

# Computational Geometry

## Orthogonal Range Queries: Fractional Cascading

Thomas Bläsius

# Searching In Many Arrays

## Situation

- consider  $\ell$  sorted arrays  $A_1, \dots, A_\ell$  with  $\leq n$  elements each
- find the position of  $x$  in all arrays
- obvious solution:  $O(\ell \log n)$

$A_1 =$ 

2	5	8	12	17	19	25	28
---	---	---	----	----	----	----	----

$A_2 =$ 

3	4	6	11	13	18	25	33
---	---	---	----	----	----	----	----

$A_3 =$ 

1	3	7	9	17	19	22	32
---	---	---	---	----	----	----	----

# Searching In Many Arrays

## Situation

- consider  $\ell$  sorted arrays  $A_1, \dots, A_\ell$  with  $\leq n$  elements each
- find the position of  $x$  in all arrays
- obvious solution:  $O(\ell \log n)$
- last lecture:  $O(\ell + \log n)$  if  $A_1 \supseteq A_2 \supseteq \dots \supseteq A_\ell$

$A_1 =$ 

2	5	8	12	17	19	25	28
---	---	---	----	----	----	----	----

$A_2 =$ 

3	4	6	11	13	18	25	33
---	---	---	----	----	----	----	----

$A_3 =$ 

1	3	7	9	17	19	22	32
---	---	---	---	----	----	----	----

# Searching In Many Arrays

## Situation

- consider  $\ell$  sorted arrays  $A_1, \dots, A_\ell$  with  $\leq n$  elements each
- find the position of  $x$  in all arrays
- obvious solution:  $O(\ell \log n)$
- last lecture:  $O(\ell + \log n)$  if  $A_1 \supseteq A_2 \supseteq \dots \supseteq A_\ell$

## Is $\ell + \log n$ Possible In General?

$A_1 =$ 

2	5	8	12	17	19	25	28
---	---	---	----	----	----	----	----

$A_2 =$ 

3	4	6	11	13	18	25	33
---	---	---	----	----	----	----	----

$A_3 =$ 

1	3	7	9	17	19	22	32
---	---	---	---	----	----	----	----

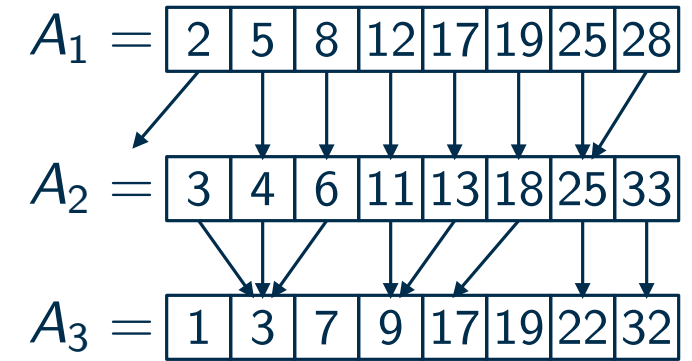
# Searching In Many Arrays

## Situation

- consider  $\ell$  sorted arrays  $A_1, \dots, A_\ell$  with  $\leq n$  elements each
- find the position of  $x$  in all arrays
- obvious solution:  $O(\ell \log n)$
- last lecture:  $O(\ell + \log n)$  if  $A_1 \supseteq A_2 \supseteq \dots \supseteq A_\ell$

## Is $\ell + \log n$ Possible In General?

- hope: search  $x$  in  $A_1$ , find  $x$  in  $A_2, \dots, A_\ell$  via pointers



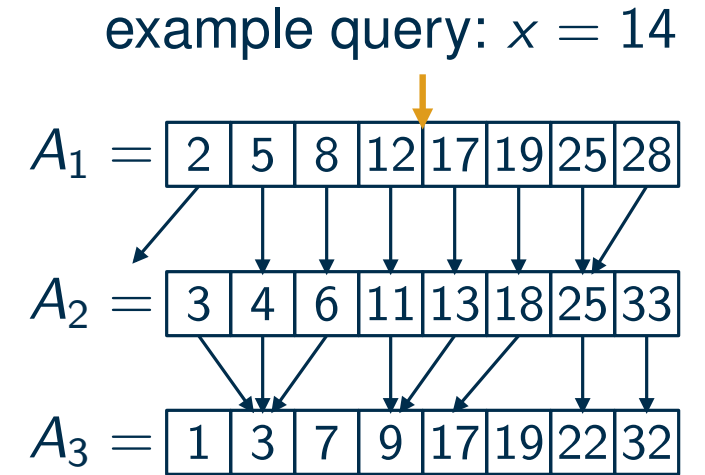
# Searching In Many Arrays

## Situation

- consider  $\ell$  sorted arrays  $A_1, \dots, A_\ell$  with  $\leq n$  elements each
- find the position of  $x$  in all arrays
- obvious solution:  $O(\ell \log n)$
- last lecture:  $O(\ell + \log n)$  if  $A_1 \supseteq A_2 \supseteq \dots \supseteq A_\ell$

## Is $\ell + \log n$ Possible In General?

- hope: search  $x$  in  $A_1$ , find  $x$  in  $A_2, \dots, A_\ell$  via pointers



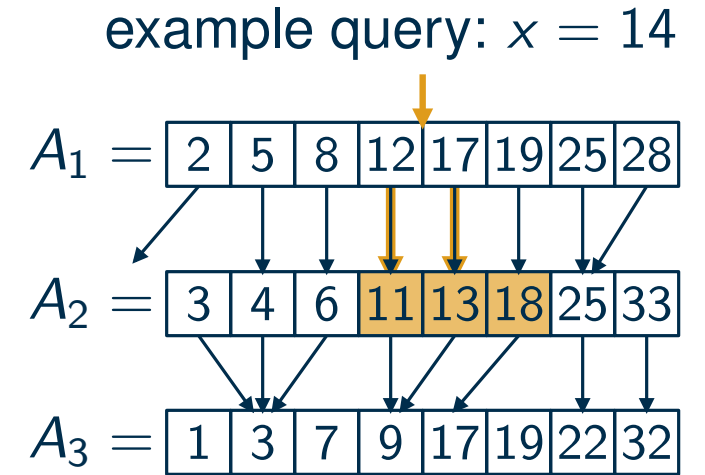
# Searching In Many Arrays

## Situation

- consider  $\ell$  sorted arrays  $A_1, \dots, A_\ell$  with  $\leq n$  elements each
- find the position of  $x$  in all arrays
- obvious solution:  $O(\ell \log n)$
- last lecture:  $O(\ell + \log n)$  if  $A_1 \supseteq A_2 \supseteq \dots \supseteq A_\ell$

## Is $\ell + \log n$ Possible In General?

- hope: search  $x$  in  $A_1$ , find  $x$  in  $A_2, \dots, A_\ell$  via pointers



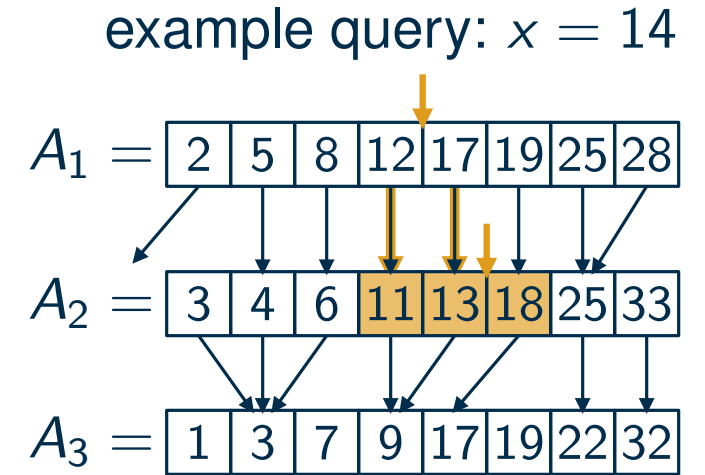
# Searching In Many Arrays

## Situation

- consider  $\ell$  sorted arrays  $A_1, \dots, A_\ell$  with  $\leq n$  elements each
- find the position of  $x$  in all arrays
- obvious solution:  $O(\ell \log n)$
- last lecture:  $O(\ell + \log n)$  if  $A_1 \supseteq A_2 \supseteq \dots \supseteq A_\ell$

## Is $\ell + \log n$ Possible In General?

- hope: search  $x$  in  $A_1$ , find  $x$  in  $A_2, \dots, A_\ell$  via pointers





