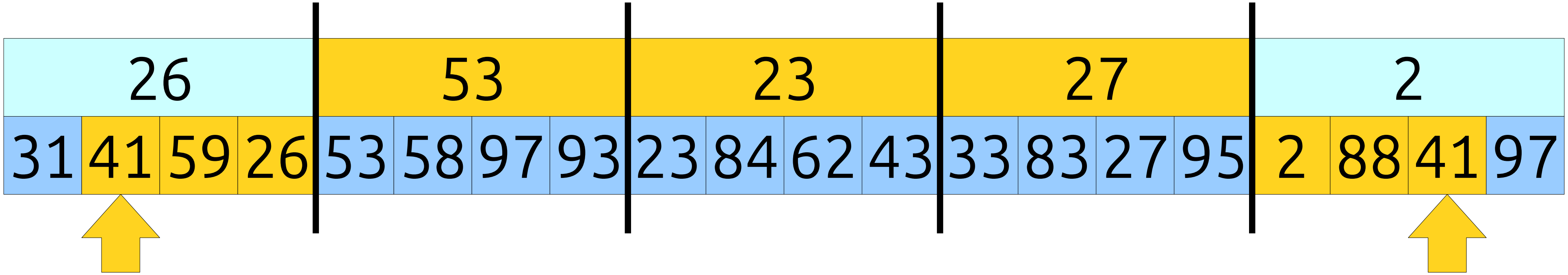


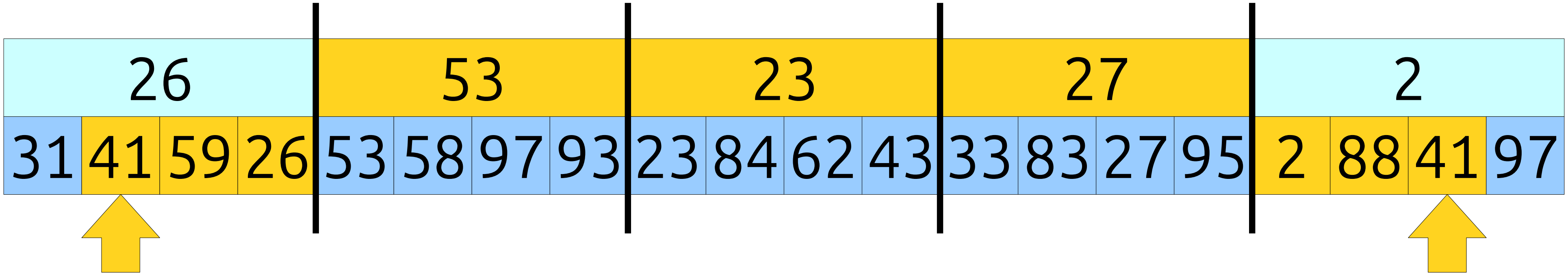
Analyzing the Approach

- Let's analyze this approach in terms of n and b.
- Preprocessing time:
  - $O(b)$ work on $O(n / b)$ blocks to find minima.
  - Total work: **$O(n)$**.
- Time to evaluate $RMQ_A(i, j)$:
  - $O(1)$ work to find block indices (divide by block size).
  - $O(b)$ work to scan inside i and j's blocks.
  - $O(n / b)$ work looking at block minima between i and j.
  - Total work: **$O(b + n / b)$**.



Intuiting O(***b*** + ***n* / *b***)

- As *b* increases:
  - The ***b*** term rises (more elements to scan within each block).
  - The ***n* / *b*** term drops (fewer blocks to look at).
- As *b* decreases:
  - The ***b*** term drops (fewer elements to scan within a block).
  - The ***n* / *b*** term rises (more blocks to look at).
- Is there an optimal choice of *b* given these constraints?



Optimizing b

- What choice of b minimizes $b + n / b$?

Formulate a hypothesis!
Discuss with your neighbors! 😃

Optimizing b

- What choice of b minimizes $b + n / b$?
- Start by taking the derivative:

Optimizing *b*

- What choice of b minimizes $b + n / b$?
- Start by taking the derivative:

$$\frac{d}{db}\left(b+n/b\right) \;=\; 1-\frac{n}{b^2}$$

Optimizing b

- What choice of b minimizes $b + n / b$?
- Start by taking the derivative:

$$\frac{d}{db}\left(b+n/b\right) = 1-\frac{n}{b^2}$$

- Setting the derivative to zero:

Optimizing b

- What choice of b minimizes $b + n / b$?
- Start by taking the derivative:

$$\frac{d}{db}\left(b+n/b\right) = 1-\frac{n}{b^2}$$

- Setting the derivative to zero:

$$1-n/b^2 = 0$$

Optimizing b

- What choice of b minimizes $b + n / b$?
- Start by taking the derivative:

$$\frac{d}{db}\left(b+n/b\right) = 1-\frac{n}{b^2}$$

- Setting the derivative to zero:

$$\begin{aligned} 1-n/b^2 &= 0 \\ 1 &= n/b^2 \end{aligned}$$

Optimizing *b*

- What choice of b minimizes $b + n / b$?
- Start by taking the derivative:

$$\frac{d}{db}\left(b+n/b\right) = 1-\frac{n}{b^2}$$

- Setting the derivative to zero:

$$\begin{aligned} 1-n/b^2 &= 0 \\ 1 &= n/b^2 \\ b^2 &= n \end{aligned}$$

Optimizing b

- What choice of b minimizes $b + n / b$?
- Start by taking the derivative:

$$\frac{d}{db}(b+n/b) = 1-\frac{n}{b^2}$$

- Setting the derivative to zero:

$$\begin{aligned} 1-n/b^2 &= 0 \\ 1 &= n/b^2 \\ b^2 &= n \\ b &= \sqrt{n} \end{aligned}$$

Optimizing b

- What choice of b minimizes $b + n / b$?
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- Asymptotically optimal runtime is when $b = n^{1/2}$.

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- Asymptotically optimal runtime is when $b = n^{1/2}$.
- In that case, the runtime is

  $O(b + n / b)$

Optimizing b

- What choice of b minimizes $b + n / b$?
- Start by taking the derivative:

$$\frac{d}{db}\left(b+n/b\right) = 1-\frac{n}{b^2}$$

- Setting the derivative to zero:

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- Asymptotically optimal runtime is when $b = n^{1/2}$.
- In that case, the runtime is

  $O(b + n / b) = O(n^{1/2} + n / n^{1/2})$

Optimizing b

- What choice of b minimizes $b + n / b$?
- Start by taking the derivative:

$$\frac{d}{db}\left(b + n/b\right) = 1 - \frac{n}{b^2}$$

- Setting the derivative to zero:

$$\begin{aligned} 1 - n/b^2 &= 0 \\ 1 &= n/b^2 \\ b^2 &= n \\ b &= \sqrt{n} \end{aligned}$$

- Asymptotically optimal runtime is when $b = n^{1/2}$.
- In that case, the runtime is

  $O(b + n / b) = O(n^{1/2} + n / n^{1/2}) = O(n^{1/2} + n^{1/2})$

Optimizing b

- What choice of b minimizes $b + n / b$?
- Start by taking the derivative:

$$\frac{d}{db}(b+n/b) = 1-\frac{n}{b^2}$$

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- Asymptotically optimal runtime is when $b = n^{1/2}$.
- In that case, the runtime is

  $O(b + n / b) = O(n^{1/2} + n / n^{1/2}) = O(n^{1/2} + n^{1/2}) = \mathbf{O(n^{1/2})}$

Summary of Approaches

- Three solutions so far:
  - Full preprocessing: $\langle O(n^2), \ O(1) \rangle$.
  - Block partition: $\langle O(n), \ O(n^{1/2}) \rangle$.
  - No preprocessing: $\langle O(1), \ O(n) \rangle$.
- Modest preprocessing yields modest performance increases.
- ***Question:*** Can we do better?

A Second Approach: ***Sparse Tables***

An Intuition

- The $\langle O(n^2), O(1) \rangle$ solution gives fast queries because every range we might look up has already been precomputed.
- The preprocessing time is slow because we have to compute the minimum of each range.
- ***Question:*** Can we still get constant-time queries without preprocessing all possible ranges?

An Observation

31	41	59	26	53	58	97	93
0	1	2	3	4	5	6	7

	0	1	2	3	4	5	6	7
0	31	31	31	26	26	26	26	26
1		41	41	26	26	26	26	26
2			59	26	26	26	26	26
3				26	26	26	26	26
4					53	53	53	53
5						58	58	58
6							97	93
7								93

An Observation

0	1	2	3	4	5	6	7
31	41	59	26	53	58	97	93

	0	1	2	3	4	5	6	7
0	31	31	31	26	26	26	26	26
1		41	41	26	26	26	26	26
2			59	26	26	26	26	26
3				26	26	26	26	26
4					53	53	53	53
5						58	58	58
6							97	93
7								93

An Observation

31	41	59	26	53	58	97	93
0	1	2	3	4	5	6	7

	0	1	2	3	4	5	6	7
0	31	31	31	26				
1		41	41	26	26			
2			59	26	26	26		
3				26	26	26	26	
4					53	53	53	53
5						58	58	58
6							97	93
7								93

An Observation

31	41	59	26	53	58	97	93
0	1	2	3	4	5	6	7

	0	1	2	3	4	5	6	7
0	31	31	31	26				
1		41	41	26	26			
2			59	26	26	26		
3				26	26	26	26	
4					53	53	53	53
5						58	58	58
6							97	93
7								93

An Observation

31	41	59	26	53	58	97	93
0	1	2	3	4	5	6	7

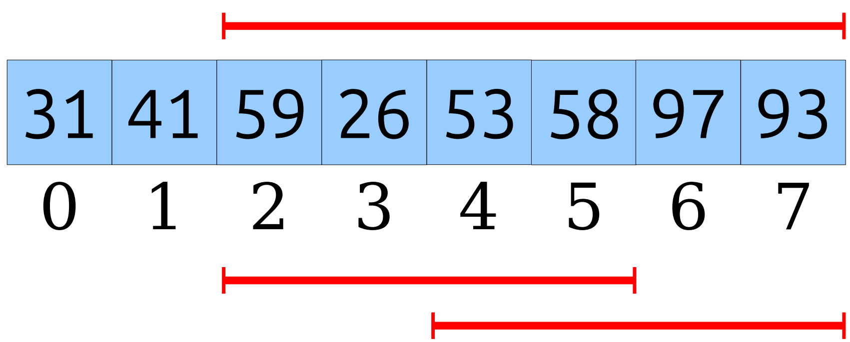
	0	1	2	3	4	5	6	7
0	31	31	31	26				
1		41	41	26	26			
2			59	26	26	26		
3				26	26	26	26	
4					53	53	53	53
5						58	58	58
6							97	93
7								93

An Observation

31	41	59	26	53	58	97	93
0	1	2	3	4	5	6	7

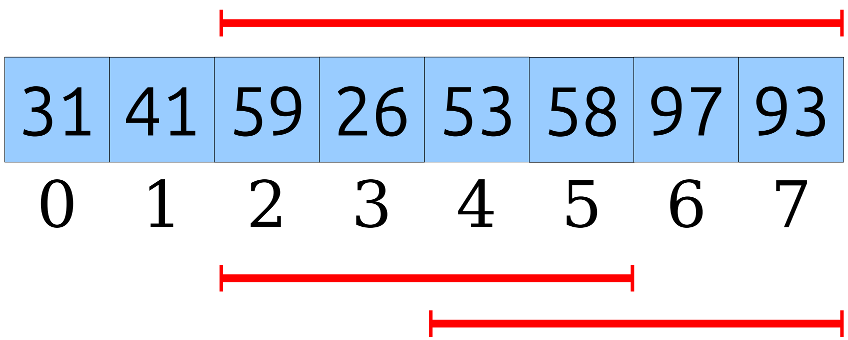
	0	1	2	3	4	5	6	7
0	31	31	31	26				
1		41	41	26	26			
2			59	26	26	26		★
3				26	26	26	26	
4					53	53	53	53
5						58	58	58
6							97	93
7								93

An Observation



	0	1	2	3	4	5	6	7
0	31	31	31	26				
1		41	41	26	26			
2			59	26	26	26		★
3				26	26	26	26	
4					53	53	53	53
5						58	58	58
6							97	93
7								93

An Observation



	0	1	2	3	4	5	6	7
0	31	31	31	26				
1		41	41	26	26			
2			59	26	26	26		★
3				26	26	26	26	
4					53	53	53	53
5						58	58	58
6							97	93
7								93

An Observation

31	41	59	26	53	58	97	93
0	1	2	3	4	5	6	7

	0	1	2	3	4	5	6	7
0	31	31	31	26				
1		41	41	26	26			
2			59	26	26	26		
3				26	26	26	26	
4					53	53	53	53
5						58	58	58
6							97	93
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31	41	59	26	53	58	97	93
0	1	2	3	4	5	6	7

	0	1	2	3	4	5	6	7
0	31	31	31	26				
1		41	41	26	26			
2			59	26	26	26		
3				26	26	26	26	
4					53	53	53	53
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An Observation

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0	1	2	3	4	5	6	7

	0	1	2	3	4	5	6	7
0	31	31	31	26				★
1		41	41	26	26			
2			59	26	26	26		
3				26	26	26	26	
4					53	53	53	53
5						58	58	58
6							97	93
7								93

An Observation

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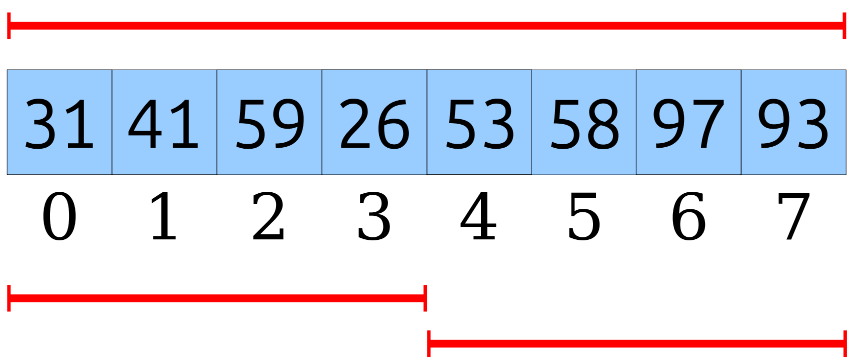
0	1	2	3	4	5	6	7

	0	1	2	3	4	5	6	7
0	31	31	31	26				★
1		41	41	26	26			
2			59	26	26	26		
3				26	26	26	26	
4					53	53	53	53
5						58	58	58
6							97	93
7								93

An Observation



	0	1	2	3	4	5	6	7
0	31	31	31	26				★
1		41	41	26	26			
2			59	26	26	26		
3				26	26	26	26	
4					53	53	53	53
5						58	58	58
6							97	93
7								93

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0	1	2	3	4	5	6	7

	0	1	2	3	4	5	6	7
0	31	31	31	26				
1		41	41	26	26			
2			59	26	26	26		
3				26	26	26	26	
4					53	53	53	53
5						58	58	58
6							97	93
7								93

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	0	1	2	3	4	5	6	7
0	31	31	31	26				
1		41	41	26	26			
2			59	26	26	26		
3				26	26	26	26	
4					53	53	53	53
5						58	58	58
6							97	93
7								93

An Observation

0	1	2	3	4	5	6	7
31	41	59	26	53	58	97	93

	0	1	2	3	4	5	6	7
0	31	31	31					
1		41	41	26				
2			59	26	26			
3				26	26	26		
4					53	53	53	
5						58	58	58
6							97	93
7								93

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0	1	2	3	4	5	6	7

	0	1	2	3	4	5	6	7
0	31	31	31					
1		41	41	26				
2			59	26	26			
3				26	26	26		
4					53	53	53	
5						58	58	58
6							97	93
7								93

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0	1	2	3	4	5	6	7

	0	1	2	3	4	5	6	7
0	31	31	31					
1		41	41	26				
2			59	26	26			
3				26	26	26		
4					53	53	53	
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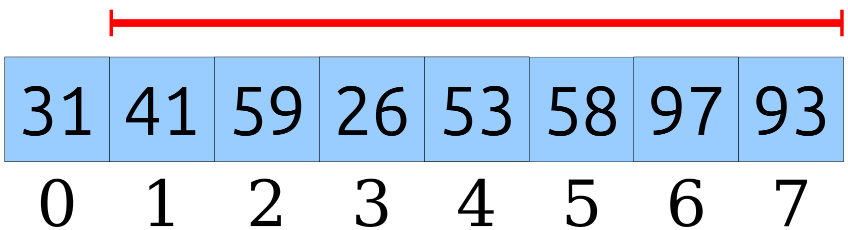
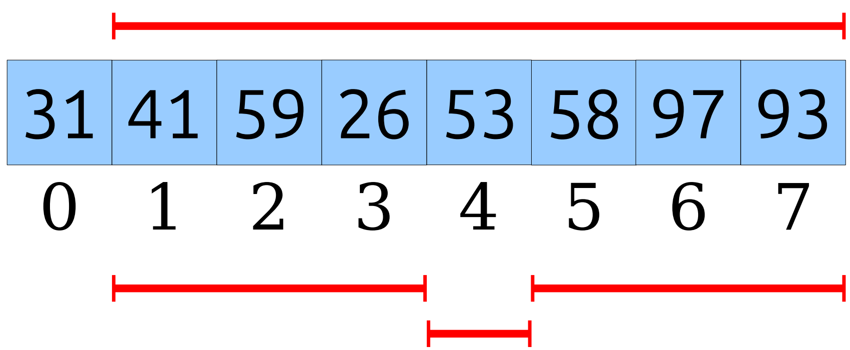
7								93