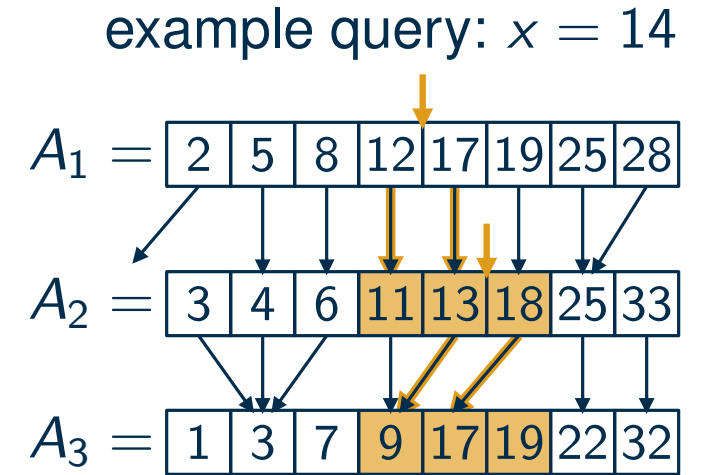
# Searching In Many Arrays

## Situation

- consider  $\ell$  sorted arrays  $A_1, \dots, A_\ell$  with  $\leq n$  elements each
- find the position of  $x$  in all arrays
- obvious solution:  $O(\ell \log n)$
- last lecture:  $O(\ell + \log n)$  if  $A_1 \supseteq A_2 \supseteq \dots \supseteq A_\ell$

## Is $\ell + \log n$ Possible In General?

- hope: search  $x$  in  $A_1$ , find  $x$  in  $A_2, \dots, A_\ell$  via pointers



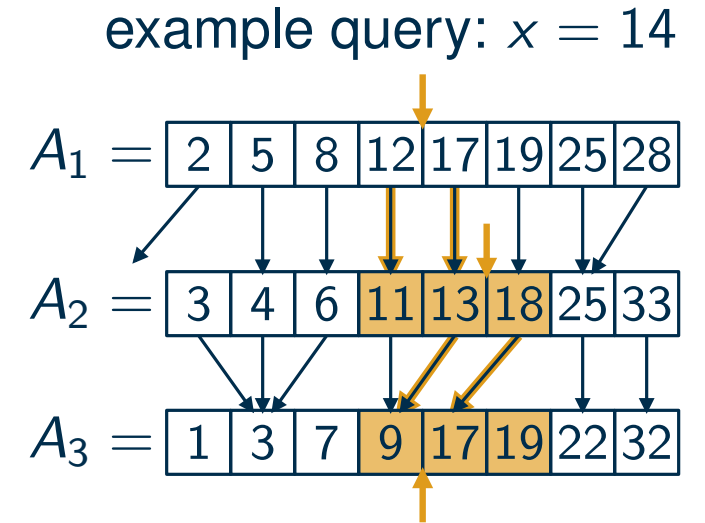
# Searching In Many Arrays

## Situation

- consider  $\ell$  sorted arrays  $A_1, \dots, A_\ell$  with  $\leq n$  elements each
- find the position of  $x$  in all arrays
- obvious solution:  $O(\ell \log n)$
- last lecture:  $O(\ell + \log n)$  if  $A_1 \supseteq A_2 \supseteq \dots \supseteq A_\ell$

## Is $\ell + \log n$ Possible In General?

- hope: search  $x$  in  $A_1$ , find  $x$  in  $A_2, \dots, A_\ell$  via pointers



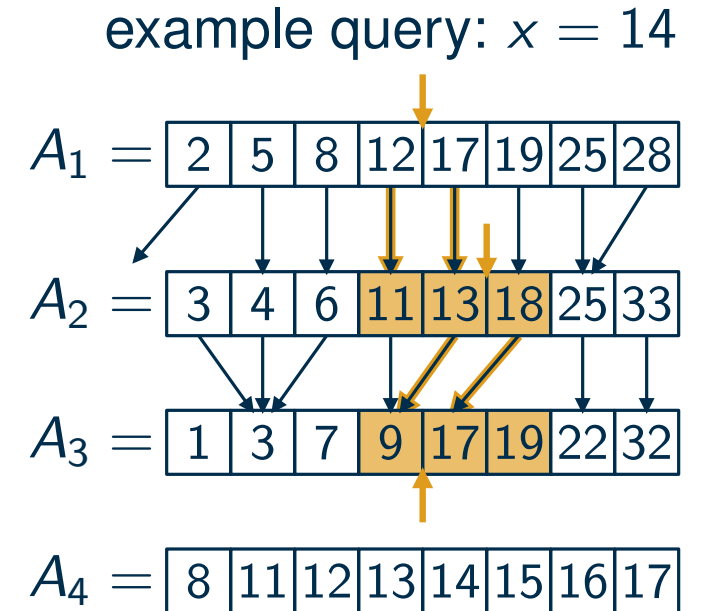
# Searching In Many Arrays

## Situation

- consider  $\ell$  sorted arrays  $A_1, \dots, A_\ell$  with  $\leq n$  elements each
- find the position of  $x$  in all arrays
- obvious solution:  $O(\ell \log n)$
- last lecture:  $O(\ell + \log n)$  if  $A_1 \supseteq A_2 \supseteq \dots \supseteq A_\ell$

## Is $\ell + \log n$ Possible In General?

- hope: search  $x$  in  $A_1$ , find  $x$  in  $A_2, \dots, A_\ell$  via pointers



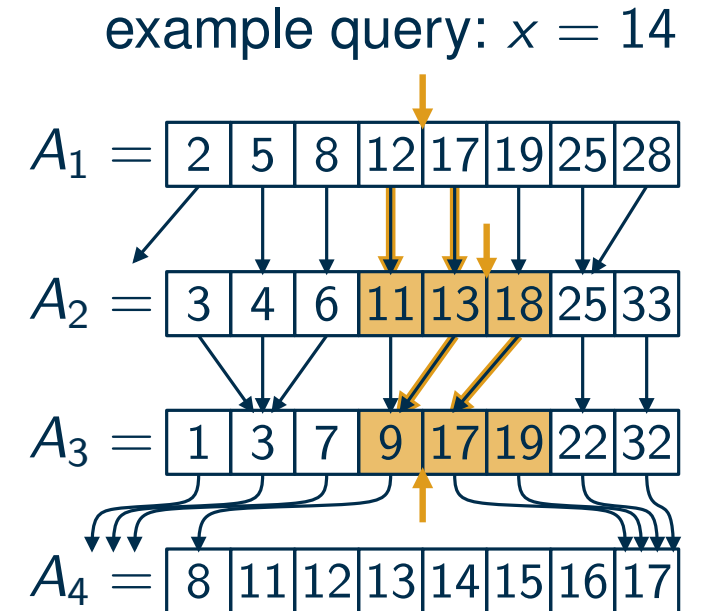
# Searching In Many Arrays

## Situation

- consider  $\ell$  sorted arrays  $A_1, \dots, A_\ell$  with  $\leq n$  elements each
- find the position of  $x$  in all arrays
- obvious solution:  $O(\ell \log n)$
- last lecture:  $O(\ell + \log n)$  if  $A_1 \supseteq A_2 \supseteq \dots \supseteq A_\ell$

## Is $\ell + \log n$ Possible In General?

- hope: search  $x$  in  $A_1$ , find  $x$  in  $A_2, \dots, A_\ell$  via pointers



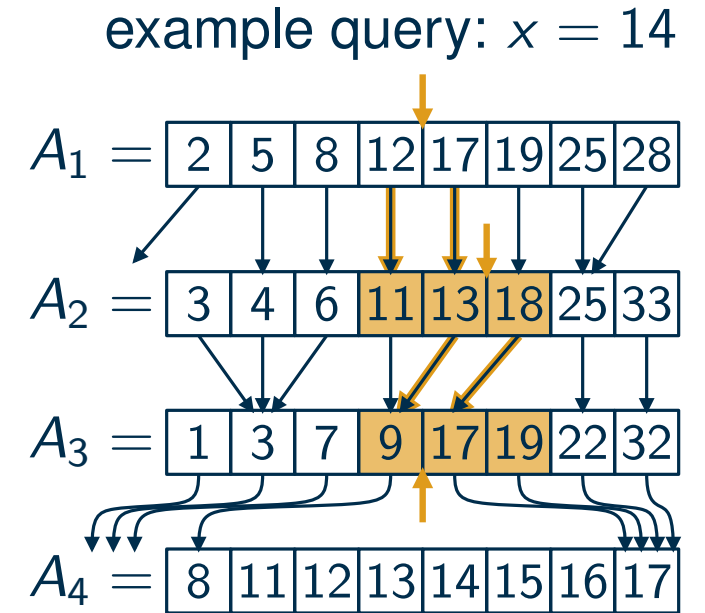
# Searching In Many Arrays

## Situation

- consider  $\ell$  sorted arrays  $A_1, \dots, A_\ell$  with  $\leq n$  elements each
- find the position of  $x$  in all arrays
- obvious solution:  $O(\ell \log n)$
- last lecture:  $O(\ell + \log n)$  if  $A_1 \supseteq A_2 \supseteq \dots \supseteq A_\ell$

## Is $\ell + \log n$ Possible In General?

- hope: search  $x$  in  $A_1$ , find  $x$  in  $A_2, \dots, A_\ell$  via pointers
- problem: position of  $x$  in  $A_i$  may not help to find position in  $A_{i+1}$



# Searching In Many Arrays

## Situation

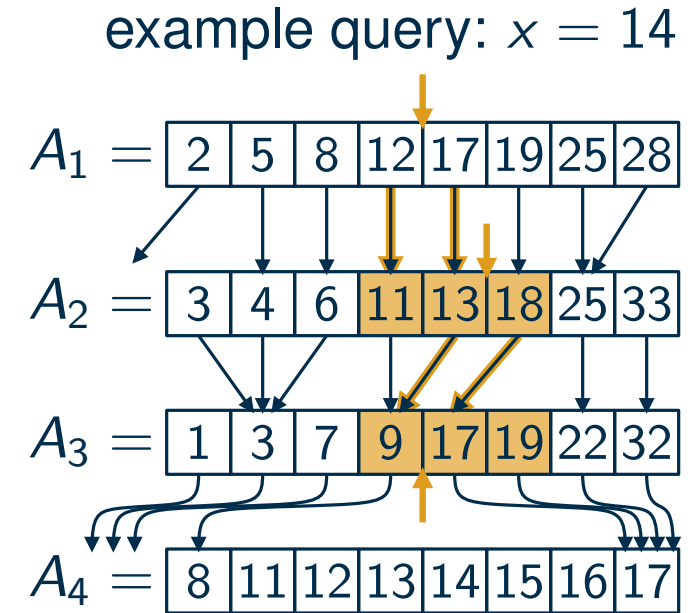
- consider  $\ell$  sorted arrays  $A_1, \dots, A_\ell$  with  $\leq n$  elements each
- find the position of  $x$  in all arrays
- obvious solution:  $O(\ell \log n)$
- last lecture:  $O(\ell + \log n)$  if  $A_1 \supseteq A_2 \supseteq \dots \supseteq A_\ell$

## Is $\ell + \log n$ Possible In General?

- hope: search  $x$  in  $A_1$ , find  $x$  in  $A_2, \dots, A_\ell$  via pointers
- problem: position of  $x$  in  $A_i$  may not help to find position in  $A_{i+1}$

## Observation

- $A_i \supseteq A_{i+1} \Rightarrow$  position in  $A_i$  determines position in  $A_{i+1}$



# Searching In Many Arrays

## Situation

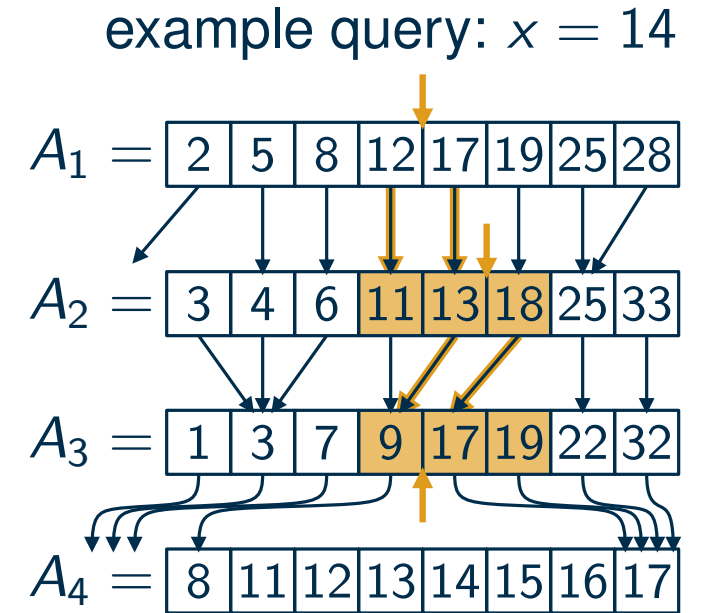
- consider  $\ell$  sorted arrays  $A_1, \dots, A_\ell$  with  $\leq n$  elements each
- find the position of  $x$  in all arrays
- obvious solution:  $O(\ell \log n)$
- last lecture:  $O(\ell + \log n)$  if  $A_1 \supseteq A_2 \supseteq \dots \supseteq A_\ell$

## Is $\ell + \log n$ Possible In General?

- hope: search  $x$  in  $A_1$ , find  $x$  in  $A_2, \dots, A_\ell$  via pointers
- problem: position of  $x$  in  $A_i$  may not help to find position in  $A_{i+1}$

## Observation

- $A_i \supseteq A_{i+1} \Rightarrow$  position in  $A_i$  determines position in  $A_{i+1}$
- $A_i$  contains many elements from  $A_{i+1} \Rightarrow$  position in  $A_i$  roughly determines position in  $A_{i+1}$



# Searching In Many Arrays

## Situation

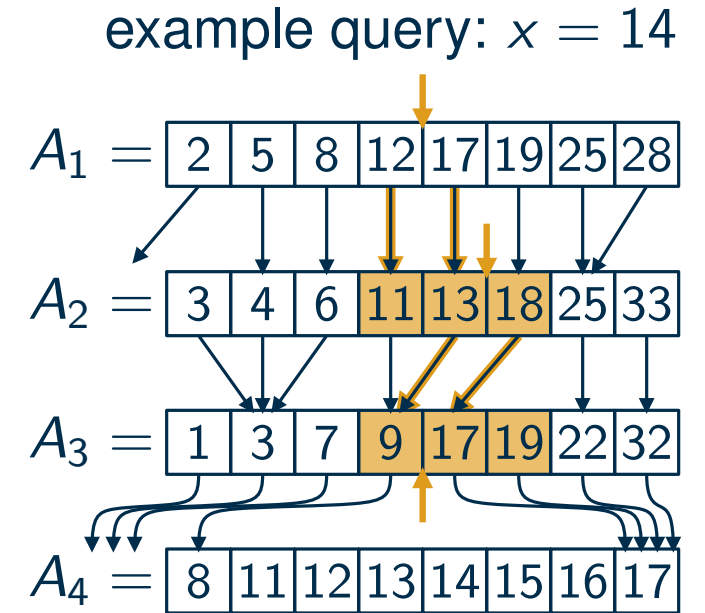
- consider  $\ell$  sorted arrays  $A_1, \dots, A_\ell$  with  $\leq n$  elements each
- find the position of  $x$  in all arrays
- obvious solution:  $O(\ell \log n)$
- last lecture:  $O(\ell + \log n)$  if  $A_1 \supseteq A_2 \supseteq \dots \supseteq A_\ell$

## Is $\ell + \log n$ Possible In General?

- hope: search  $x$  in  $A_1$ , find  $x$  in  $A_2, \dots, A_\ell$  via pointers
- problem: position of  $x$  in  $A_i$  may not help to find position in  $A_{i+1}$

## Observation

- $A_i \supseteq A_{i+1} \Rightarrow$  position in  $A_i$  determines position in  $A_{i+1}$
- $A_i$  contains many elements from  $A_{i+1} \Rightarrow$  position in  $A_i$  roughly determines position in  $A_{i+1}$
- idea: insert some elements from  $A_{i+1}$  into  $A_i$





# Fractional Cascading

## Shared Elements

- new array  $A'_3$ : insert every other element from  $A_4$  into  $A_3$

$A_3 =$ 

1	3	7	9	17	19	22	32
---	---	---	---	----	----	----	----

$A'_3 =$ 

1	3	7	8	9	12	14	16	17	19	22	32
---	---	---	---	---	----	----	----	----	----	----	----

$A_4 =$ 

8	11	12	13	14	15	16	17
---	----	----	----	----	----	----	----

$A_4 =$ 

8	11	12	13	14	15	16	17
---	----	----	----	----	----	----	----

# Fractional Cascading

## Shared Elements

- new array  $A'_3$ : insert every other element from  $A_4$  into  $A_3$
- store **pointers** to copies

$A_3 =$ 

1	3	7	9	17	19	22	32
---	---	---	---	----	----	----	----

$A_4 =$ 

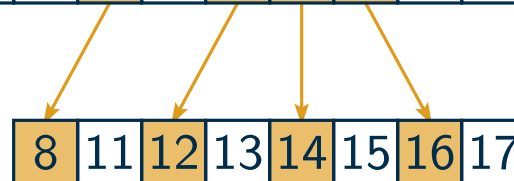
8	11	12	13	14	15	16	17
---	----	----	----	----	----	----	----

$A'_3 =$ 

1	3	7	8	9	12	14	16	17	19	22	32
---	---	---	---	---	----	----	----	----	----	----	----

$A_4 =$ 

8	11	12	13	14	15	16	17
---	----	----	----	----	----	----	----



# Fractional Cascading

## Shared Elements

- new array  $A'_3$ : insert every other element from  $A_4$  into  $A_3$
- store **pointers** to copies
- **pointers** from  $A'_3 \setminus A_4$  to prev / next element from  $A_4 \Rightarrow$  position in  $A'_3$  gives position in  $A_4 (\pm 1)$

How?