An Observation



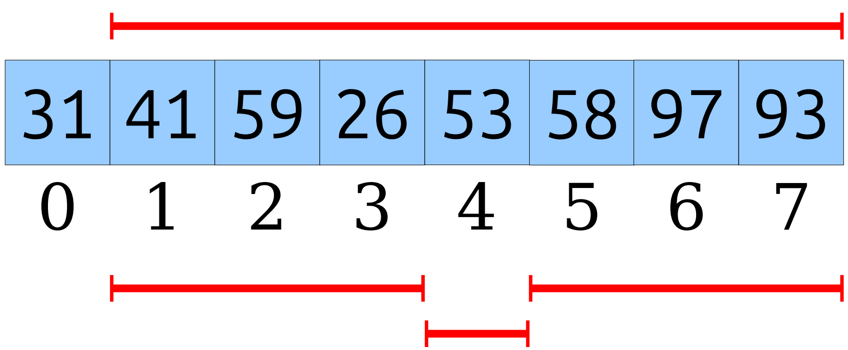
	0	1	2	3	4	5	6	7
0	31	31	31					
1		41	41	26				★
2			59	26	26			
3				26	26	26		
4					53	53	53	
5						58	58	58
6							97	93
7								93

An Observation



	0	1	2	3	4	5	6	7
0	31	31	31					
1		41	41	26				★
2			59	26	26			
3				26	26	26		
4					53	53	53	
5						58	58	58
6							97	93
7								93

An Observation



	0	1	2	3	4	5	6	7
0	31	31	31					
1		41	41	26				★
2			59	26	26			
3				26	26	26		
4					53	53	53	
5						58	58	58
6							97	93
7								93

An Observation

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	0	1	2	3	4	5	6	7
0	31	31	31					
1		41	41	26				
2			59	26	26			
3				26	26	26		
4					53	53	53	
5						58	58	58
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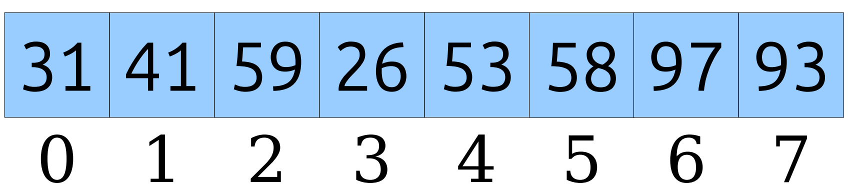
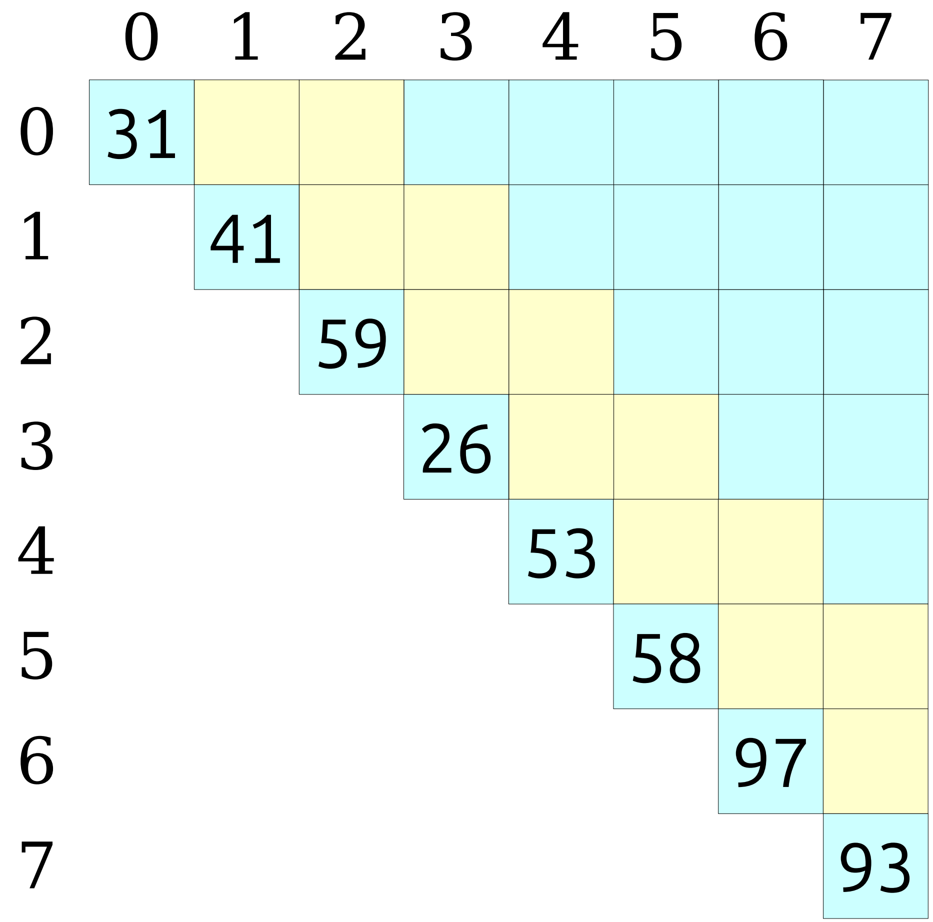
	0	1	2	3	4	5	6	7
0	31	31	31					
1		41	41	26				
2			59	26	26			
3				26	26	26		
4					53	53	53	
5						58	58	58
6							97	93
7								93

An Observation



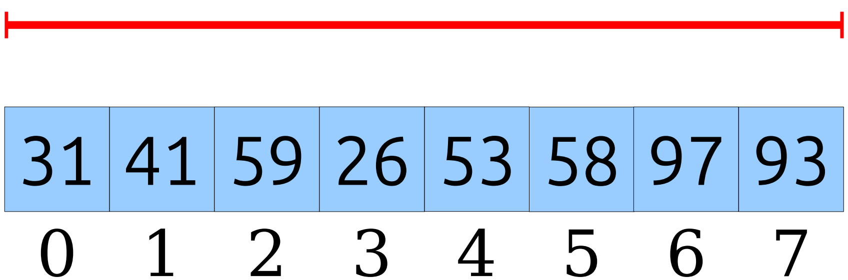


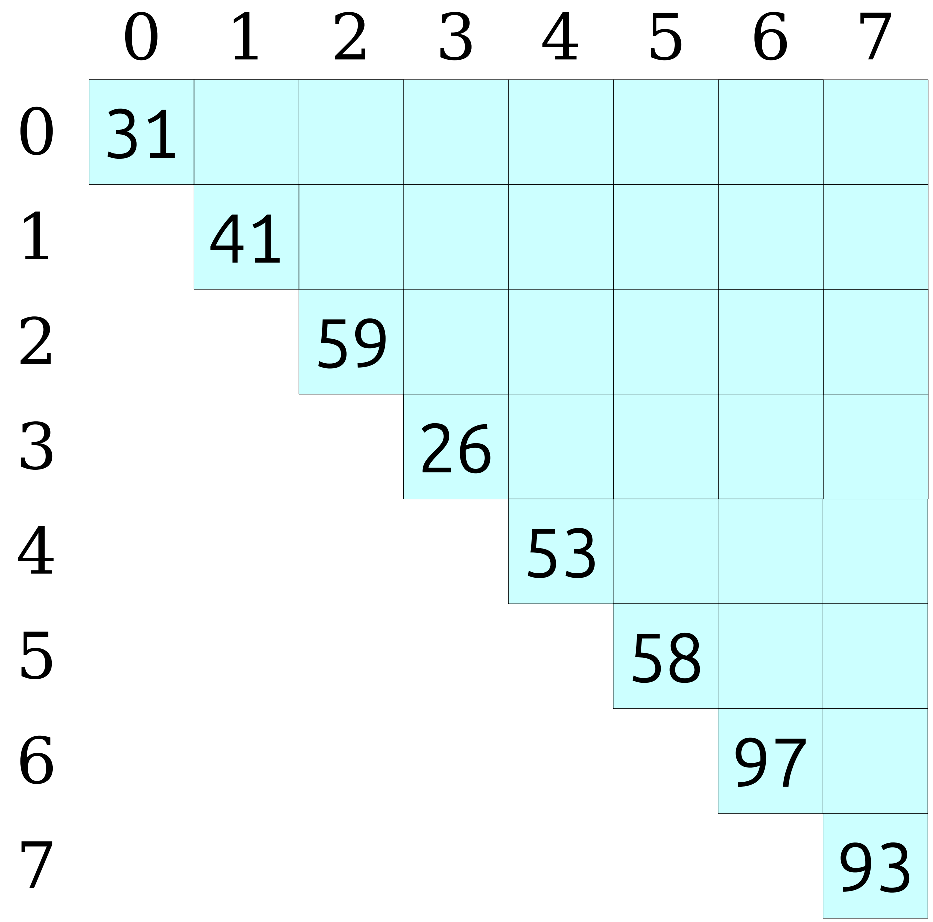
An Observation

31	41	59	26	53	58	97	93
0	1	2	3	4	5	6	7

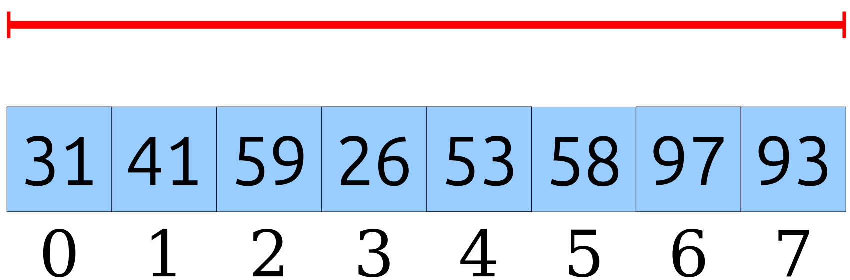
	0	1	2	3	4	5	6	7
0	31							
1		41						
2			59					
3				26				
4					53			
5						58		
6							97	
7								93

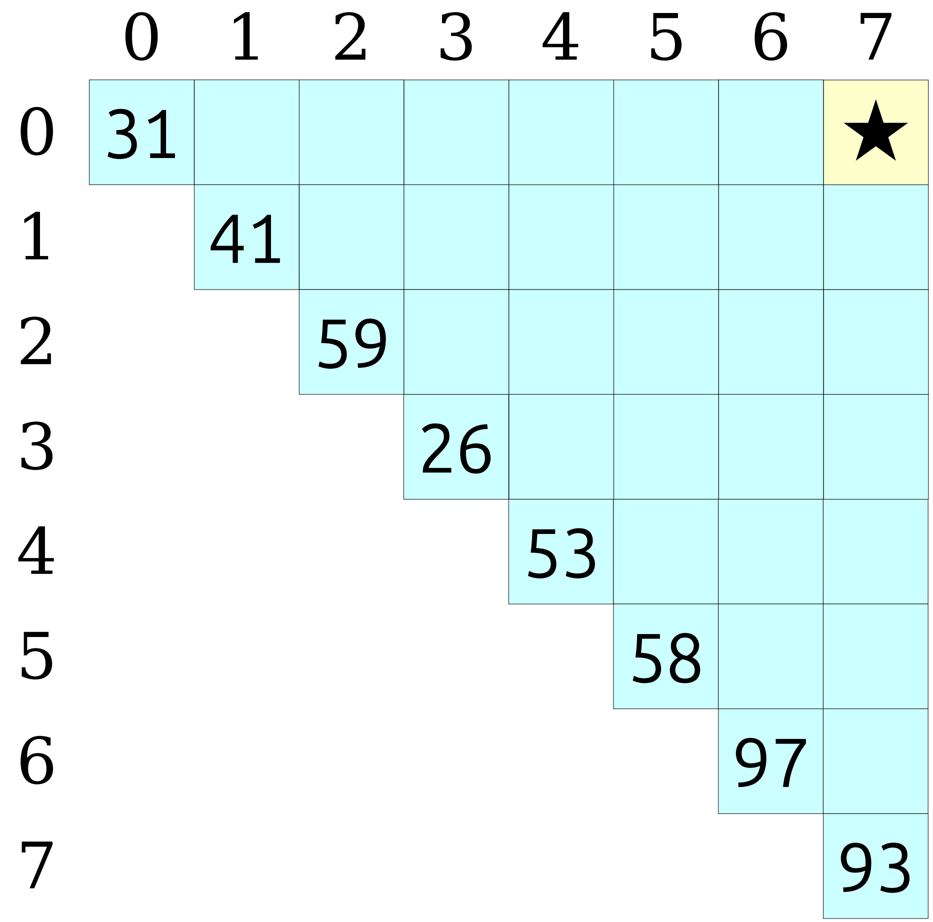
An Observation



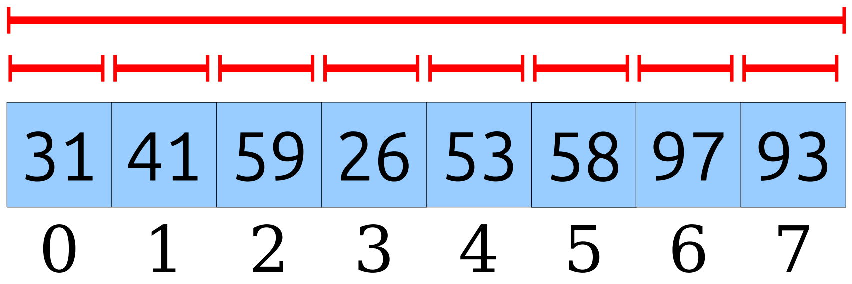


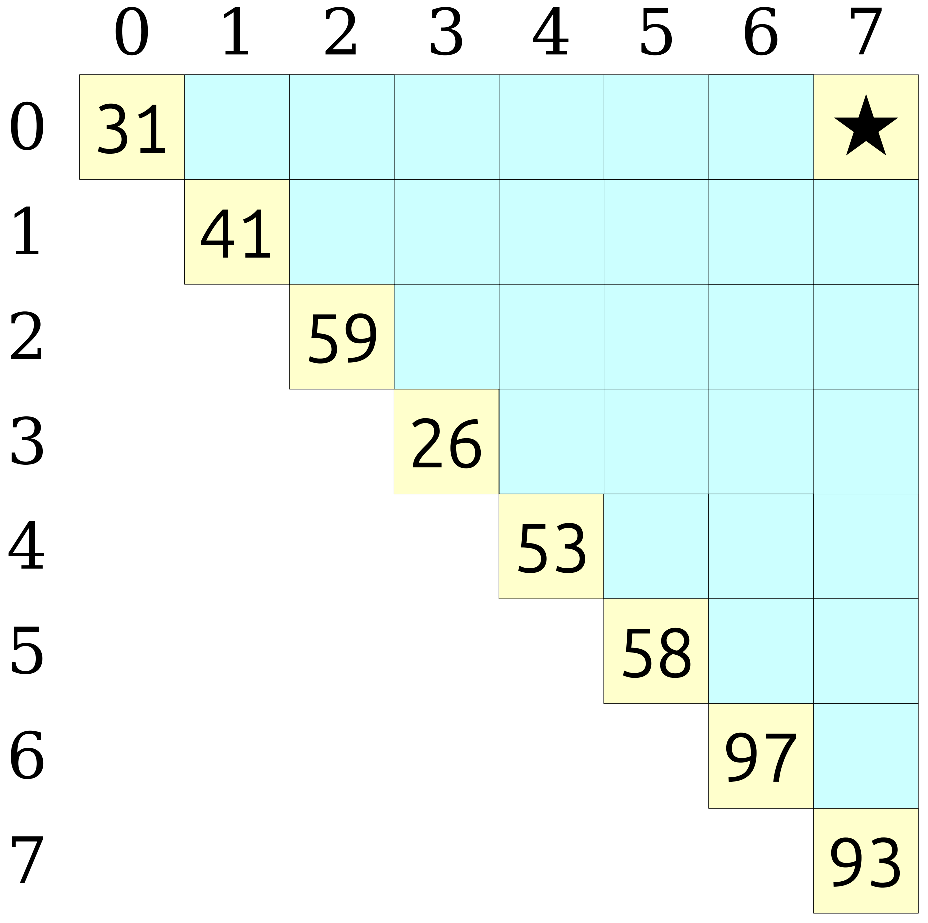
An Observation





An Observation

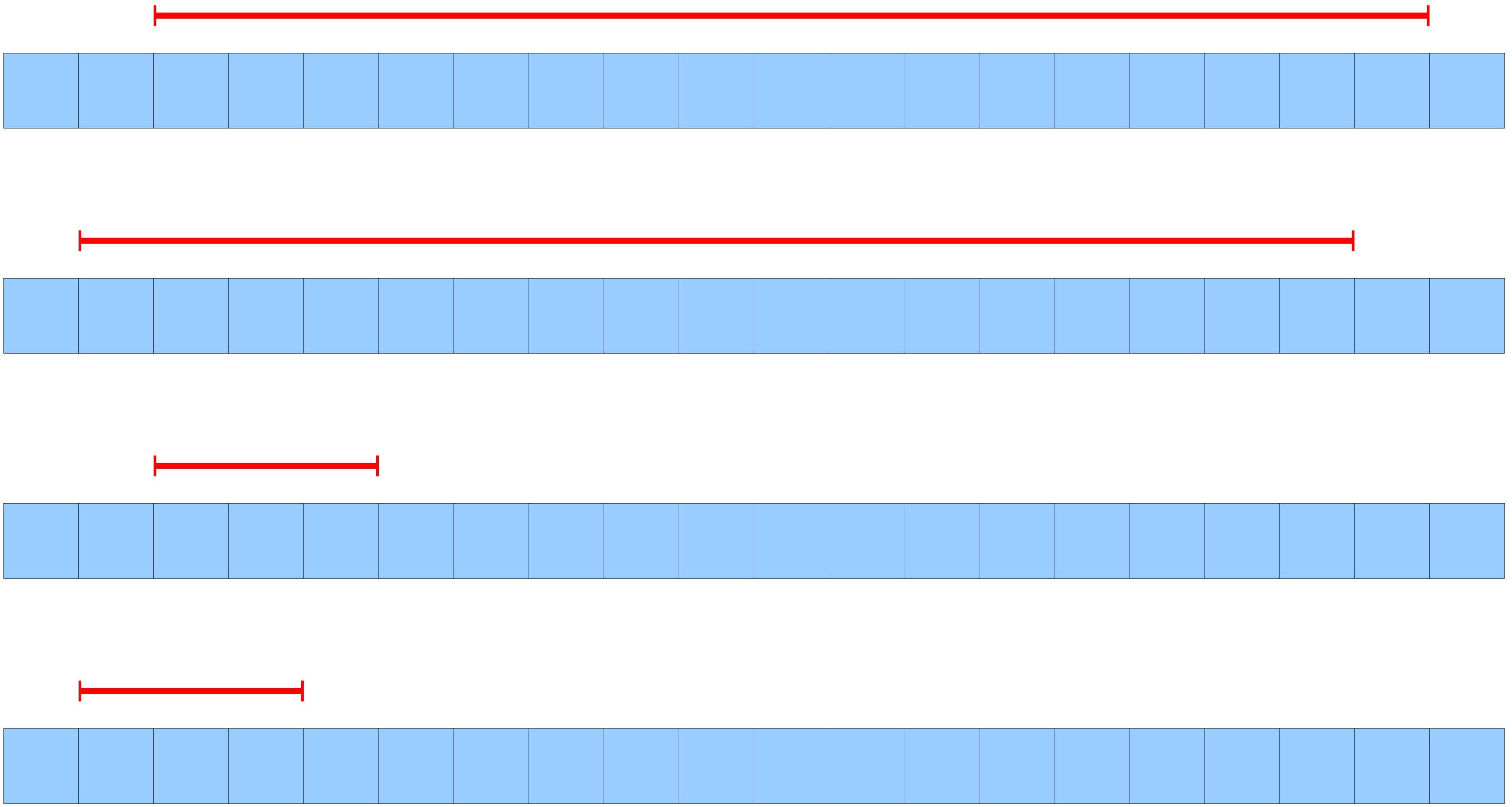




The Intuition

- It's still possible to answer any query in time O(1) without precomputing RMQ over all ranges.
- If we precompute the answers over too many ranges, the preprocessing time will be too large.
- If we precompute the answers over too few ranges, the query time won't be O(1).
- ***Goal:*** Precompute RMQ over a set of ranges where
    - there are $o(n^2)$ total ranges, but
    - there are enough ranges to support O(1) query times.

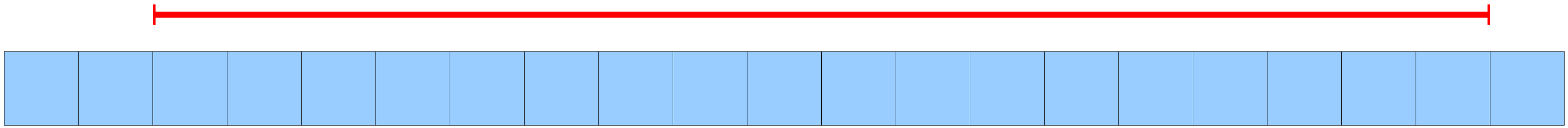
Some Observations



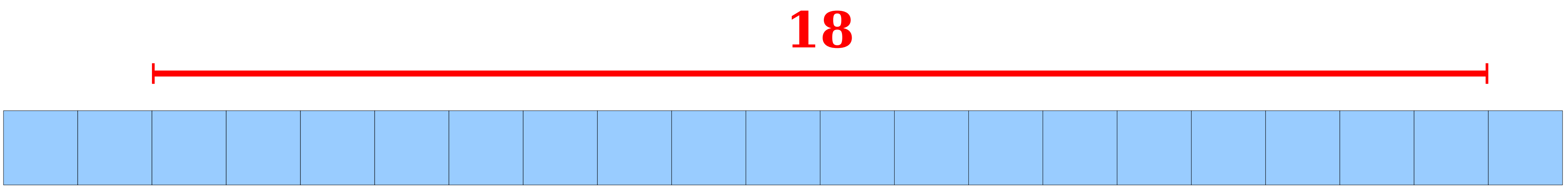
The Approach

- For each index i, compute RMQ for ranges starting at i of size 1, 2, 4, 8, 16, …, 2^k as long as they fit in the array.
  - This gives large and small ranges starting at any point in the array.
  - We only compute O(log n) ranges for each array element.
  - Total number of ranges: O(n log n).
- ***Claim:*** Any range in the array can be formed as the union of two of these ranges.

Creating Ranges



Creating Ranges



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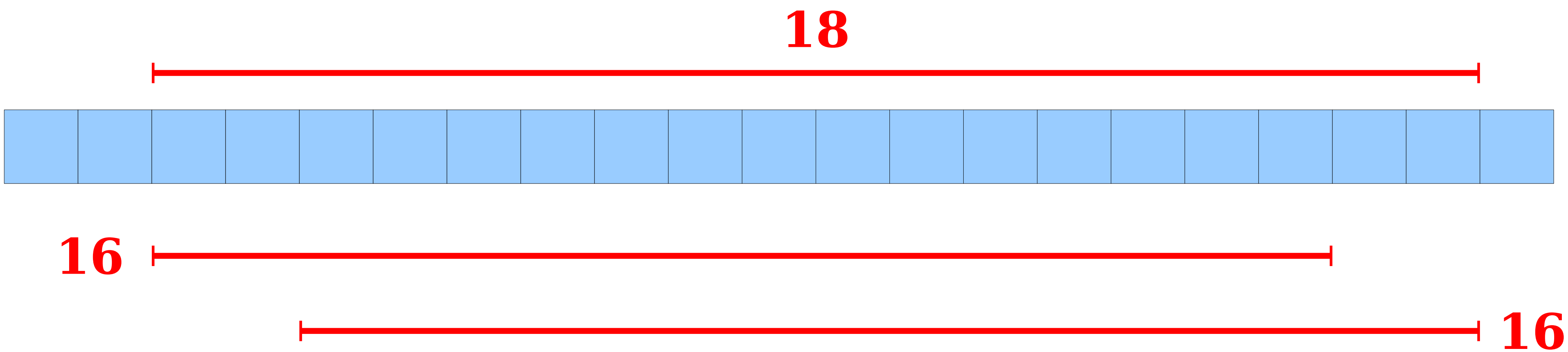

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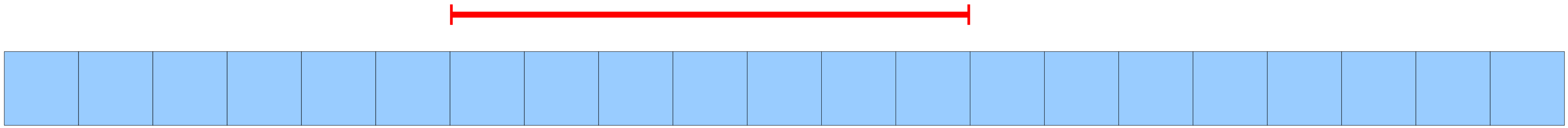

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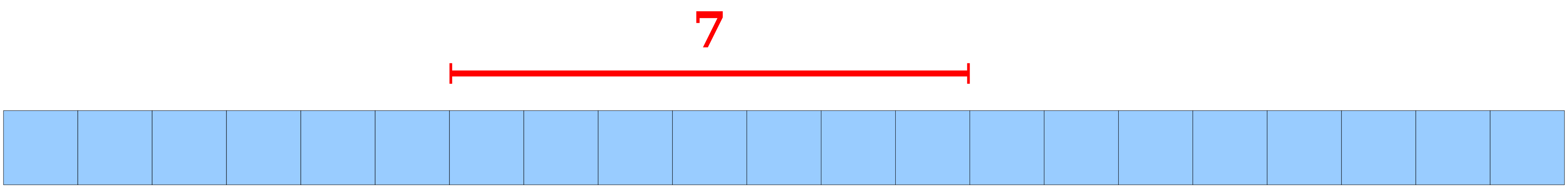

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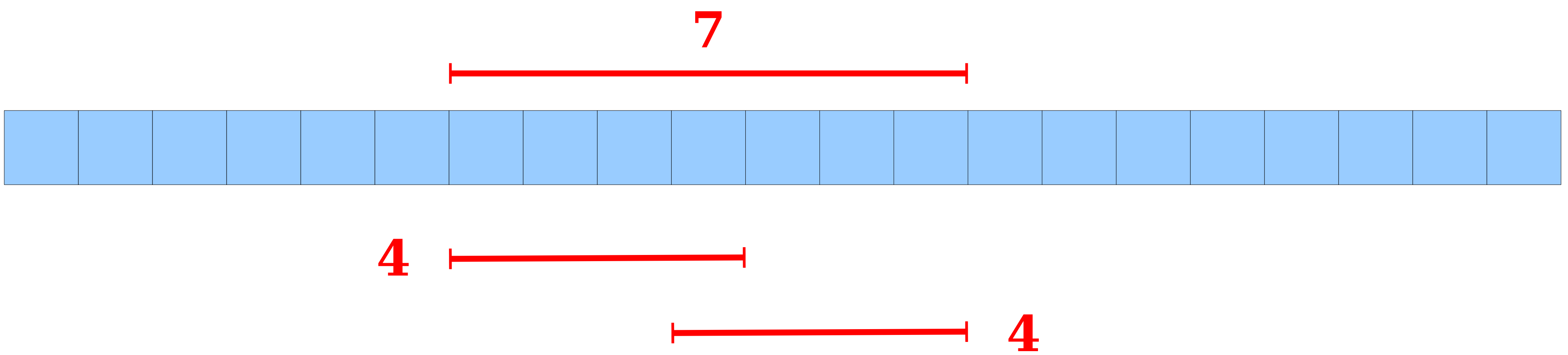

Doing a Query

- To answer $RMQ_A(i, j)$:
  - Find the largest k such that $2^k \leq j - i + 1$.
    - With the right preprocessing, this can be done in time O(1); you'll figure out how in an upcoming assignment. 😃
  - The range $[i, j]$ can be formed as the (overlapping) union of ranges $[i, i + 2^k - 1]$ and $[j - 2^k + 1, j]$.
  - The minimum value in each range can be looked up in time O(1).
  - Total time: **O(1)**.

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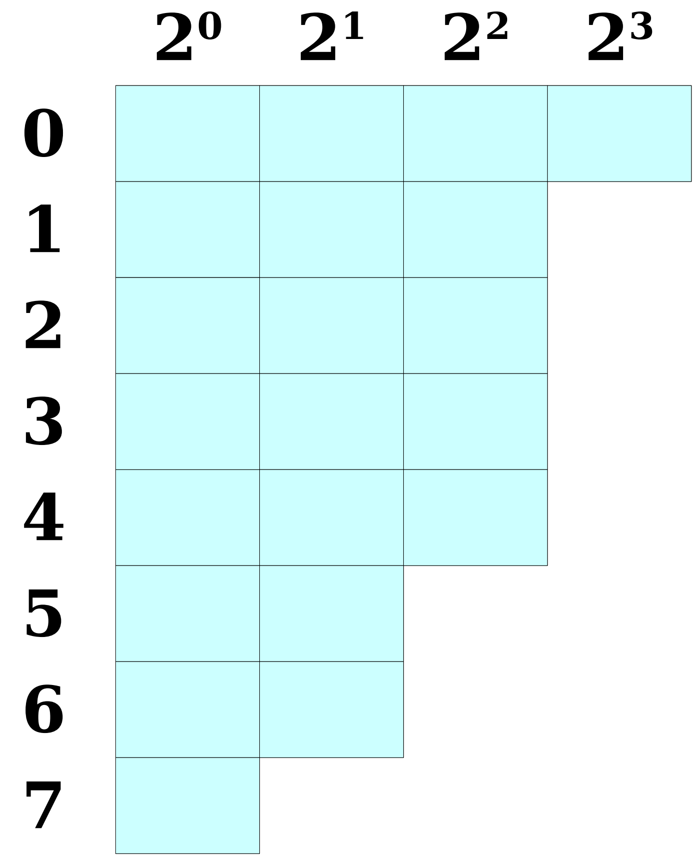
- There are O(n log n) ranges to precompute.
- Using dynamic programming, we can compute all of them in time O(n log n).



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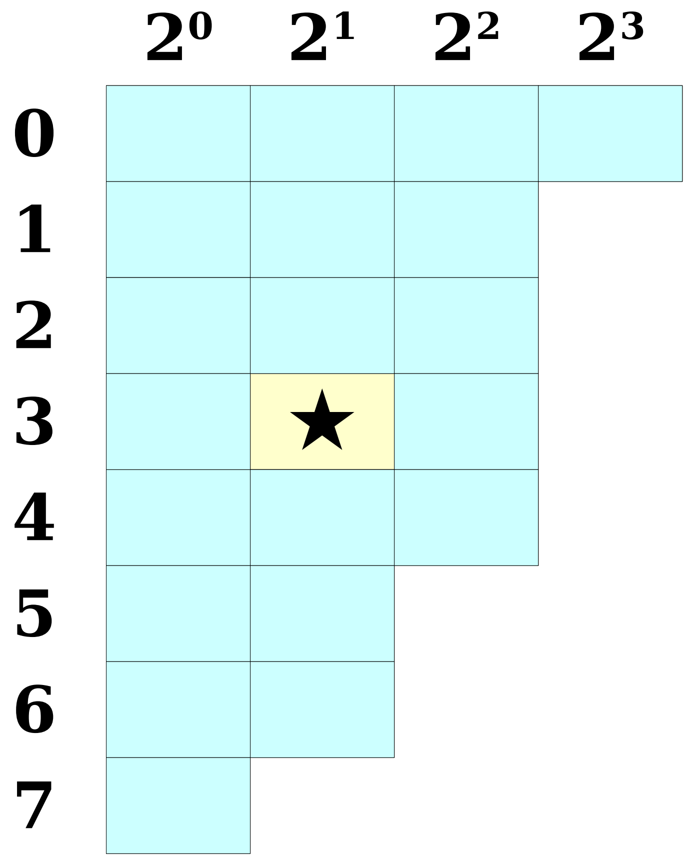

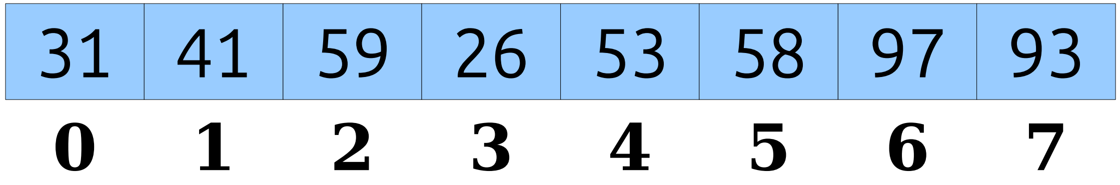

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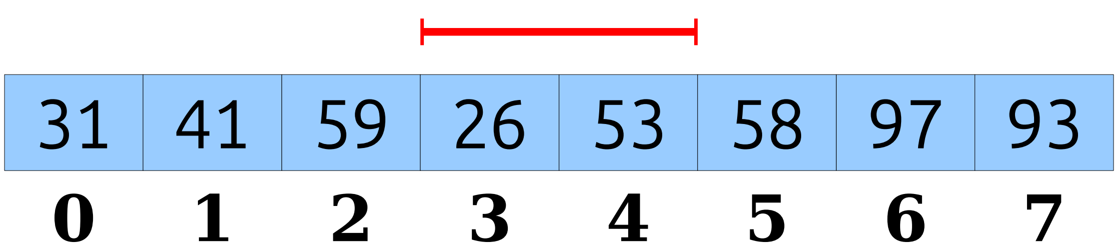

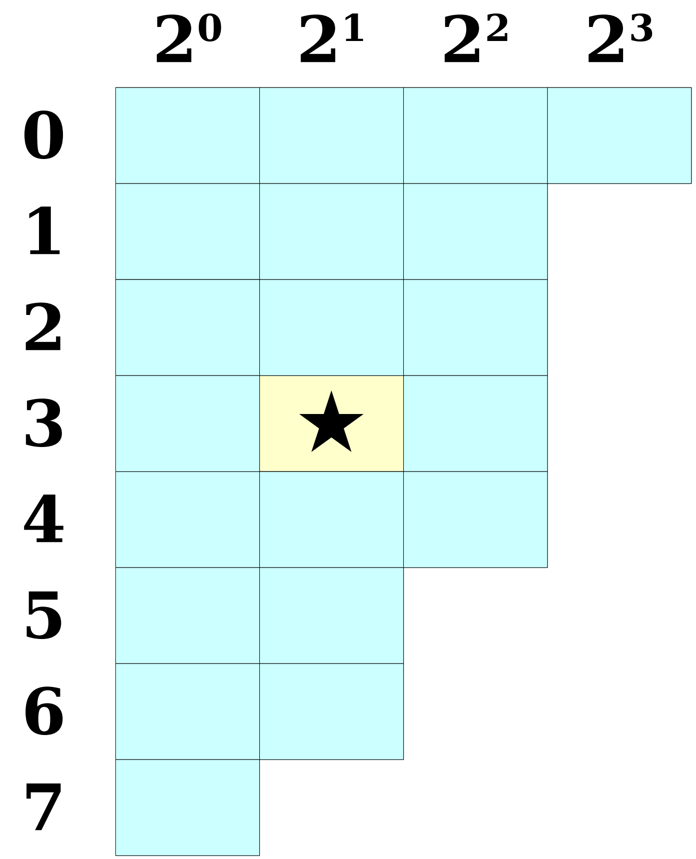

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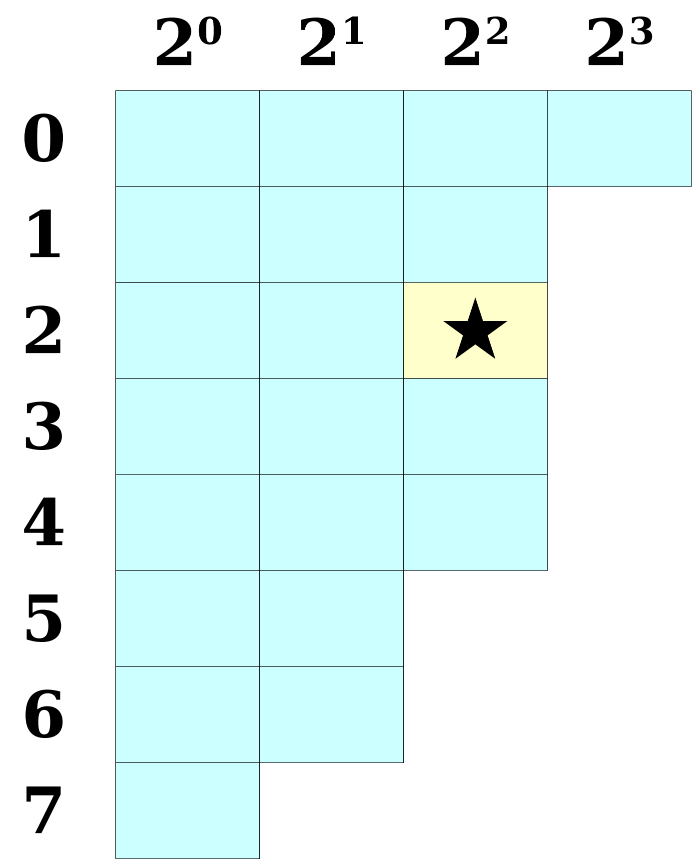