$A_3 =$ 

1	3	7	9	17	19	22	32
---	---	---	---	----	----	----	----

$A_4 =$ 

8	11	12	13	14	15	16	17
---	----	----	----	----	----	----	----

$A'_3 =$



$A_4 =$



# Fractional Cascading

## Shared Elements

- new array  $A'_3$ : insert every other element from  $A_4$  into  $A_3$
- store **pointers** to copies
- **pointers** from  $A'_3 \setminus A_4$  to prev / next element from  $A_4 \Rightarrow$  position in  $A'_3$  gives position in  $A_4 (\pm 1)$
- **pointers** from elements in  $A_4$  to prev / next in  $A'_3 \setminus A_4$

How?

Why do we need that?

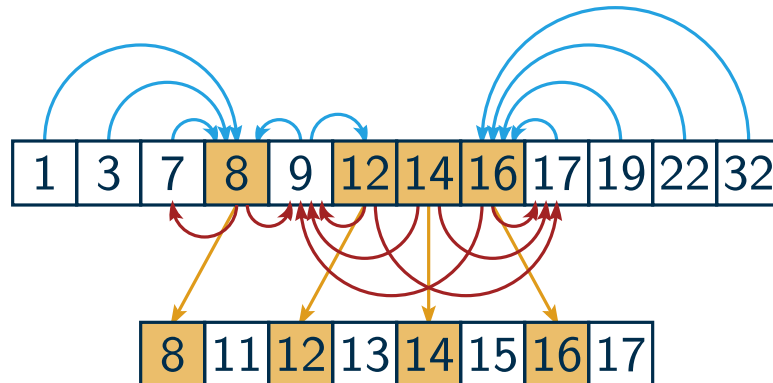
$A_3 =$ 

1	3	7	9	17	19	22	32
---	---	---	---	----	----	----	----

$A_4 =$ 

8	11	12	13	14	15	16	17
---	----	----	----	----	----	----	----

$A'_3 =$



# Fractional Cascading

## Shared Elements

- new array  $A'_3$ : insert every other element from  $A_4$  into  $A_3$
- store **pointers** to copies
- **pointers** from  $A'_3 \setminus A_4$  to prev / next element from  $A_4 \Rightarrow$  position in  $A'_3$  gives position in  $A_4 (\pm 1)$
- **pointers** from elements in  $A_4$  to prev / next in  $A'_3 \setminus A_4 \Rightarrow$  position in  $A'_3$  gives position in  $A_3$

How?

Why do we need that?

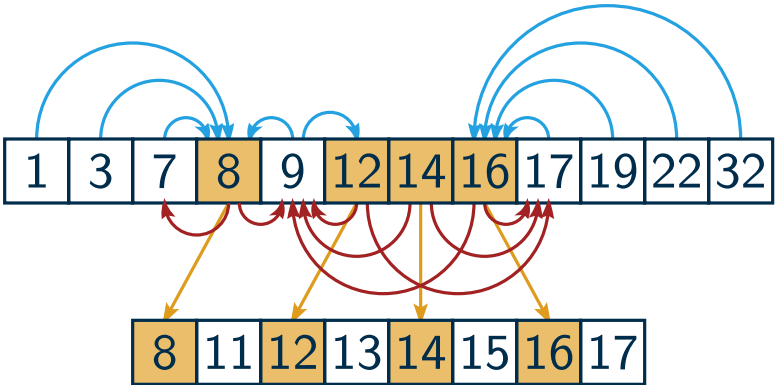
$A_3 =$ 

1	3	7	9	17	19	22	32
---	---	---	---	----	----	----	----

$A_4 =$ 

8	11	12	13	14	15	16	17
---	----	----	----	----	----	----	----

$A'_3 =$



# Fractional Cascading

## Shared Elements

- new array  $A'_3$ : insert every other element from  $A_4$  into  $A_3$
- store **pointers** to copies
- **pointers** from  $A'_3 \setminus A_4$  to prev / next element from  $A_4 \Rightarrow$  position in  $A'_3$  gives position in  $A_4 (\pm 1)$
- **pointers** from elements in  $A_4$  to prev / next in  $A'_3 \setminus A_4 \Rightarrow$  position in  $A'_3$  gives position in  $A_3$
- cascade the process for all previous  $A_i$

How?

Why do we need that?

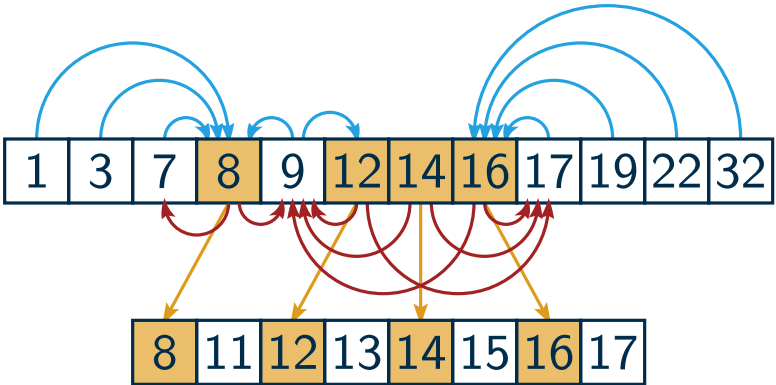
$A_3 =$ 

1	3	7	9	17	19	22	32
---	---	---	---	----	----	----	----

$A_4 =$ 

8	11	12	13	14	15	16	17
---	----	----	----	----	----	----	----

$A'_3 =$



$A_4 =$

# Fractional Cascading

## Shared Elements

- new array  $A'_3$ : insert every other element from  $A_4$  into  $A_3$
- store pointers to copies
- pointers from  $A'_3 \setminus A_4$  to prev / next element from  $A_4 \Rightarrow$  position in  $A'_3$  gives position in  $A_4$  ( $\pm 1$ )
- pointers from elements in  $A_4$  to prev / next in  $A'_3 \setminus A_4 \Rightarrow$  position in  $A'_3$  gives position in  $A_3$
- cascade the process for all previous  $A_i$

$A_1 =$ 

2	5	8	12	17	19	25	28
---	---	---	----	----	----	----	----

$A_2 =$ 

3	4	6	11	13	18	25	33
---	---	---	----	----	----	----	----

$A_3 =$ 

1	3	7	9	17	19	22	32
---	---	---	---	----	----	----	----

$A_4 =$ 

8	11	12	13	14	15	16	17
---	----	----	----	----	----	----	----

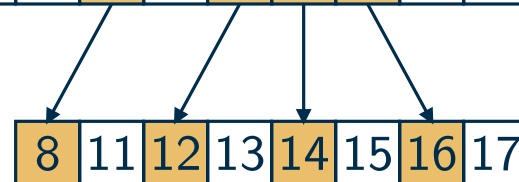
$A'_2 =$

$A'_3 =$

1	3	7	8	9	12	14	16	17	19	22	32
---	---	---	---	---	----	----	----	----	----	----	----

$A_4 =$

8	11	12	13	14	15	16	17
---	----	----	----	----	----	----	----



# Fractional Cascading

## Shared Elements

- new array  $A'_3$ : insert every other element from  $A_4$  into  $A_3$
- store pointers to copies
- pointers from  $A'_3 \setminus A_4$  to prev / next element from  $A_4 \Rightarrow$  position in  $A'_3$  gives position in  $A_4$  ( $\pm 1$ )
- pointers from elements in  $A_4$  to prev / next in  $A'_3 \setminus A_4 \Rightarrow$  position in  $A'_3$  gives position in  $A_3$
- cascade the process for all previous  $A_i$

$A_1 =$ 

2	5	8	12	17	19	25	28
---	---	---	----	----	----	----	----

$A_2 =$ 

3	4	6	11	13	18	25	33
---	---	---	----	----	----	----	----

$A_3 =$ 

1	3	7	9	17	19	22	32
---	---	---	---	----	----	----	----

$A_4 =$ 

8	11	12	13	14	15	16	17
---	----	----	----	----	----	----	----

$A'_2 =$ 

1	3	4	6	7	9	11	13	14	17	18	22	25	33
---	---	---	---	---	---	----	----	----	----	----	----	----	----

$A'_3 =$ 

1	3	7	8	9	12	14	16	17	19	22	32
---	---	---	---	---	----	----	----	----	----	----	----