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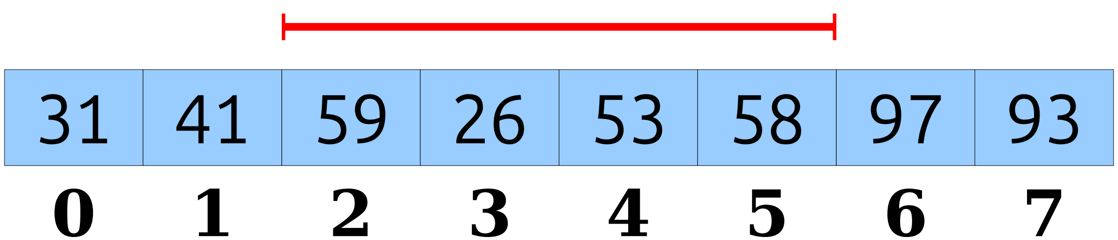

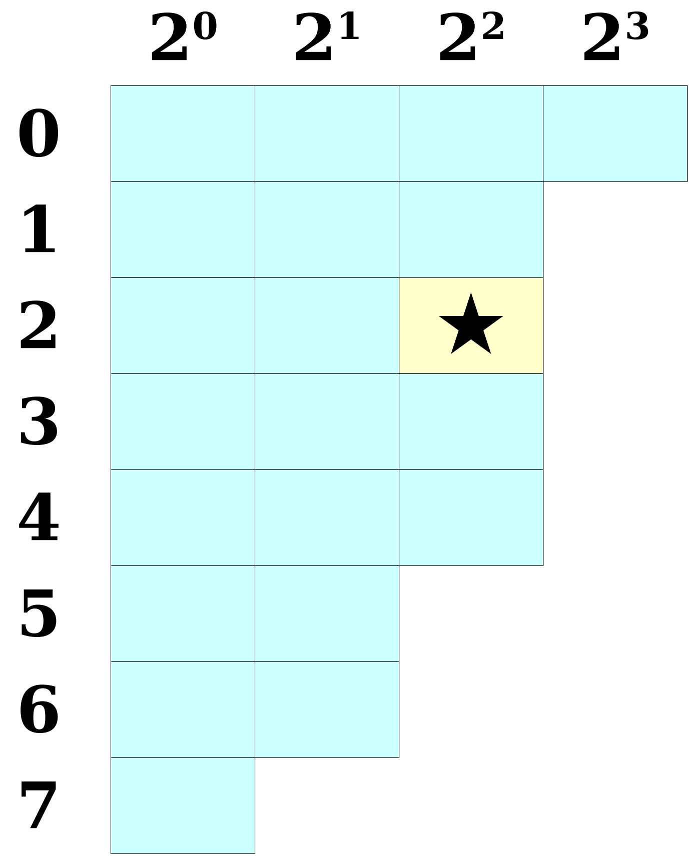

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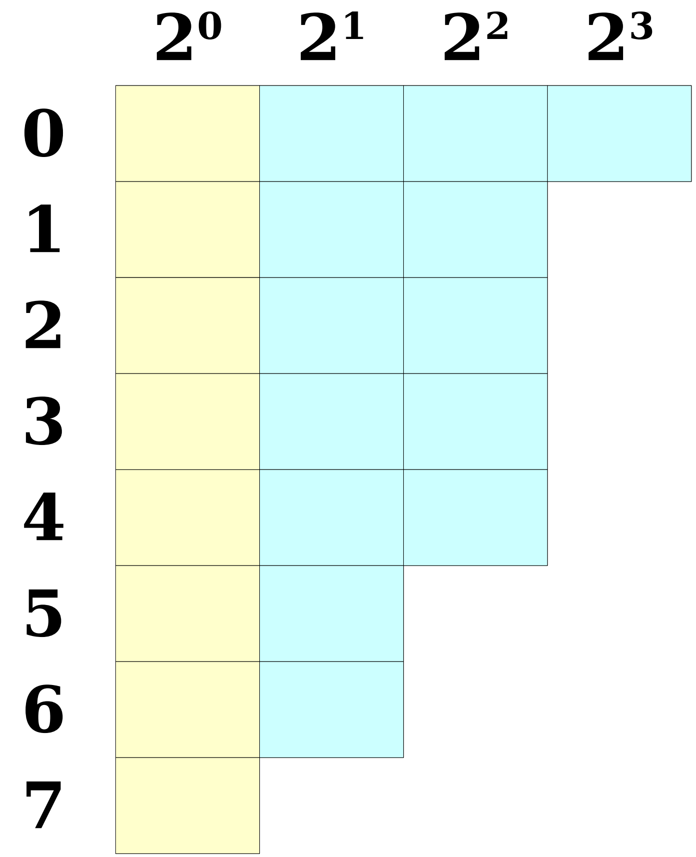

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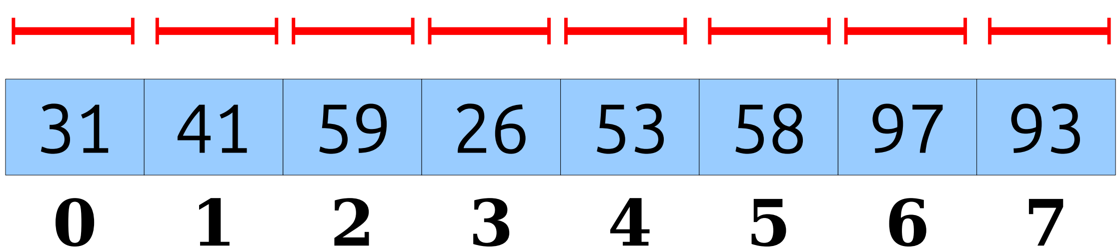

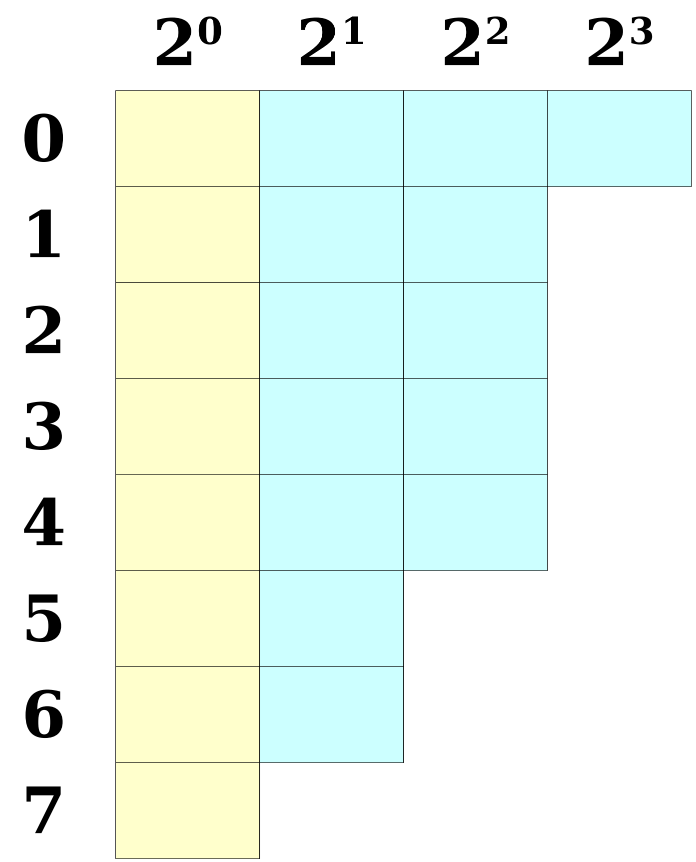

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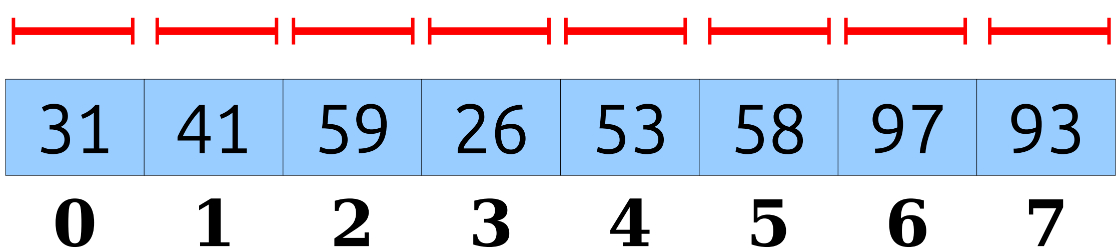

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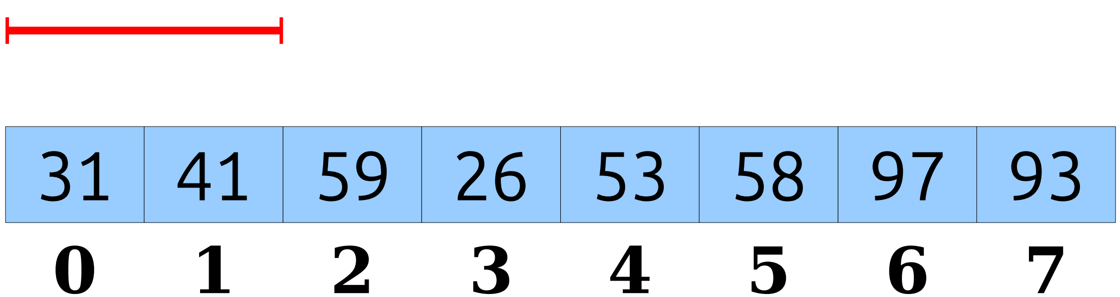

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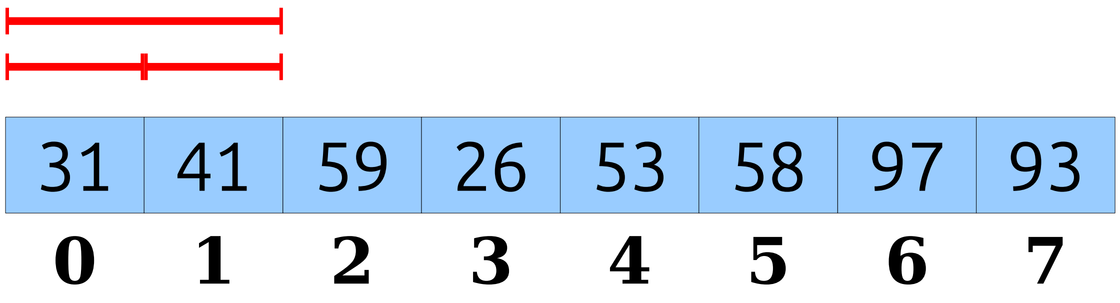

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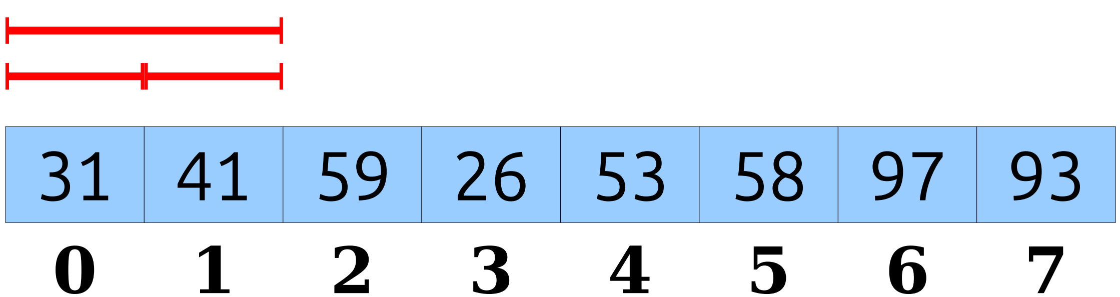

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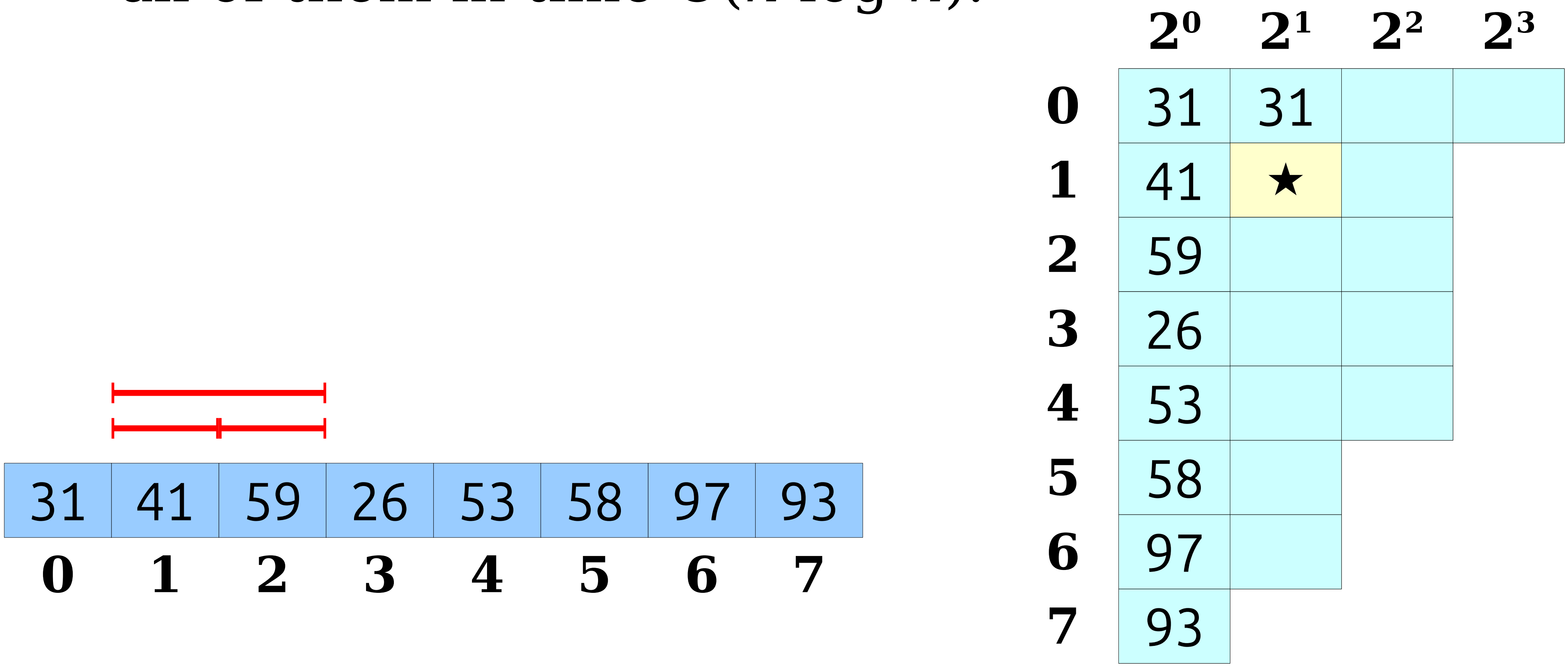

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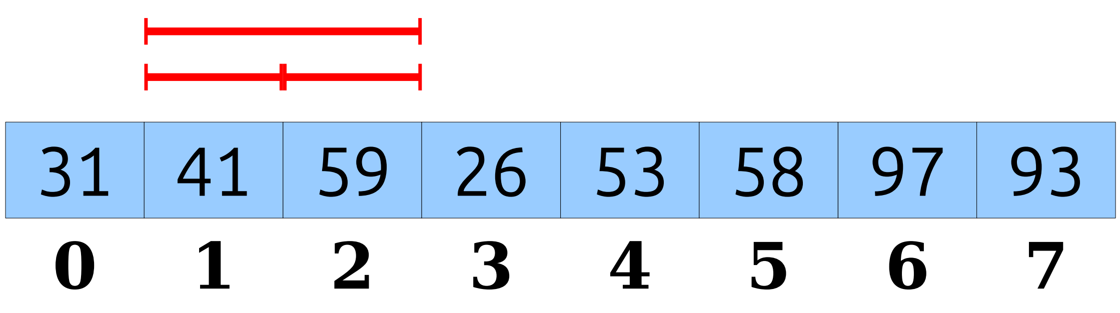

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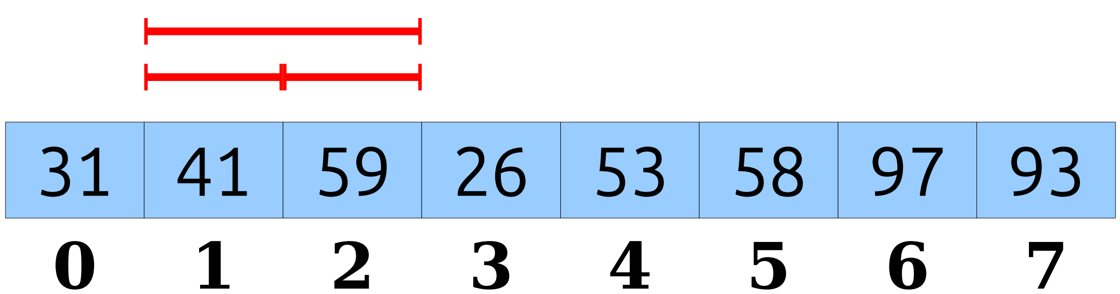

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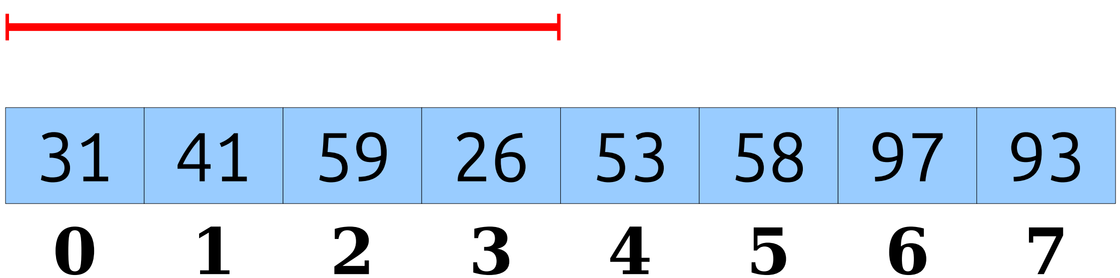

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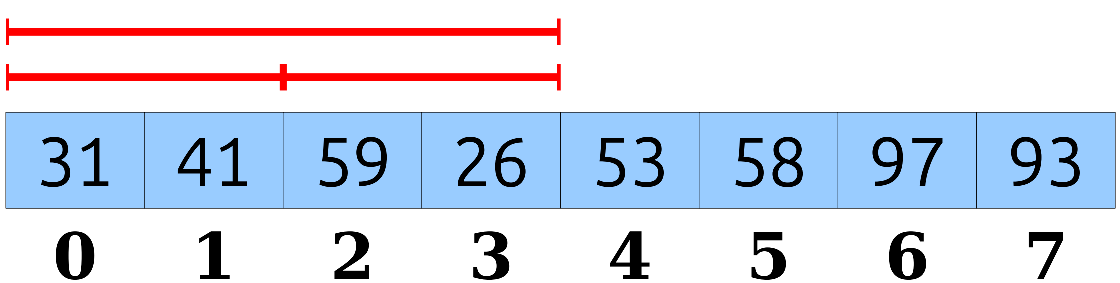

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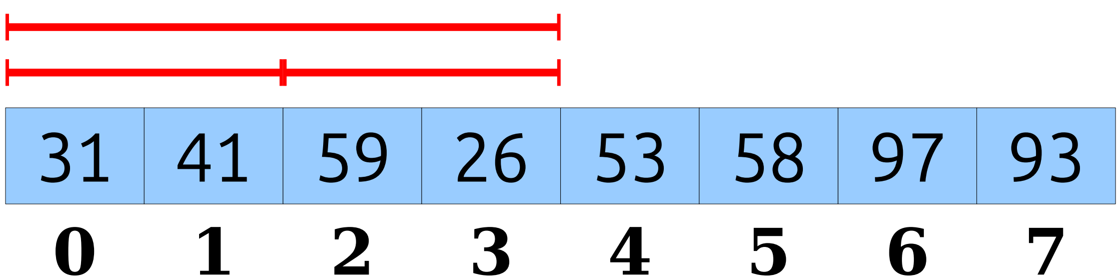

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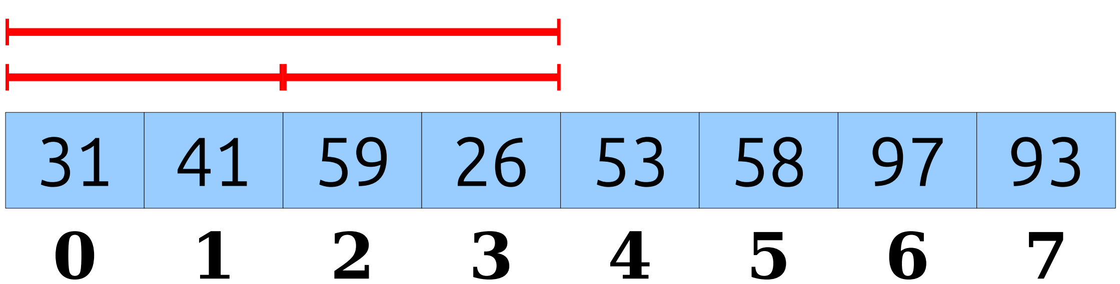

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Sparse Tables

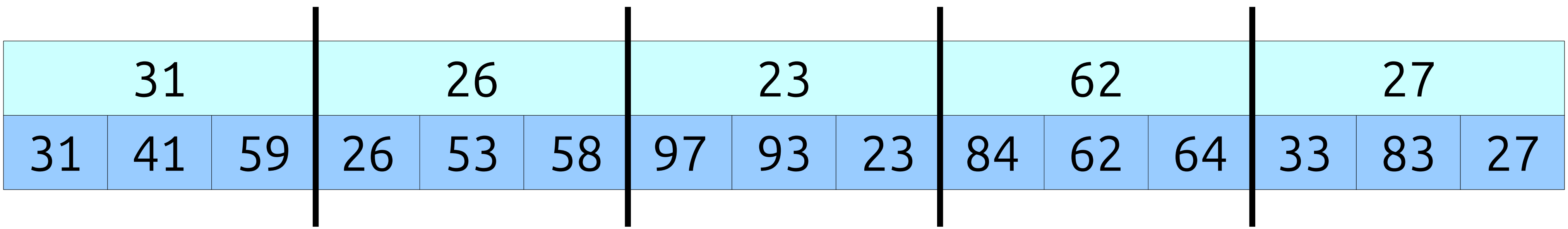
- This data structure is called a ***sparse table***.
- It gives an **⟨O(*n* log *n*), O(1)⟩** solution to RMQ.
- This is asymptotically better than precomputing all possible ranges!

The Story So Far

- We now have the following solutions for RMQ:
  - Precompute all: $\langle O(n^2), O(1) \rangle$.
  - Sparse table: $\langle O(n \log n), O(1) \rangle$.
  - Blocking: $\langle O(n), O(n^{1/2}) \rangle$.
  - Precompute none: $\langle O(1), O(n) \rangle$.
- ***Can we do better?***

A Third Approach: ***Hybrid Strategies***

Blocking Revisited



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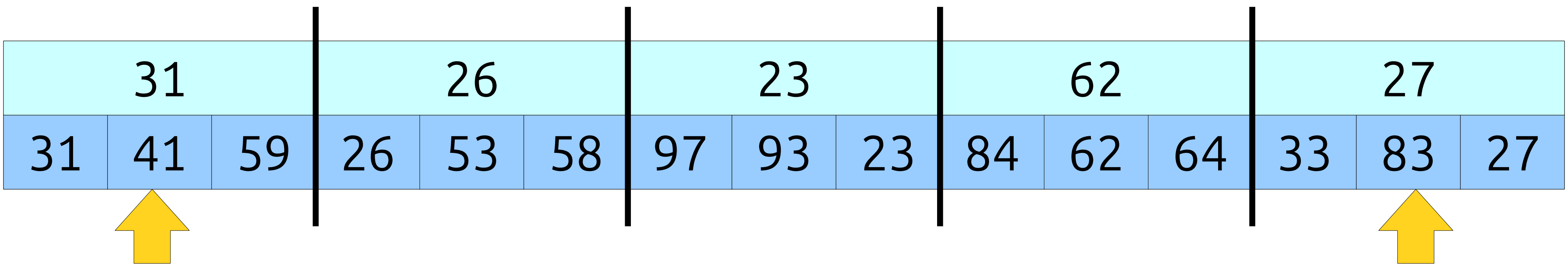

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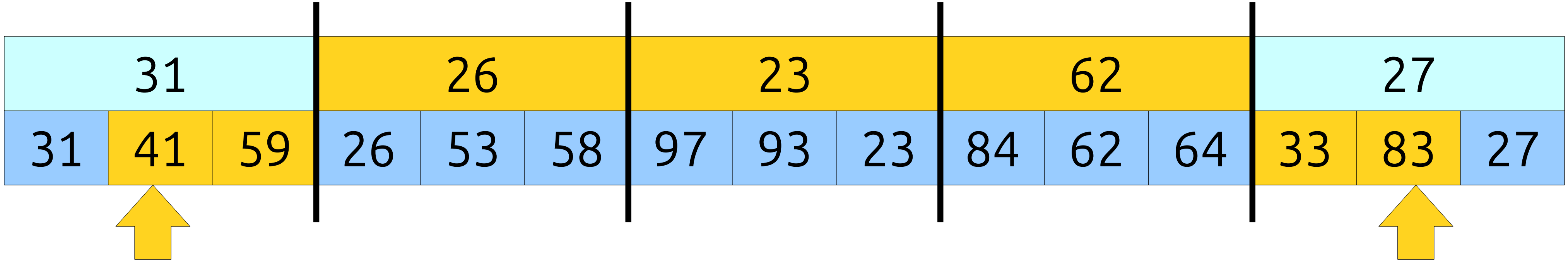

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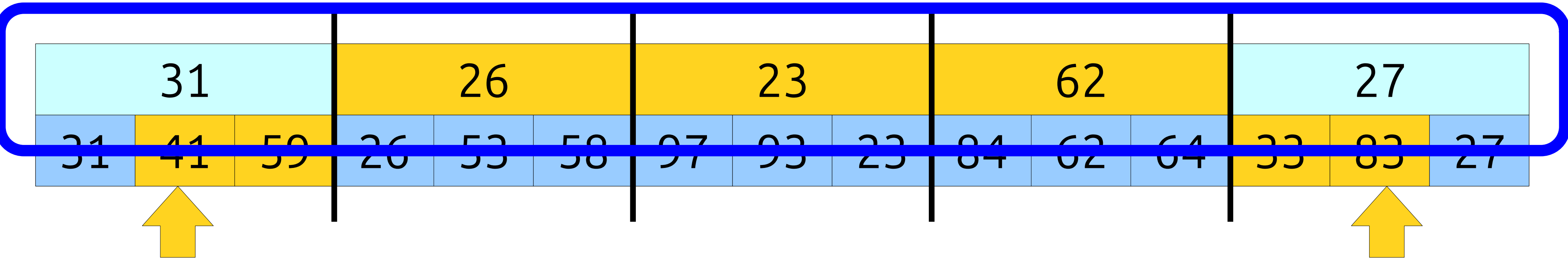

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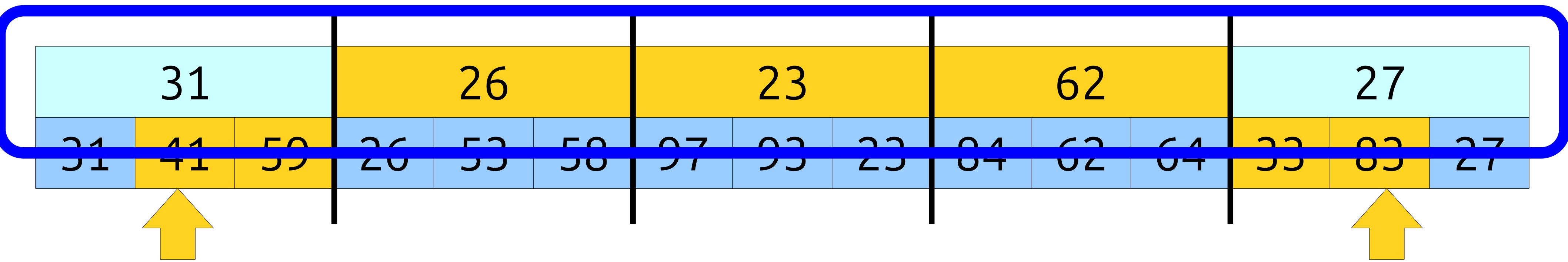
This is just RMQ on the block minima!



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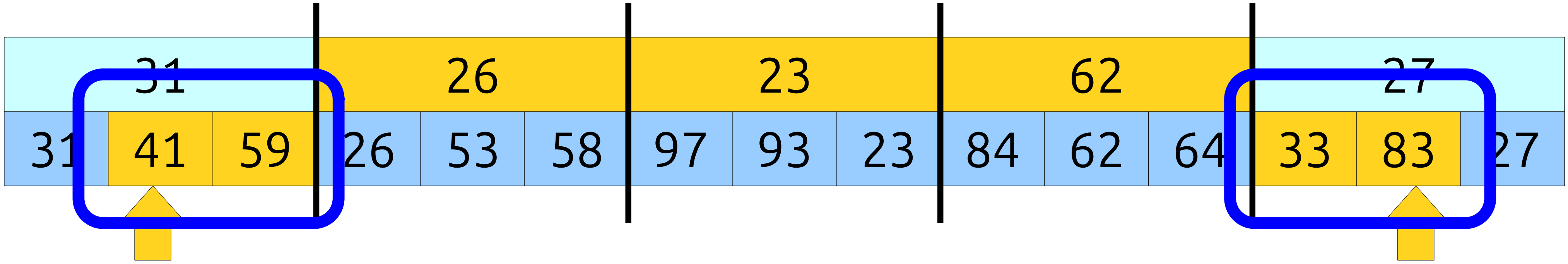

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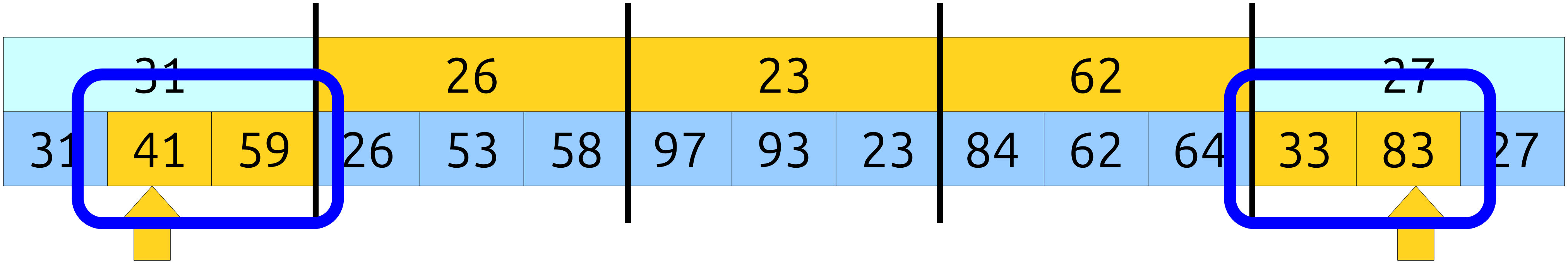
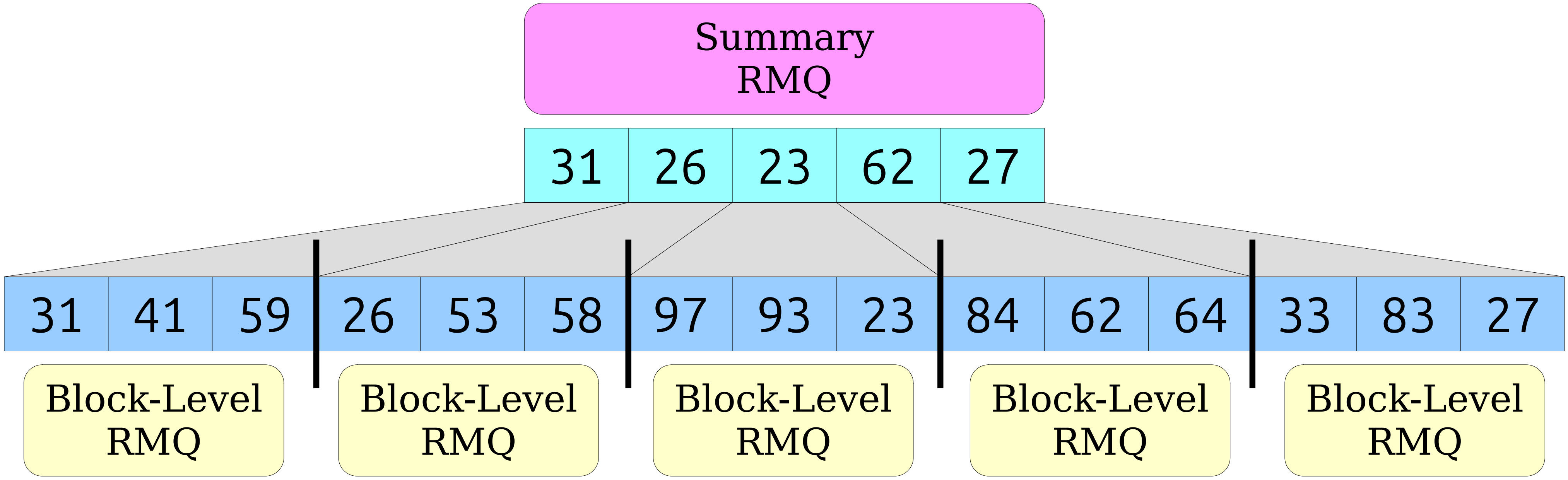


This is just RMQ inside the blocks!