$A_4 =$ 

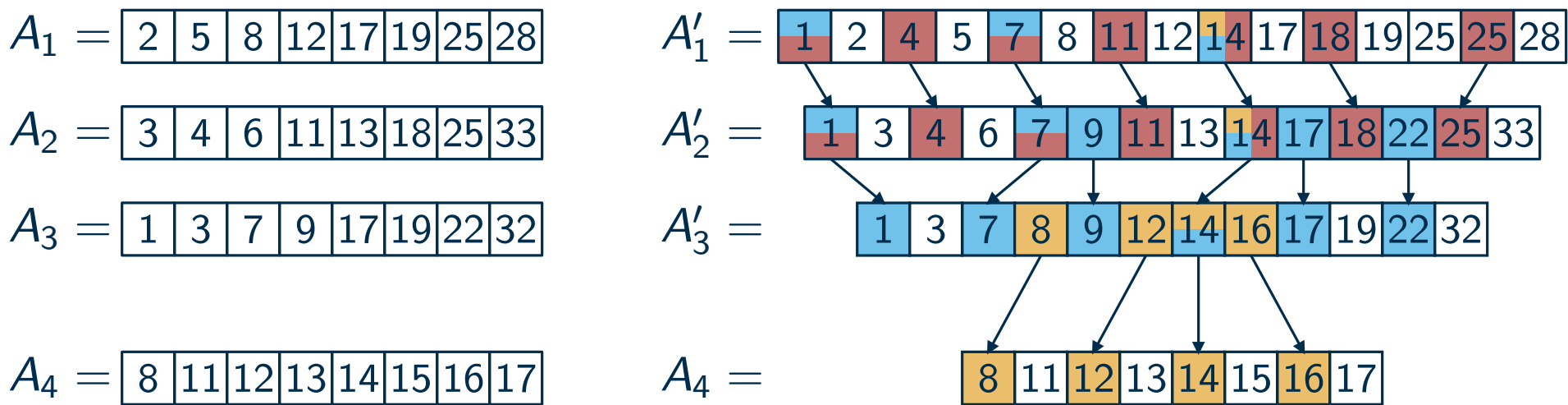
8	11	12	13	14	15	16	17
---	----	----	----	----	----	----	----



# Fractional Cascading

## Shared Elements

- new array  $A'_3$ : insert every other element from  $A_4$  into  $A_3$
- store pointers to copies
- pointers from  $A'_3 \setminus A_4$  to prev / next element from  $A_4 \Rightarrow$  position in  $A'_3$  gives position in  $A_4 (\pm 1)$
- pointers from elements in  $A_4$  to prev / next in  $A'_3 \setminus A_4 \Rightarrow$  position in  $A'_3$  gives position in  $A_3$
- cascade the process for all previous  $A_i$



# Fractional Cascading – Running Time

## Cost For The Search

# Fractional Cascading – Running Time

## Cost For The Search

- one search in  $A'_1 \rightarrow O(\log(|A'_1|))$
  - $O(1)$  for every subsequent array  $\rightarrow O(\ell)$
- } total:  $O(\ell + \log(|A'_1|))$

# Fractional Cascading – Running Time

## Cost For The Search

- one search in  $A'_1 \rightarrow O(\log(|A'_1|))$
  - $O(1)$  for every subsequent array  $\rightarrow O(\ell)$
- } total:  $O(\ell + \log(|A'_1|))$

## How Large is $A'_1$ ?

(assumption:  $|A_i| = n$  for all  $i$ )

# Fractional Cascading – Running Time

## Cost For The Search

- one search in  $A'_1 \rightarrow O(\log(|A'_1|))$
  - $O(1)$  for every subsequent array  $\rightarrow O(\ell)$
- } total:  $O(\ell + \log(|A'_1|))$

## How Large is $A'_1$ ?

(assumption:  $|A_i| = n$  for all  $i$ )

- $|A'_{\ell-1}| = (\frac{1}{2} + 1)n$

# Fractional Cascading – Running Time

## Cost For The Search

- one search in  $A'_1 \rightarrow O(\log(|A'_1|))$
  - $O(1)$  for every subsequent array  $\rightarrow O(\ell)$
- } total:  $O(\ell + \log(|A'_1|))$

## How Large is $A'_1$ ?

(assumption:  $|A_i| = n$  for all  $i$ )

- $|A'_{\ell-1}| = (\frac{1}{2} + 1)n$
- $|A'_{\ell-2}| = (\frac{1}{4} + \frac{1}{2} + 1)n$

# Fractional Cascading – Running Time

## Cost For The Search

- one search in  $A'_1 \rightarrow O(\log(|A'_1|))$
  - $O(1)$  for every subsequent array  $\rightarrow O(\ell)$
- } total:  $O(\ell + \log(|A'_1|))$

## How Large is $A'_1$ ?

(assumption:  $|A_i| = n$  for all  $i$ )

- $|A'_{\ell-1}| = (\frac{1}{2} + 1)n$
- $|A'_{\ell-2}| = (\frac{1}{4} + \frac{1}{2} + 1)n$
- $|A'_{\ell-3}| = (\frac{1}{8} + \frac{1}{4} + \frac{1}{2} + 1)n$

# Fractional Cascading – Running Time

## Cost For The Search

- one search in  $A'_1 \rightarrow O(\log(|A'_1|))$
  - $O(1)$  for every subsequent array  $\rightarrow O(\ell)$
- } total:  $O(\ell + \log(|A'_1|))$

## How Large is $A'_1$ ?

(assumption:  $|A_i| = n$  for all  $i$ )

- $|A'_{\ell-1}| = (\frac{1}{2} + 1)n$
  - $|A'_{\ell-2}| = (\frac{1}{4} + \frac{1}{2} + 1)n$
  - $|A'_{\ell-3}| = (\frac{1}{8} + \frac{1}{4} + \frac{1}{2} + 1)n$
  - $|A'_1| \leq 2n$
- $\Rightarrow$  search takes  $O(\ell + \log n)$  time



# Fractional Cascading – Running Time

## Cost For The Search

- one search in  $A'_1 \rightarrow O(\log(|A'_1|))$
  - $O(1)$  for every subsequent array  $\rightarrow O(\ell)$
- } total:  $O(\ell + \log(|A'_1|))$

## How Large is $A'_1$ ?

(assumption:  $|A_i| = n$  for all  $i$ )

- $|A'_{\ell-1}| = (\frac{1}{2} + 1)n$
- $|A'_{\ell-2}| = (\frac{1}{4} + \frac{1}{2} + 1)n$
- $|A'_{\ell-3}| = (\frac{1}{8} + \frac{1}{4} + \frac{1}{2} + 1)n$
- $|A'_1| \leq 2n \Rightarrow$  search takes  $O(\ell + \log n)$  time

## Memory Consumption

- only a constant factor overhead
- also true if not all arrays have the same size

# Fractional Cascading – Running Time

## Cost For The Search

- one search in  $A'_1 \rightarrow O(\log(|A'_1|))$
  - $O(1)$  for every subsequent array  $\rightarrow O(\ell)$
- } total:  $O(\ell + \log(|A'_1|))$

## How Large is $A'_1$ ?

(assumption:  $|A_i| = n$  for all  $i$ )

- $|A'_{\ell-1}| = (\frac{1}{2} + 1)n$
  - $|A'_{\ell-2}| = (\frac{1}{4} + \frac{1}{2} + 1)n$
  - $|A'_{\ell-3}| = (\frac{1}{8} + \frac{1}{4} + \frac{1}{2} + 1)n$
  - $|A'_1| \leq 2n$
- $\Rightarrow$  search takes  $O(\ell + \log n)$  time

## Memory Consumption

- only a constant factor overhead
- also true if not all arrays have the same size