The Framework

- Split the input into blocks of size *b*.
- Form an array of the block minima.
- Construct a "summary" RMQ structure over the block minima.
- Construct "block" RMQ structures for each block.
- Aggregate the results together.



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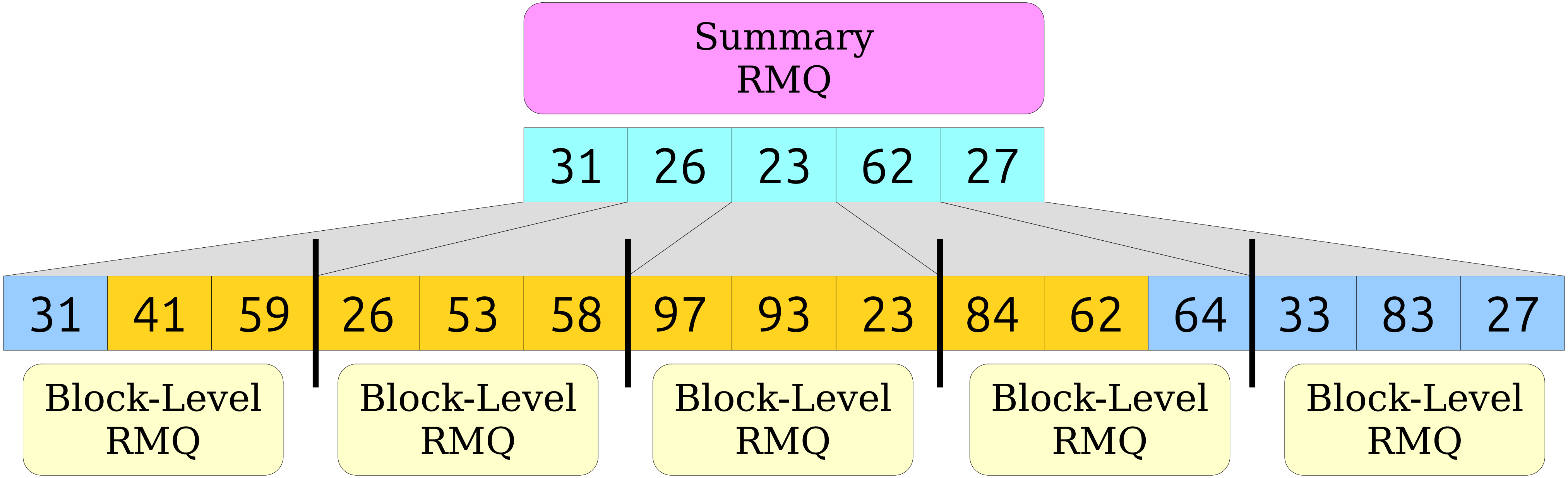

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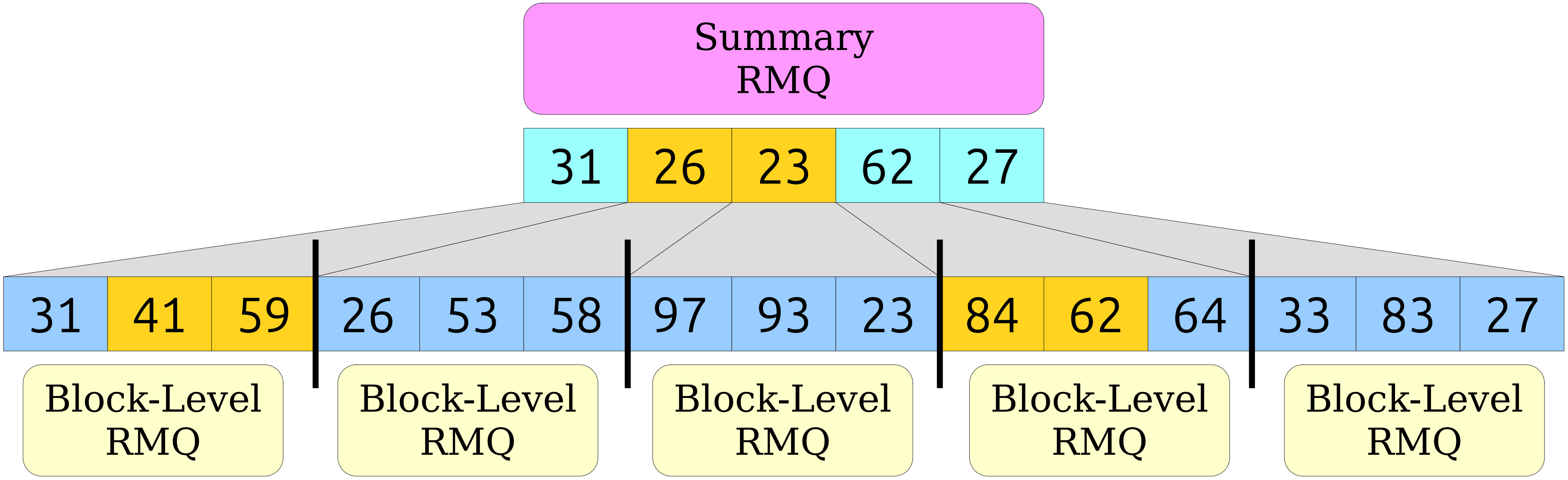

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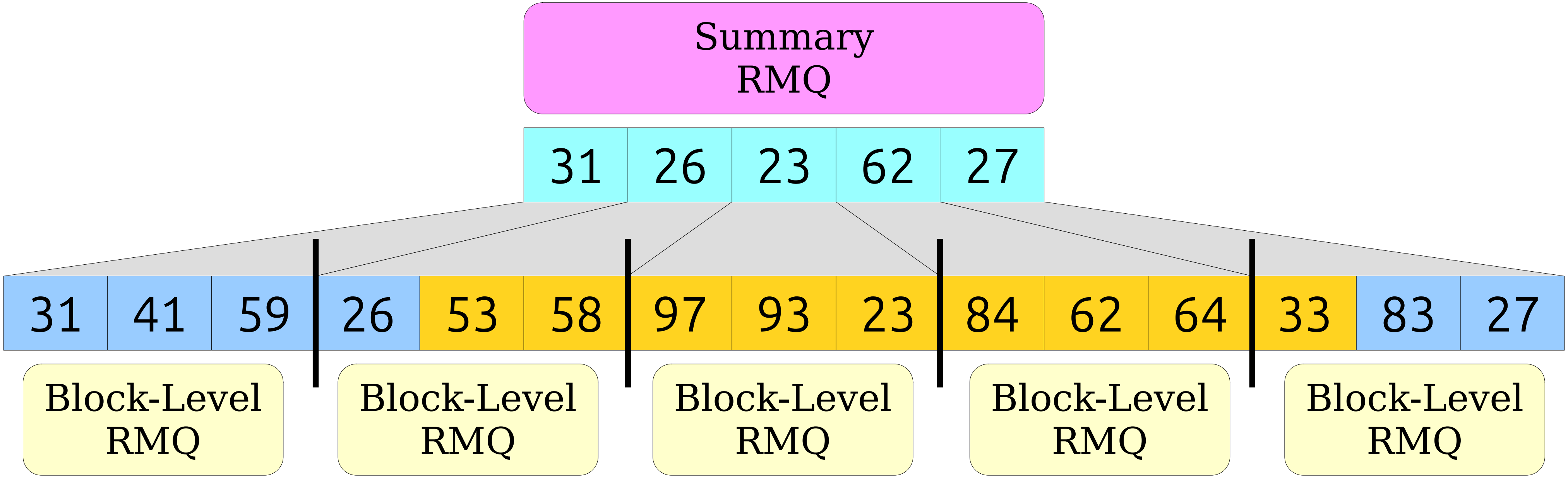
- Split the input into blocks of size *b*.
- Form an array of the block minima.
- Construct a "summary" RMQ structure over the block minima.
- Construct "block" RMQ structures for each block.
- Aggregate the results together.



The Framework

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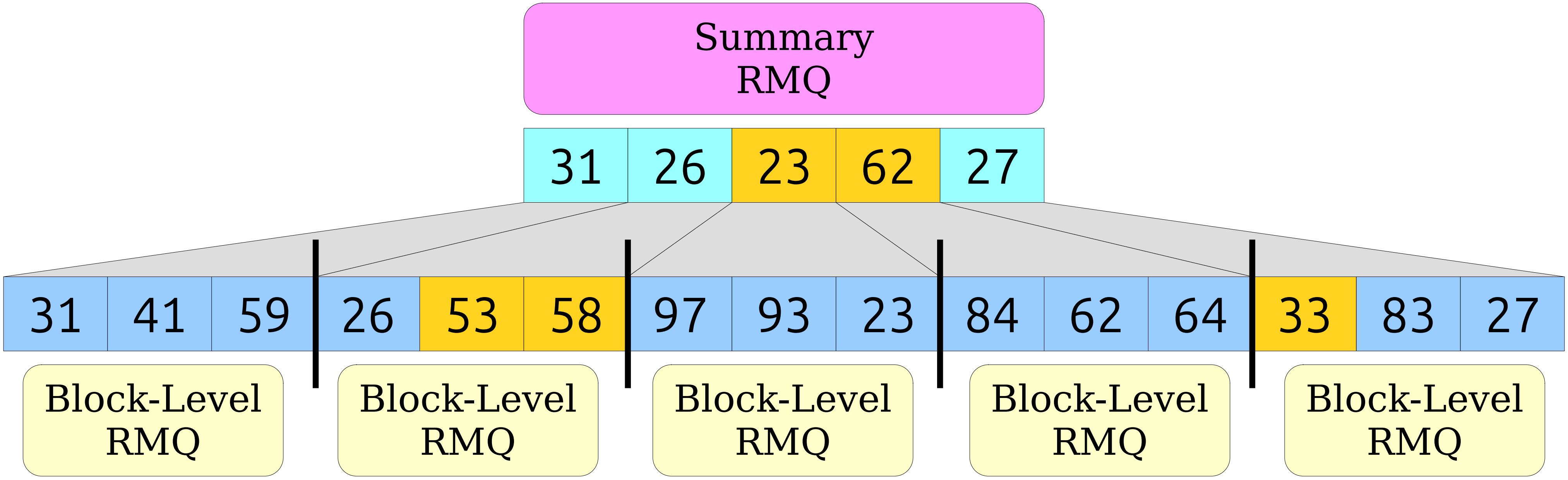
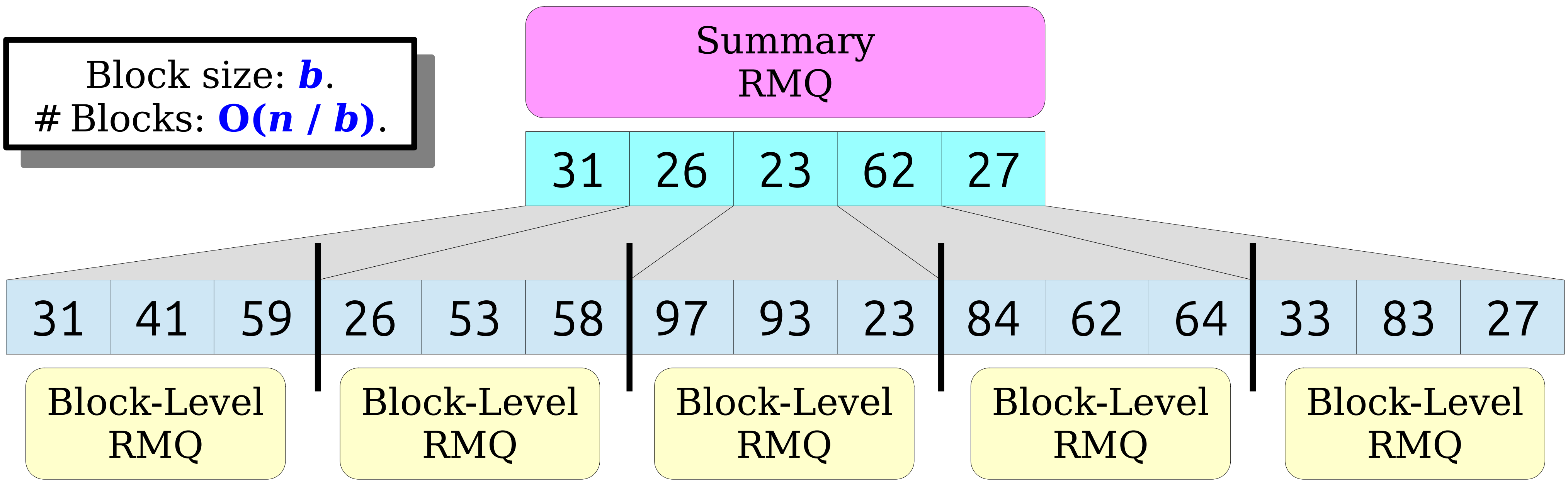


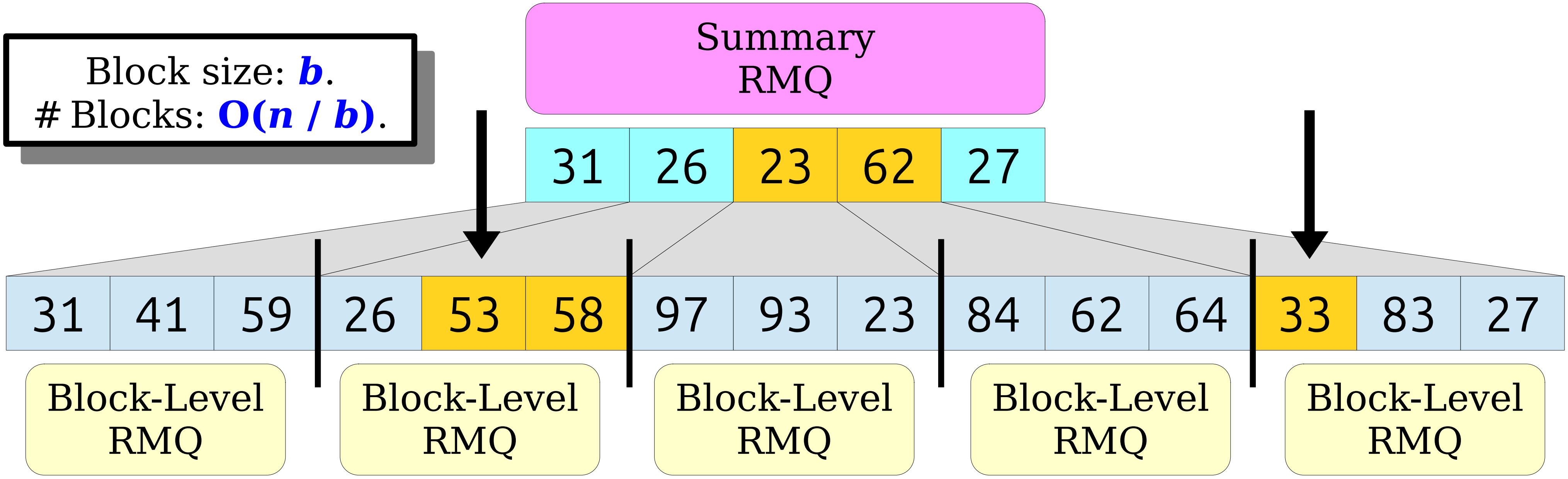
Analyzing Efficiency

- Suppose we use a ⟨$p_1(n)$, $q_1(n)$⟩-time RMQ for the summary RMQ and a ⟨$p_2(n)$, $q_2(n)$⟩-time RMQ for each block, with block size b.
- What is the preprocessing time for this hybrid structure?
  - **$O(n)$** time to compute the minima of each block.
  - **$O(p_1(n / b))$** time to construct RMQ on the minima.
  - **$O((n / b)\ p_2(b))$** time to construct the block RMQs.
- Total construction time is **$O(n + p_1(n / b) + (n / b)\ p_2(b))$**.



Analyzing Efficiency

- Suppose we use a $\langle p_1(n), q_1(n)\rangle$-time RMQ for the summary RMQ and a $\langle p_2(n), q_2(n)\rangle$-time RMQ for each block, with block size b.
- What is the query time for this hybrid structure?
  - $\mathbf{O(q_1(n / b))}$ time to query the summary RMQ.
  - $\mathbf{O(q_2(b))}$ time to query the block RMQs.
- Total query time: $\mathbf{O(q_1(n / b) + q_2(b))}$.