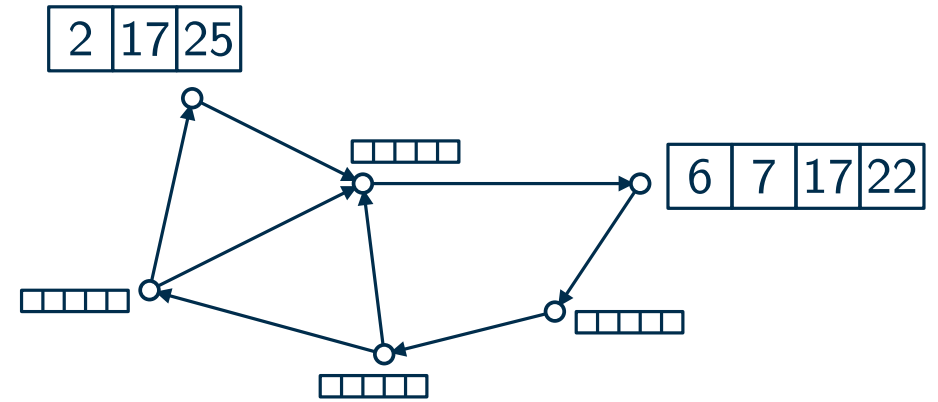
## Precomputation Time

- linear in the input

# General Fractional Cascading

**Now With A Directed Graph  $G = (V, E)$**

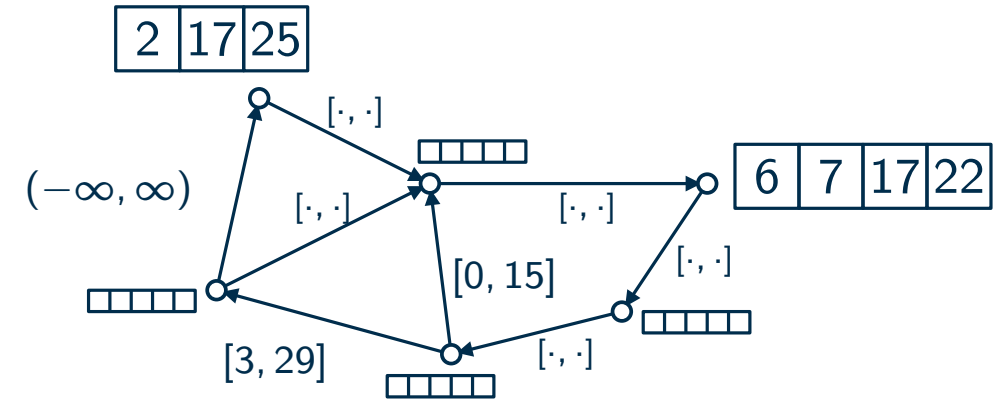
- sorted array  $A_v$  for every vertex  $v$



# General Fractional Cascading

## Now With A Directed Graph $G = (V, E)$

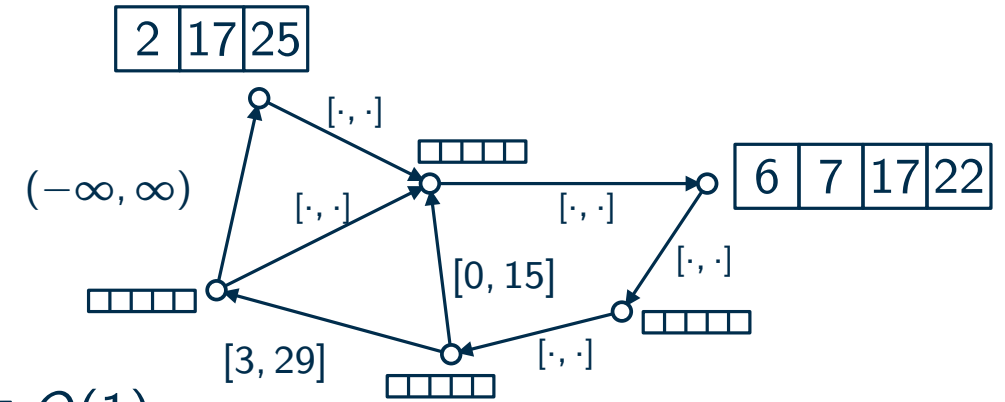
- sorted array  $A_v$  for every vertex  $v$
- an interval  $I_e$  for every edge  $e$



# General Fractional Cascading

## Now With A Directed Graph $G = (V, E)$

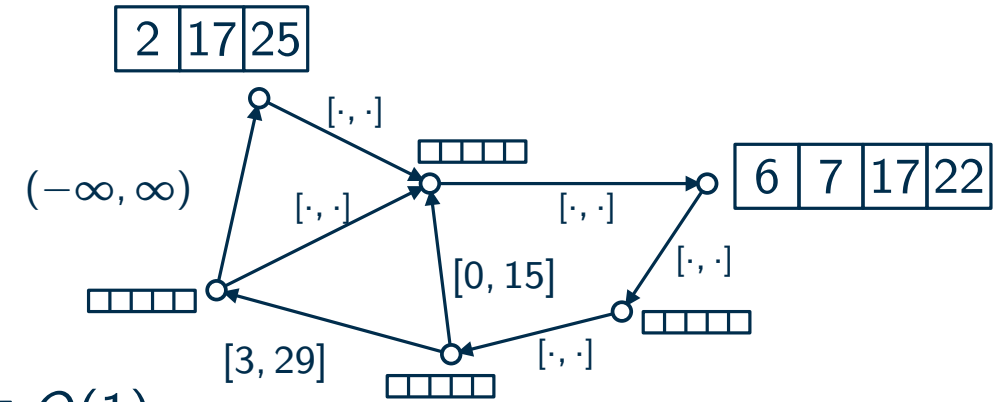
- sorted array  $A_v$  for every vertex  $v$
- an interval  $I_e$  for every edge  $e$
- for every number  $x$  and  $u \in V$ :  $|\{uv \in E \mid x \in I_{uv}\}| \in O(1)$



# General Fractional Cascading

## Now With A Directed Graph $G = (V, E)$

- sorted array  $A_v$  for every vertex  $v$
- an interval  $I_e$  for every edge  $e$
- for every number  $x$  and  $u \in V$ :  $|\{uv \in E \mid x \in I_{uv}\}| \in O(1)$



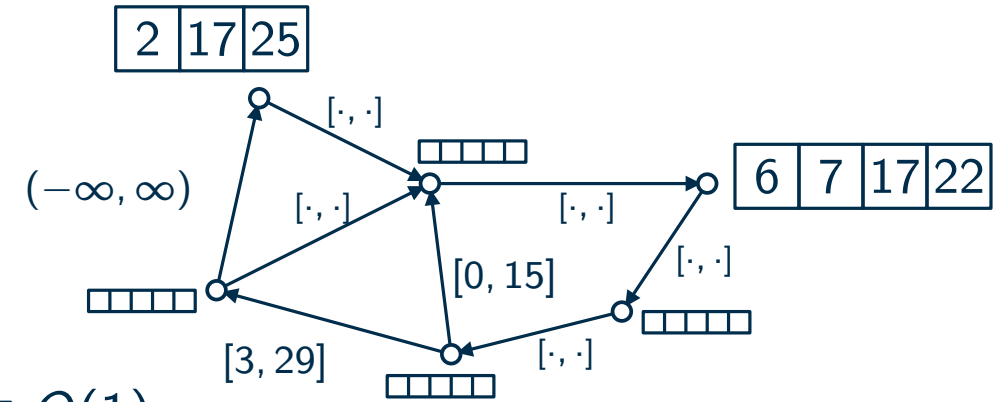
## A Game Between Alice And Bob



# General Fractional Cascading

## Now With A Directed Graph $G = (V, E)$

- sorted array  $A_v$  for every vertex  $v$
- an interval  $I_e$  for every edge  $e$
- for every number  $x$  and  $u \in V$ :  $|\{uv \in E \mid x \in I_{uv}\}| \in O(1)$



## A Game Between Alice And Bob

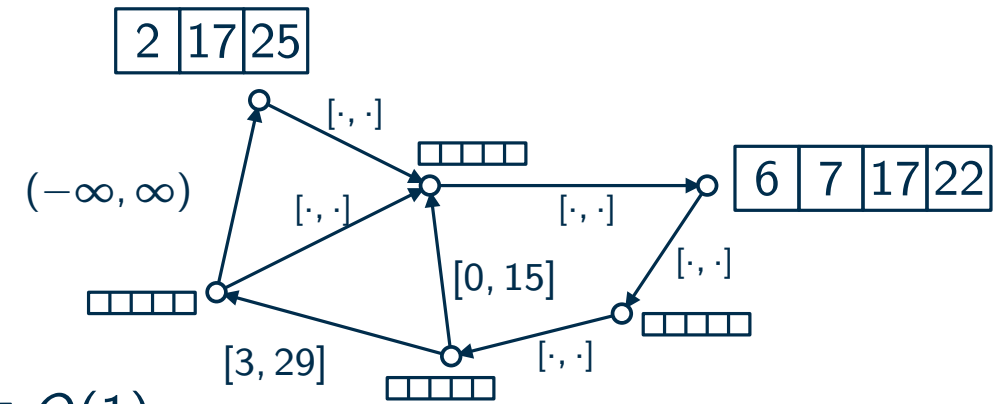
- precomputes a data structure



# General Fractional Cascading

## Now With A Directed Graph $G = (V, E)$

- sorted array  $A_v$  for every vertex  $v$
- an interval  $I_e$  for every edge  $e$
- for every number  $x$  and  $u \in V$ :  $|\{uv \in E \mid x \in I_{uv}\}| \in O(1)$