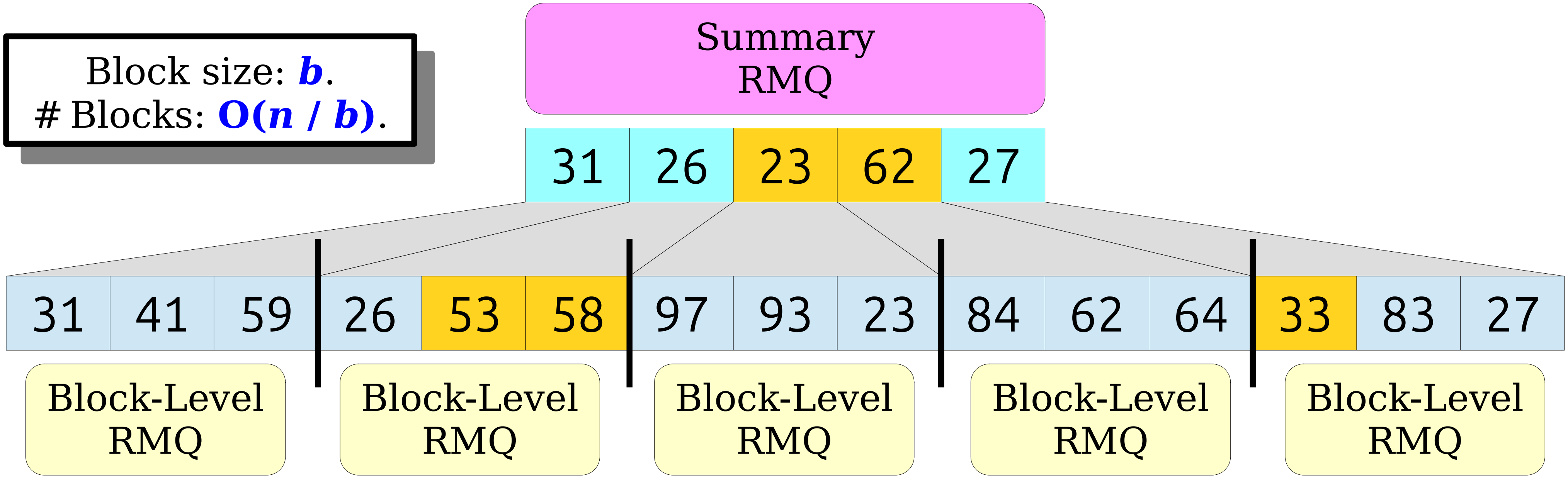
Analyzing Efficiency

- Suppose we use a $\langle p_1(n), q_1(n)\rangle$-time RMQ for the summary RMQ and a $\langle p_2(n), q_2(n)\rangle$-time RMQ for each block, with block size b.
- Hybrid preprocessing time:

$$\mathbf{O(n + p_1(n / b) + (n / b)p_2(b))}$$

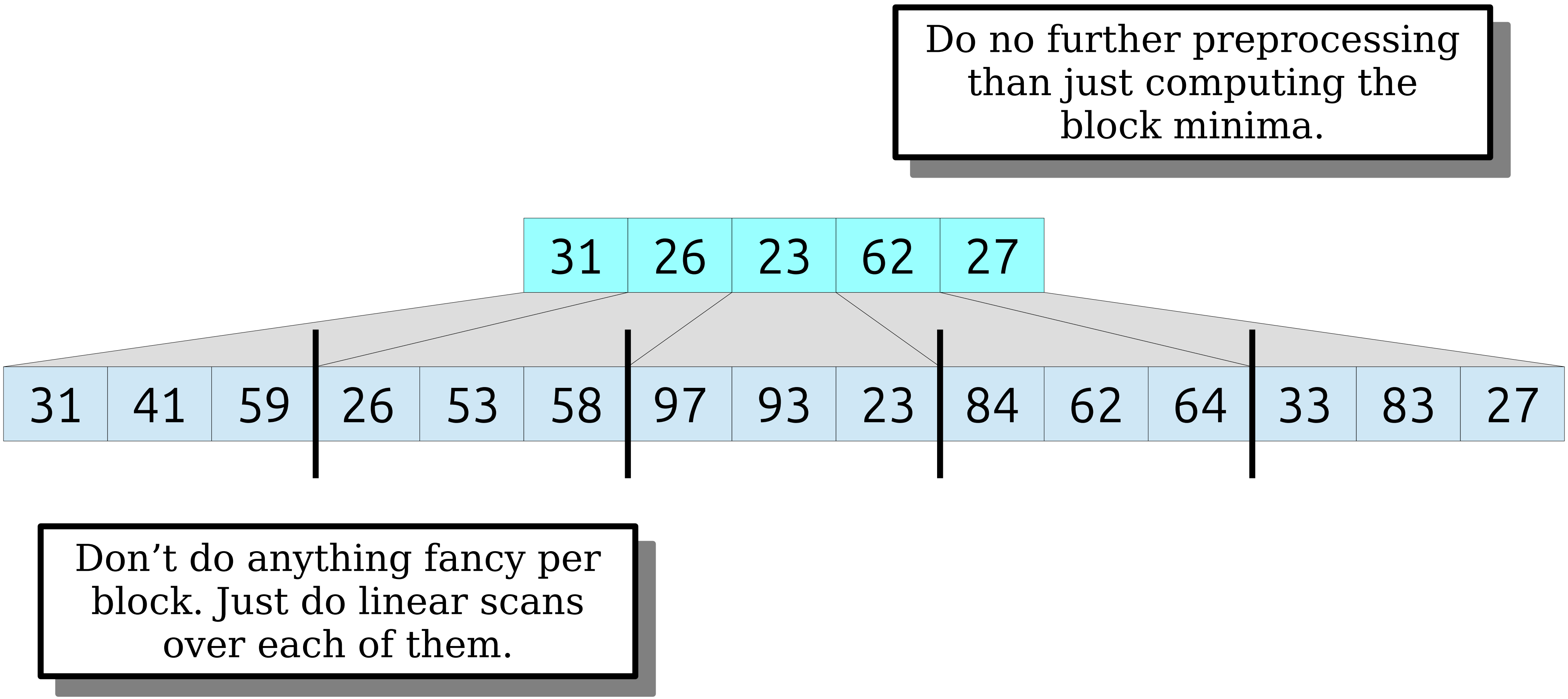
- Hybrid query time:

$$\mathbf{O(q_1(n / b) + q_2(b))}$$



A Sanity Check

- The ⟨O(n), O($n^{1/2}$)⟩ block-based structure from earlier uses this framework with the ⟨O(1), O(n)⟩ no-preprocessing RMQ structure and $b = n^{1/2}$.



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For Reference

$p_1(n) = O(1)$
$q_1(n) = O(n)$

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$$O(n + p_1(n / b) + (n / b)\ p_2(b))$$

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- According to our formulas, the preprocessing time should be

$$\begin{aligned} &O(n + p_1(n / b) + (n / b)\, p_2(b)) \\ = &O(n + 1 + n / b) \end{aligned}$$

For Reference

$$p_1(n) = O(1)$$
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A Sanity Check

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$$\begin{aligned} &O(n + p_1(n / b) + (n / b)\, p_2(b)) \\ &= O(n + 1 + n / b) \\ &= \mathbf{O(n)} \end{aligned}$$

- The query time should be

$$O(q_1(n / b) + q_2(b))$$

For Reference

$p_1(n) = O(1)$
$q_1(n) = O(n)$

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- The query time should be

$$\begin{aligned} & O(q_1(n / b) + q_2(b)) \\ = & O(n / b + b) \end{aligned}$$

For Reference

$p_1(n) = O(1)$
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\begin{aligned}
& O(n + p_1(n / b) + (n / b)\, p_2(b)) \\
= \;& O(n + 1 + n / b) \\
= \;& \mathbf{O(n)}
\end{aligned}
$$

- The query time should be

$$
\begin{aligned}
& O(q_1(n / b) + q_2(b)) \\
= \;& O(n / b + b) \\
= \;& \mathbf{O(n^{1/2})}
\end{aligned}
$$

- Looks good so far!

For Reference

$p_1(n) = O(1)$
$q_1(n) = O(n)$

$p_2(n) = O(1)$
$q_2(n) = O(n)$

$b = n^{1/2}$

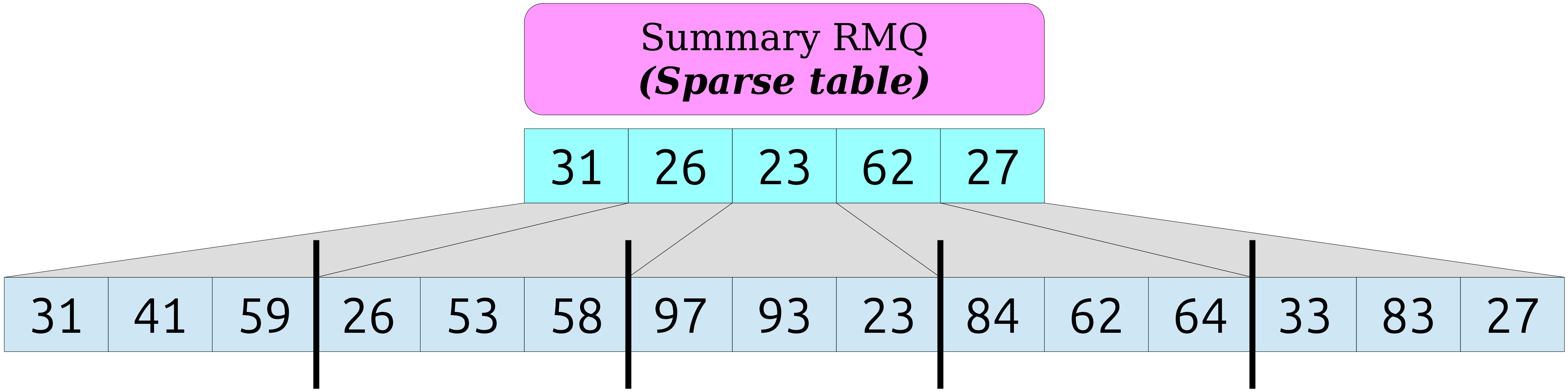
An Observation

- We can use any data structures we'd like for the summary and block RMQs.
- Suppose we use an $\langle O(n \log n), O(1) \rangle$ sparse table for the summary RMQ.
- If the block size is b, the time to construct a sparse table over the (n / b) blocks is $\mathbf{O((n / b) \log (n / b))}$.
- ***Cute trick:*** If $\mathbf{b = \Theta(\log n)}$, the time to construct a sparse table over the minima is

$$
\begin{aligned}
& O((n / \log n) \log (n / \log n)) \\
= {} & O((n / \log n) \log n) && \textit{(O is an upper bound)} \\
= {} & \mathbf{O(n)}. && \textit{(logs cancel out)}
\end{aligned}
$$

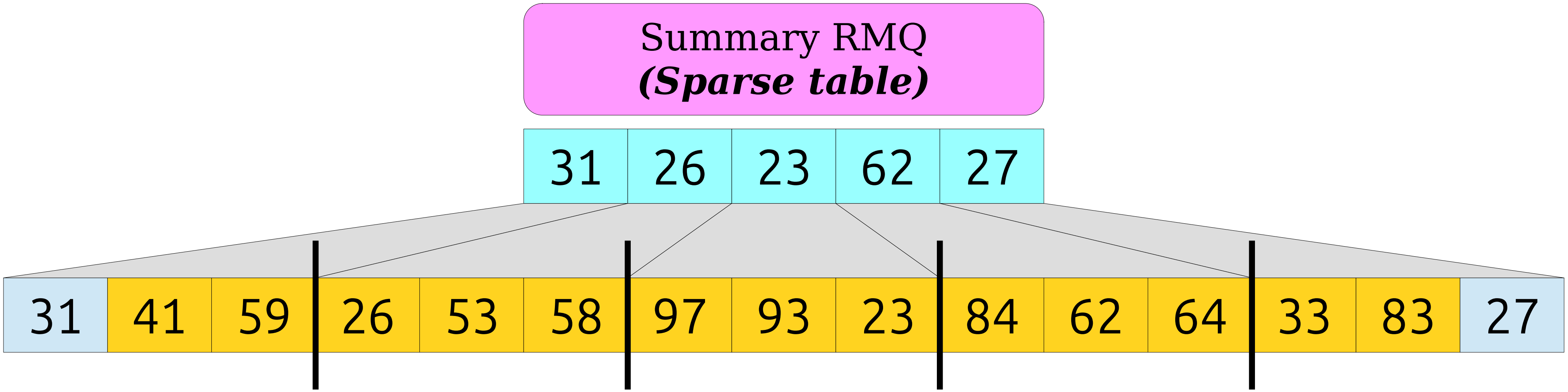
One Possible Hybrid

- Set the block size to log *n*.
- Use a sparse table for the summary RMQ.
- Use the "no preprocessing" structure for each block.



One Possible Hybrid

- Set the block size to log *n*.
- Use a sparse table for the summary RMQ.
- Use the “no preprocessing” structure for each block.



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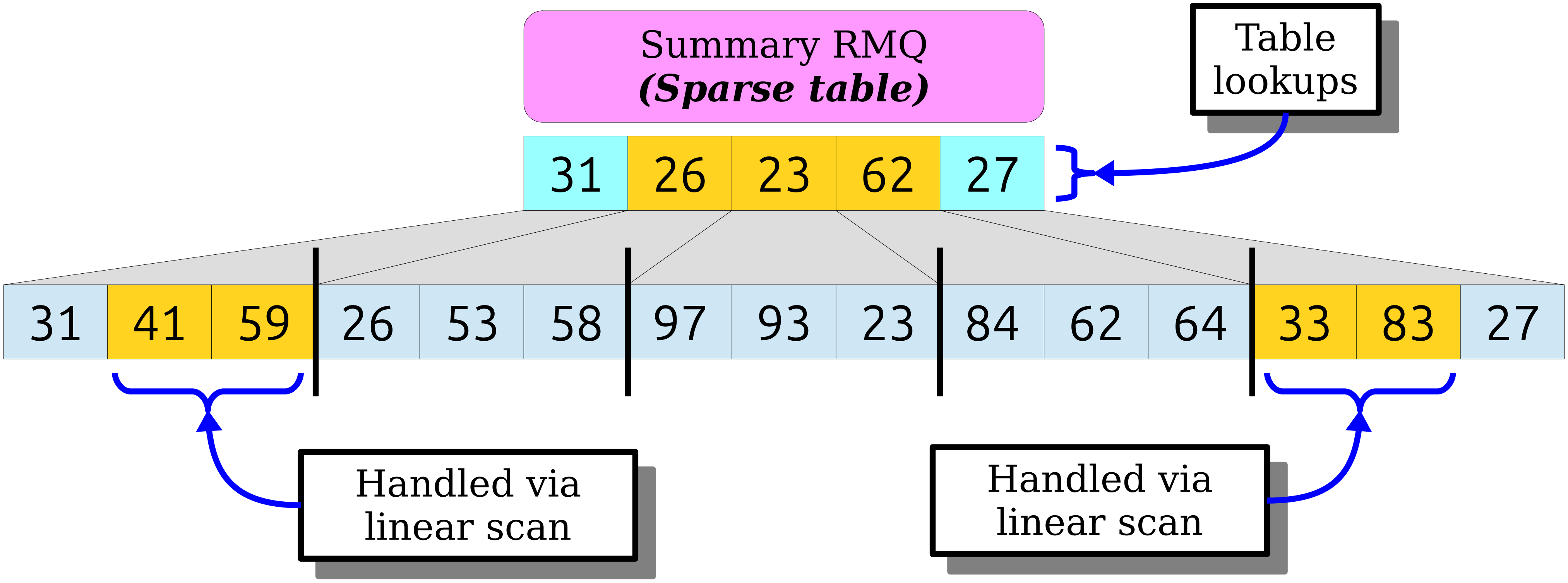

One Possible Hybrid

- Set the block size to log n.
- Use a sparse table for the summary RMQ.
- Use the “no preprocessing” structure for each block.

For Reference

$p_1(n) = O(n \log n)$
$q_1(n) = O(1)$

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$b = \log n$

One Possible Hybrid

- Set the block size to log n.
- Use a sparse table for the summary RMQ.
- Use the “no preprocessing” structure for each block.
- Preprocessing time:

$$O(n + p_1(n / b) + (n / b)\, p_2(b))$$

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$$O(n + p_1(n / b) + (n / b)\, p_2(b))$$
$$= O(n + n + n / b)$$

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- Query time:

$$O(q_1(n / b) + q_2(b))$$

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\begin{aligned}
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=\ &O(n + n + n / b) \\
=\ &\mathbf{O(n)}
\end{aligned}
$$

- Query time:

$$
\begin{aligned}
&O(q_1(n / b) + q_2(b)) \\
=\ &O(1 + b)
\end{aligned}
$$

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= {}&O(n + n + n / b) \\
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\end{aligned}
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$$\begin{aligned} & O(q_1(n / b) + q_2(b)) \\ = & O(1 + b) \\ = & \mathbf{O(\log n)} \end{aligned}$$

- An **⟨O(n), O(log n)⟩** solution!

For Reference

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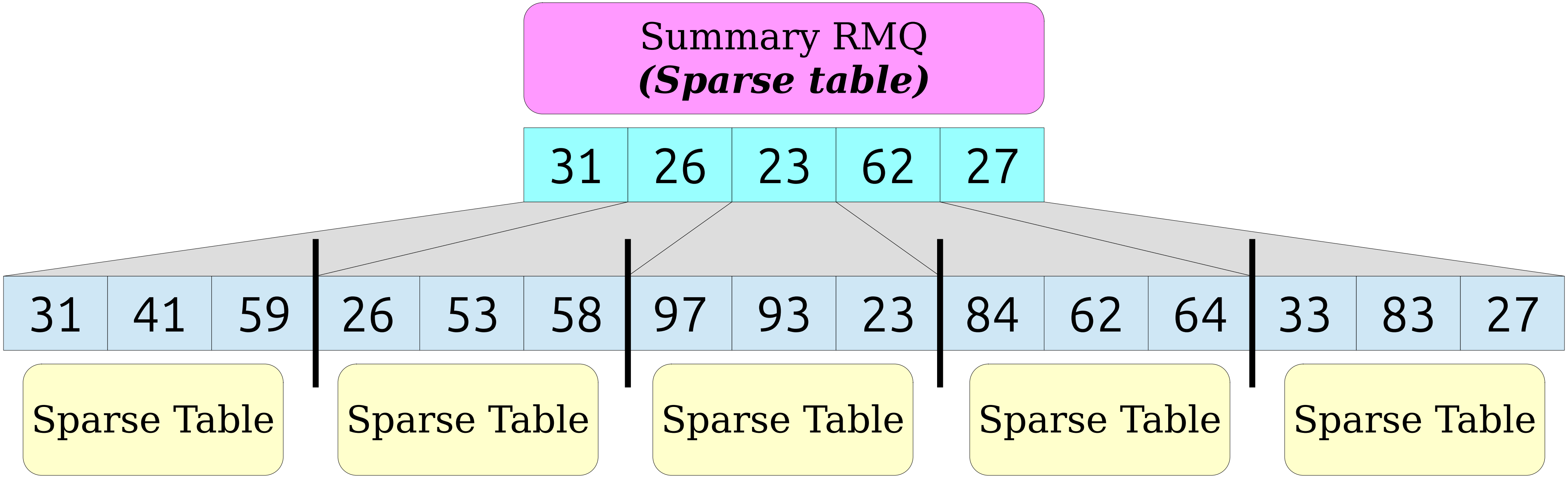
Another Hybrid

- Let's suppose we use the ⟨O(n log n), O(1)⟩ sparse table for both the summary and block RMQ structures with a block size of log n.