## A Game Between Alice And Bob

- precomputes a data structure



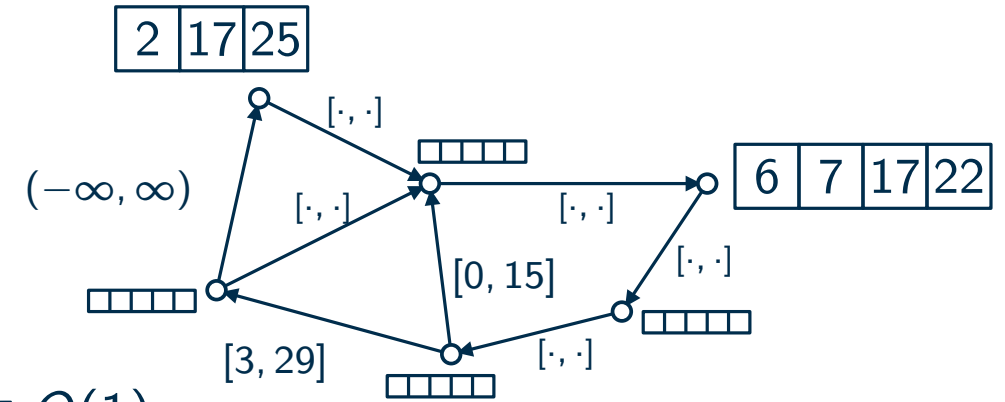
- choose a number  $x$  and  $u \in V$
- asks where  $x$  lies in  $A_u$



# General Fractional Cascading

## Now With A Directed Graph $G = (V, E)$

- sorted array  $A_v$  for every vertex  $v$
- an interval  $I_e$  for every edge  $e$
- for every number  $x$  and  $u \in V$ :  $|\{uv \in E \mid x \in I_{uv}\}| \in O(1)$



## A Game Between Alice And Bob



- precomputes a data structure
- answers the question

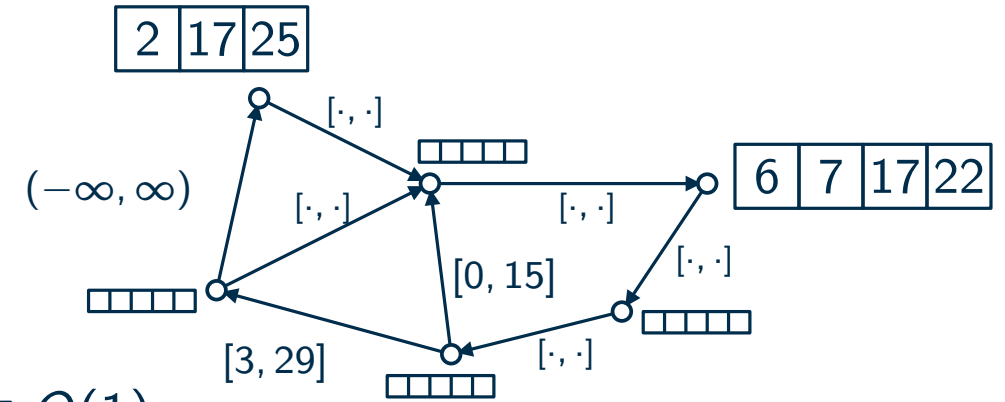


- choose a number  $x$  and  $u \in V$
- asks where  $x$  lies in  $A_u$

# General Fractional Cascading

## Now With A Directed Graph $G = (V, E)$

- sorted array  $A_v$  for every vertex  $v$
- an interval  $I_e$  for every edge  $e$
- for every number  $x$  and  $u \in V$ :  $|\{uv \in E \mid x \in I_{uv}\}| \in O(1)$



## A Game Between Alice And Bob



- precomputes a data structure
- answers the question

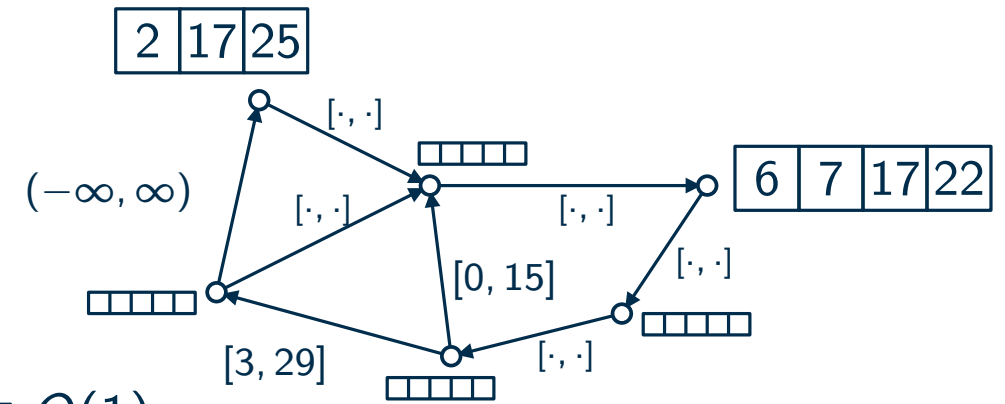


- choose a number  $x$  and  $u \in V$
- asks where  $x$  lies in  $A_u$
- choose edge  $uv$  with  $x \in I_{uv}$
- asks where  $x$  lies in  $A_v$

# General Fractional Cascading

## Now With A Directed Graph $G = (V, E)$

- sorted array  $A_v$  for every vertex  $v$
- an interval  $I_e$  for every edge  $e$
- for every number  $x$  and  $u \in V$ :  $|\{uv \in E \mid x \in I_{uv}\}| \in O(1)$



## A Game Between Alice And Bob



- precomputes a data structure
- answers the question
- answers the question

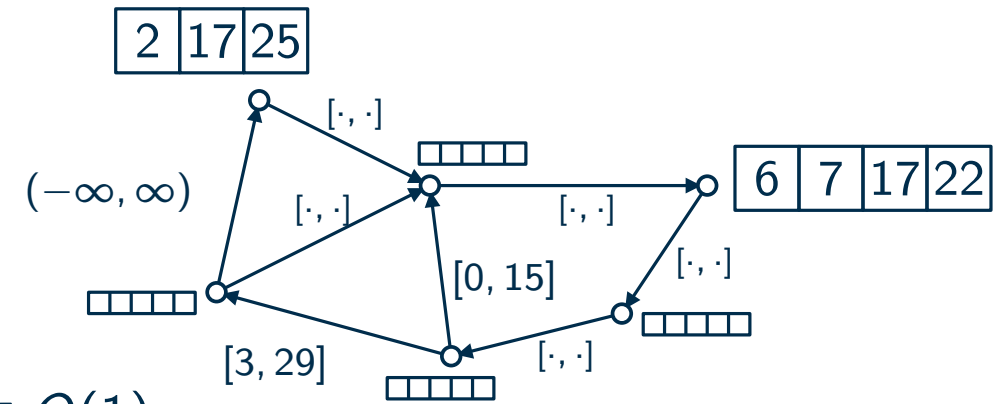


- choose a number  $x$  and  $u \in V$
- asks where  $x$  lies in  $A_u$
- choose edge  $uv$  with  $x \in I_{uv}$
- asks where  $x$  lies in  $A_v$

# General Fractional Cascading

## Now With A Directed Graph $G = (V, E)$

- sorted array  $A_v$  for every vertex  $v$
- an interval  $I_e$  for every edge  $e$
- for every number  $x$  and  $u \in V$ :  $|\{uv \in E \mid x \in I_{uv}\}| \in O(1)$



## A Game Between Alice And Bob



- precomputes a data structure
- answers the question
- answers the question

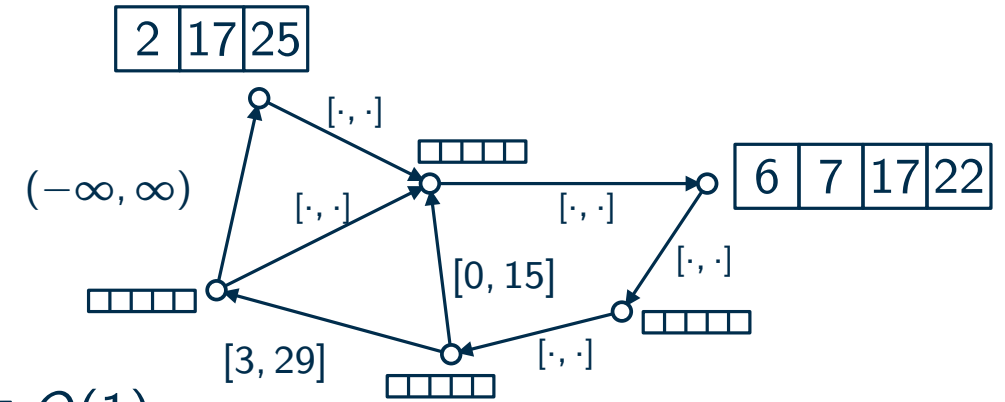


- choose a number  $x$  and  $u \in V$
- asks where  $x$  lies in  $A_u$
- choose edge  $uv$  with  $x \in I_{uv}$
- asks where  $x$  lies in  $A_v$

# General Fractional Cascading

## Now With A Directed Graph $G = (V, E)$

- sorted array  $A_v$  for every vertex  $v$
- an interval  $I_e$  for every edge  $e$
- for every number  $x$  and  $u \in V$ :  $|\{uv \in E \mid x \in I_{uv}\}| \in O(1)$



How is this a generalization?