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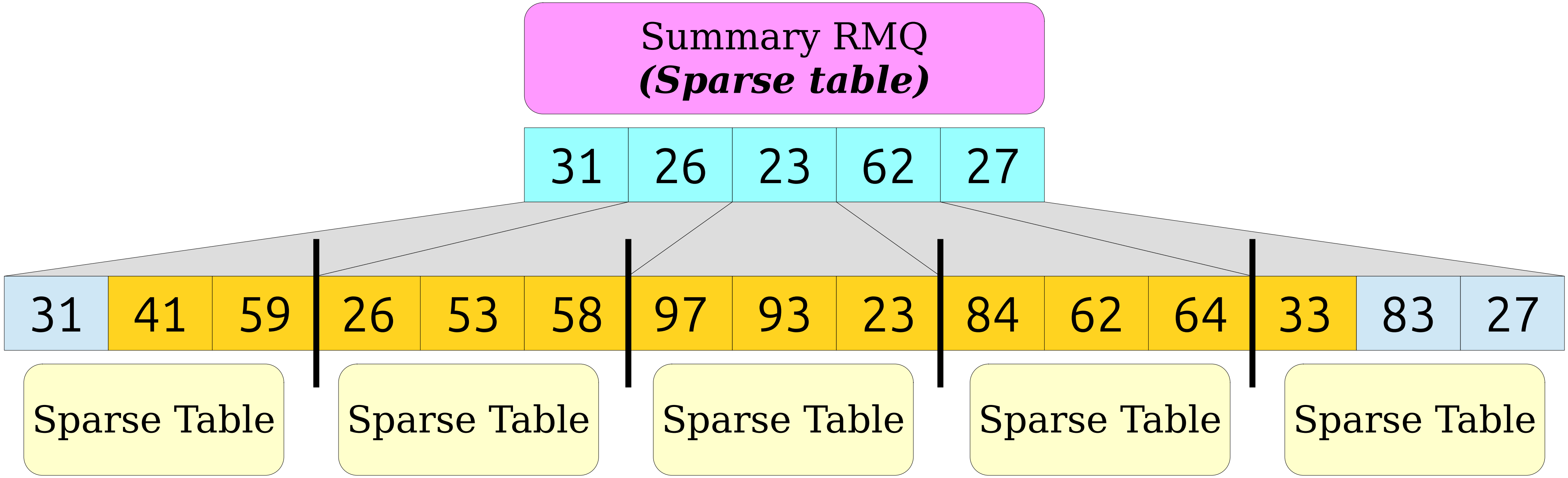

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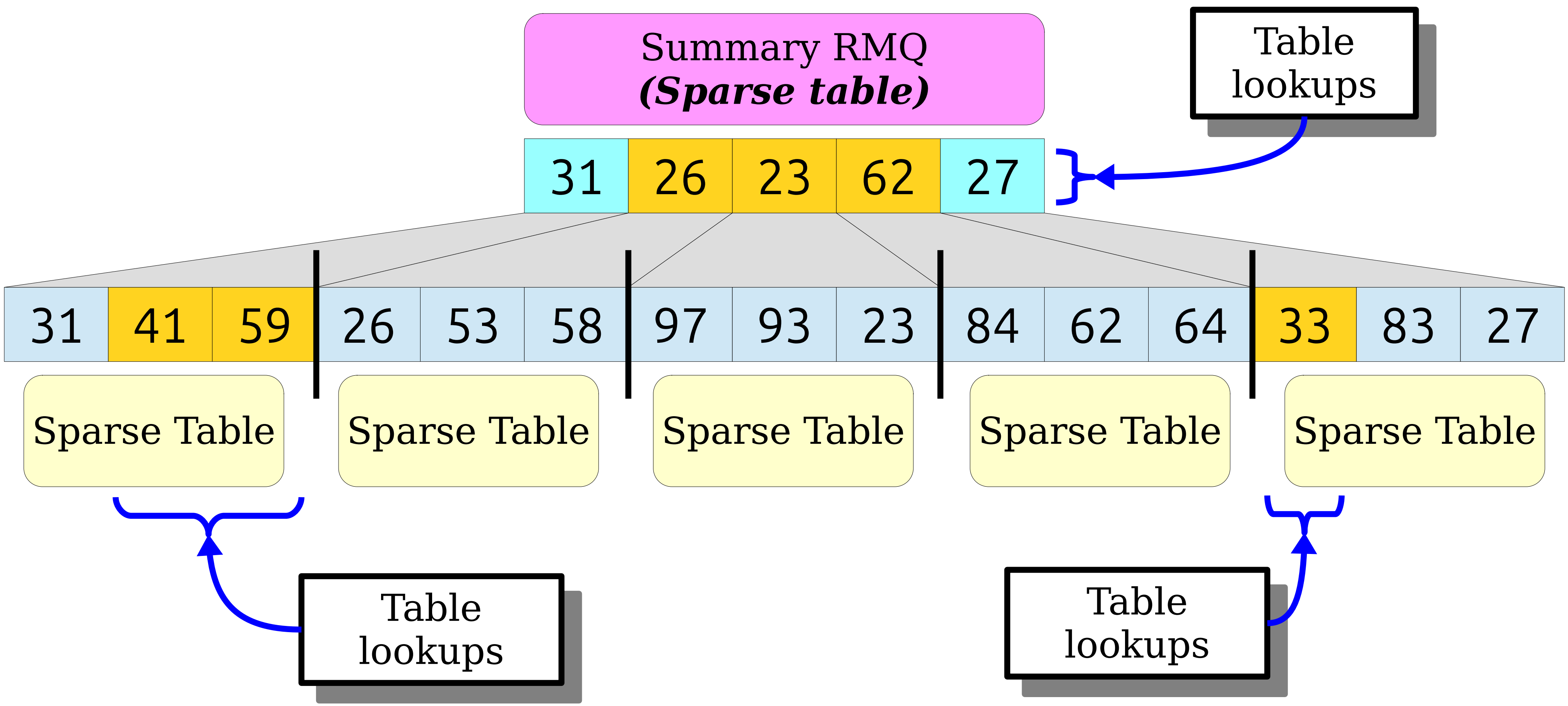

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$b = \log n$

Another Hybrid

- Let's suppose we use the $\langle O(n \log n), O(1)\rangle$ sparse table for both the summary and block RMQ structures with a block size of $\log n$.
- The preprocessing time is

$$O(n + p_1(n / b) + (n / b)\ p_2(b))$$

For Reference

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$$
\begin{aligned}
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= {}&O(n + n + (n / b)\ b \log b)
\end{aligned}
$$

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=\ & O(n + n + (n / b)\, b \log b) \\
=\ & O(n + n \log b) \\
=\ & \mathbf{O(n \log \log n)}
\end{aligned}
$$

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- The query time is

$$O(q_1(n / b) + q_2(b))$$

For Reference

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\begin{aligned}
& O(n + p_1(n / b) + (n / b)\, p_2(b)) \\
&= O(n + n + (n / b)\, b \log b) \\
&= O(n + n \log b) \\
&= \mathbf{O(n \log \log n)}
\end{aligned}
$$

- The query time is

$$
\begin{aligned}
& O(q_1(n / b) + q_2(b)) \\
&= \mathbf{O(1)}
\end{aligned}
$$

- We have an **⟨O(n log log n), O(1)⟩** solution to RMQ!

For Reference

$p_1(n) = O(n \log n)$
$q_1(n) = O(1)$

$p_2(n) = O(n \log n)$
$q_2(n) = O(1)$

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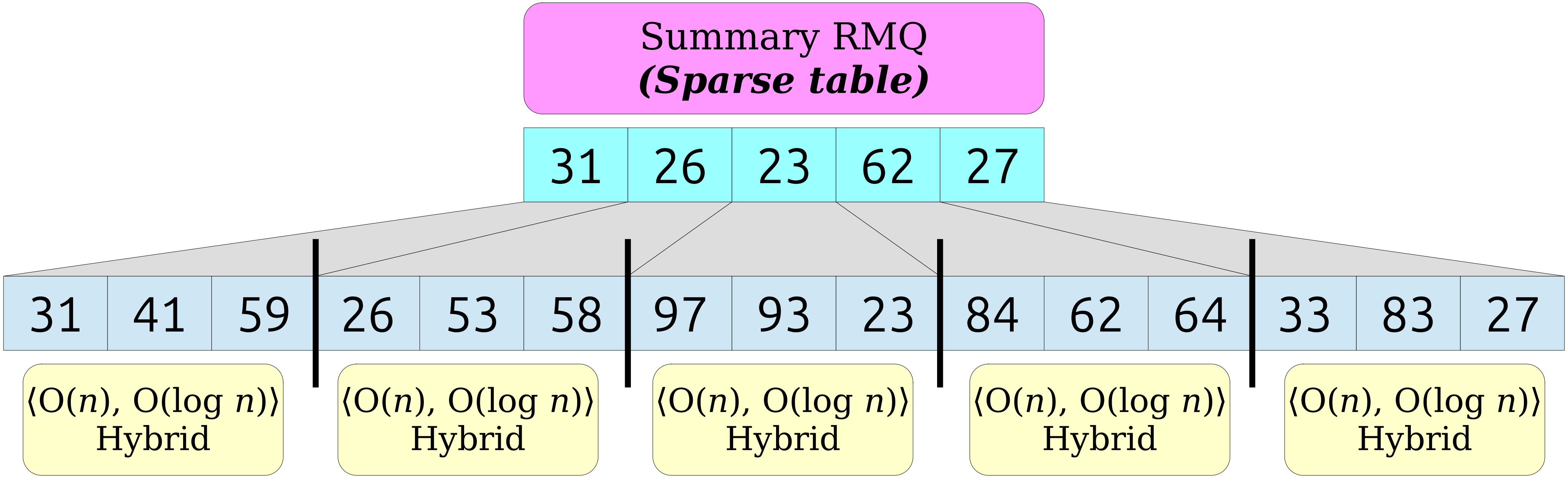
One Last Hybrid

- Suppose we use a sparse table for the summary RMQ and the ⟨O(n), O(log n)⟩ solution for the block RMQs. Let's choose b = log n.



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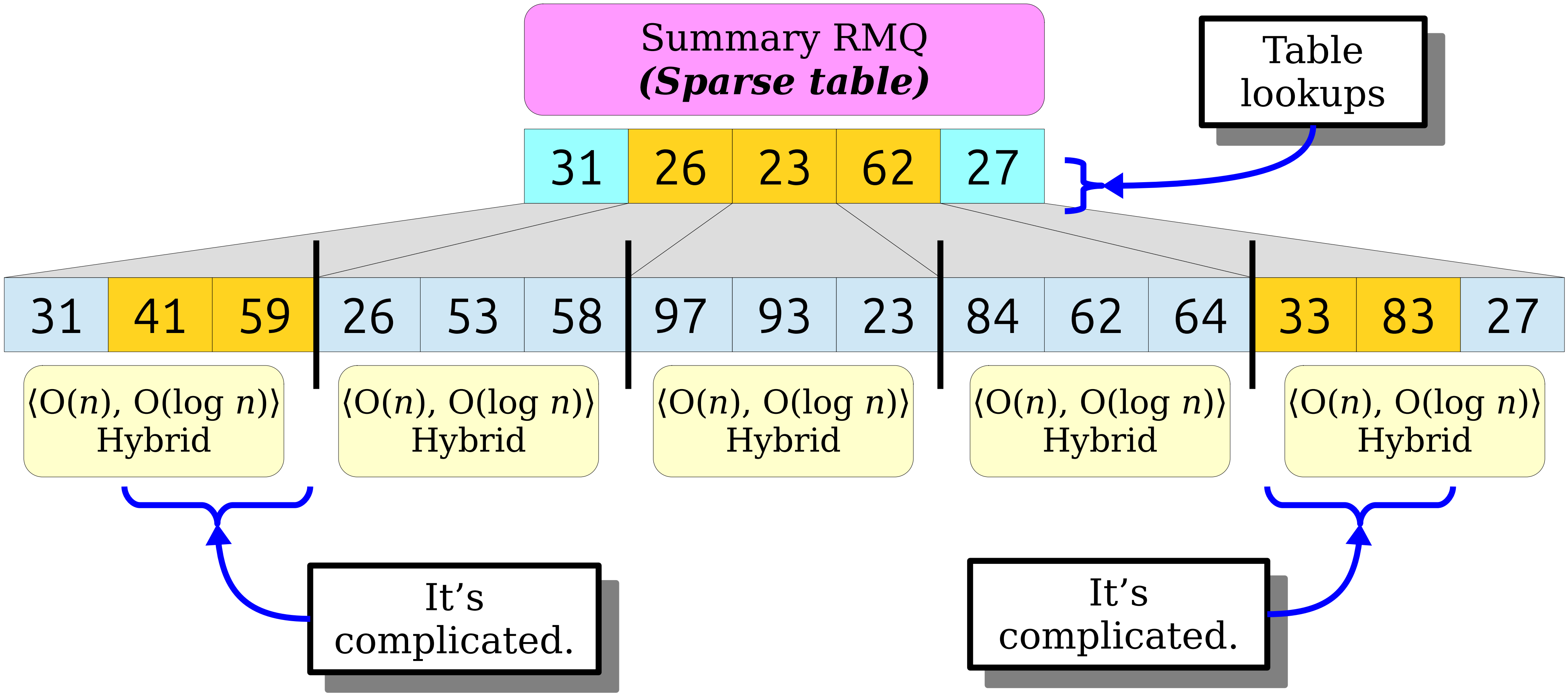

One Last Hybrid

- Suppose we use a sparse table for the summary RMQ and the ⟨O(n), O(log n)⟩ solution for the block RMQs. Let's choose $b = \log n$.

For Reference

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$p_2(n) = O(n)$
$q_2(n) = O(\log n)$

$b = \log n$

One Last Hybrid

- Suppose we use a sparse table for the summary RMQ and the ⟨O(n), O($\log n$)⟩ solution for the block RMQs. Let's choose $b = \log n$.
- The preprocessing time is

$$O(n + p_1(n / b) + (n / b)\ p_2(b))$$

For Reference

$p_1(n) = O(n \log n)$
$q_1(n) = O(1)$

$p_2(n) = O(n)$
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$$O(n + p_1(n / b) + (n / b)\ p_2(b))$$
$$= O(n + n + (n / b)\ b)$$

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$$
\begin{aligned}
&O(n + p_1(n / b) + (n / b)\, p_2(b)) \\
= {} &O(n + n + (n / b)\, b) \\
= {} &\mathbf{O(n)}
\end{aligned}
$$

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- The query time is

$$O(q_1(n / b) + q_2(b))$$

For Reference

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&O(n + p_1(n / b) + (n / b)\, p_2(b)) \\
= &O(n + n + (n / b)\, b) \\
= &\mathbf{O(n)}
\end{aligned}
$$

- The query time is

$$
\begin{aligned}
&O(q_1(n / b) + q_2(b)) \\
= &O(1 + \log b)
\end{aligned}
$$

For Reference

$p_1(n) = O(n \log n)$
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One Last Hybrid

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- The preprocessing time is

$$
\begin{aligned}
&O(n + p_1(n / b) + (n / b)\, p_2(b)) \\
=\ &O(n + n + (n / b)\, b) \\
=\ &\mathbf{O(n)}
\end{aligned}
$$

- The query time is

$$
\begin{aligned}
&O(q_1(n / b) + q_2(b)) \\
=\ &O(1 + \log b) \\
=\ &\mathbf{O(\log \log n)}
\end{aligned}
$$

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$$\begin{aligned} & O(n + p_1(n / b) + (n / b)\, p_2(b)) \\ =\ & O(n + n + (n / b)\, b) \\ =\ & \mathbf{O(n)} \end{aligned}$$

- The query time is

$$\begin{aligned} & O(q_1(n / b) + q_2(b)) \\ =\ & O(1 + \log b) \\ =\ & \mathbf{O(\log \log n)} \end{aligned}$$

- We have an **⟨O(n), O(log log n)⟩** solution to RMQ!

For Reference

$p_1(n) = O(n \log n)$
$q_1(n) = O(1)$

$p_2(n) = O(n)$
$q_2(n) = O(\log n)$

$b = \log n$

Where We Stand

- We've seen a bunch of RMQ structures today:
  - No preprocessing: $\langle O(1), O(n) \rangle$
  - Full preprocessing: $\langle O(n^2), O(1) \rangle$
  - Block partition: $\langle O(n), O(n^{1/2}) \rangle$
  - Sparse table: $\langle O(n \log n), O(1) \rangle$
  - Hybrid 1: $\langle O(n), O(\log n) \rangle$
  - Hybrid 2: $\langle O(n \log \log n), O(1) \rangle$
  - Hybrid 3: $\langle O(n), O(\log \log n) \rangle$

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- Hybrid 1: ⟨O(n), O(log n)⟩
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- Hybrid 3: ⟨O(n), O(log log n)⟩

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Is there an $\langle O(n), O(1) \rangle$ solution to RMQ?

Yes!

Next Time

- ***Cartesian Trees***
  - A data structure closely related to RMQ.
- ***The Method of Four Russians***
  - A technique for shaving off log factors.
- ***The Fischer-Heun Structure***
  - A clever, asymptotically optimal RMQ structure.