## A Game Between Alice And Bob



- precomputes a data structure
- answers the question
- answers the question

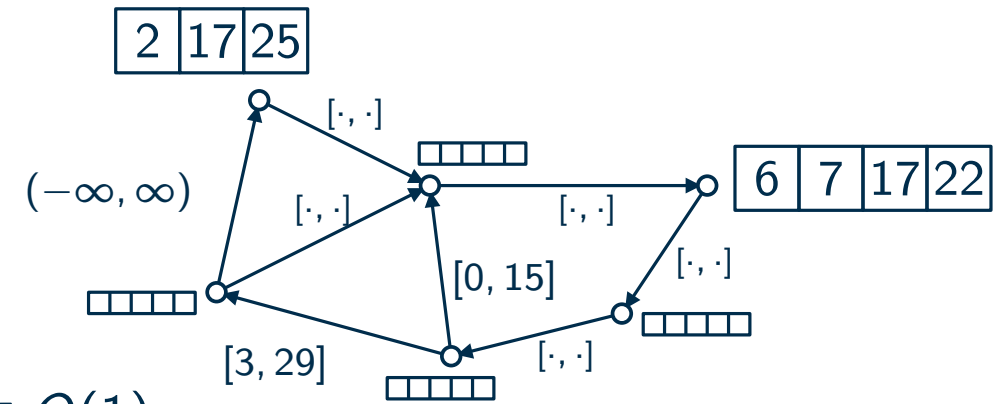


- choose a number  $x$  and  $u \in V$
- asks where  $x$  lies in  $A_u$
- choose edge  $uv$  with  $x \in I_{uv}$
- asks where  $x$  lies in  $A_v$

# General Fractional Cascading

## Now With A Directed Graph $G = (V, E)$

- sorted array  $A_v$  for every vertex  $v$
- an interval  $I_e$  for every edge  $e$
- for every number  $x$  and  $u \in V$ :  $|\{uv \in E \mid x \in I_{uv}\}| \in O(1)$



How is this a generalization?

## A Game Between Alice And Bob



- precomputes a data structure
- answers the question
- answers the question



- choose a number  $x$  and  $u \in V$
- asks where  $x$  lies in  $A_u$
- choose edge  $uv$  with  $x \in I_{uv}$
- asks where  $x$  lies in  $A_v$

## Similar Guarantee To The Path Setting (without proof)

( $s$  = Gesamtgröße der Arrays)

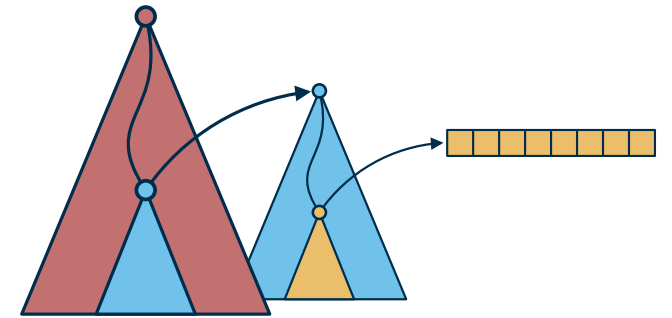
- precomputation:  $O(s)$  time and  $O(s)$  space
- query:  $O(\log s)$  for the first, then  $O(1)$

# Back To The Range Queries

# Back To The Range Queries

## Query In 3D Range Tree (Simple Variant)

query:  $[a_1, b_1] \times [a_2, b_2] \times [a_3, b_3]$   
direction:  $x \quad y \quad z$



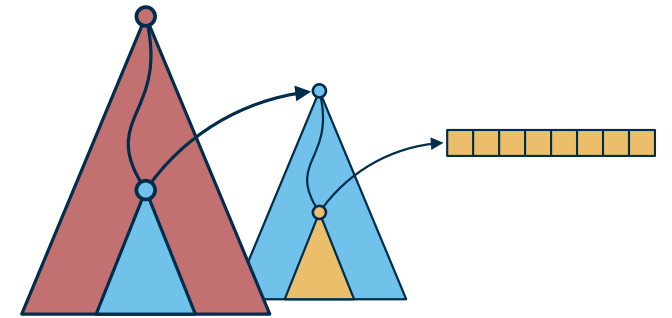


# Back To The Range Queries

## Query In 3D Range Tree (Simple Variant)

- walk down the **x-tree**  $\rightarrow O(\log n)$

query:  $[a_1, b_1] \times [a_2, b_2] \times [a_3, b_3]$   
direction:  $\begin{matrix} \text{red box} & \text{blue box} & \text{yellow box} \\ x & y & z \end{matrix}$

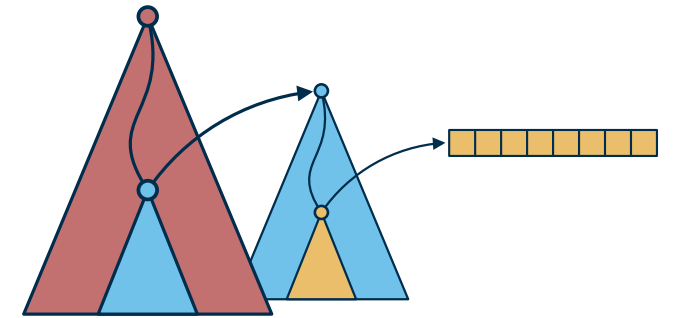


# Back To The Range Queries

## Query In 3D Range Tree (Simple Variant)

- walk down the **x-tree**  $\rightarrow O(\log n)$
- walk down in  $O(\log n)$  **y-trees**  $\rightarrow O(\log n \log n)$

query:  $[a_1, b_1] \times [a_2, b_2] \times [a_3, b_3]$   
direction:  $\begin{matrix} \text{red box} & \text{blue box} & \text{yellow box} \\ x & y & z \end{matrix}$

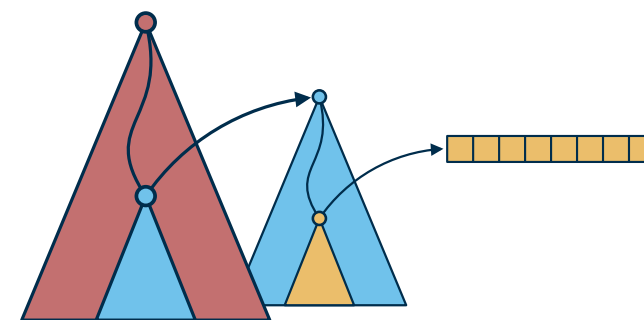


# Back To The Range Queries

## Query In 3D Range Tree (Simple Variant)

- walk down the  $x$ -tree  $\rightarrow O(\log n)$
- walk down in  $O(\log n)$   $y$ -trees  $\rightarrow O(\log n \log n)$
- search in  $O(\log n \log n)$   $z$ -arrays  $\rightarrow O(\log n \log n \log n)$

query:  $[a_1, b_1] \times [a_2, b_2] \times [a_3, b_3]$   
direction:  $x \quad y \quad z$



# Back To The Range Queries

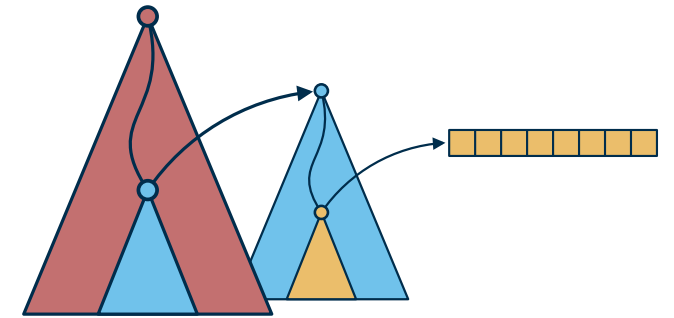
## Query In 3D Range Tree (Simple Variant)

- walk down the  $x$ -tree  $\rightarrow O(\log n)$
- walk down in  $O(\log n)$   $y$ -trees  $\rightarrow O(\log n \log n)$
- search in  $O(\log n \log n)$   $z$ -arrays  $\rightarrow O(\log n \log n \log n)$

## Last Lecture: Do $z$ -Search Earlier

- walk down the  $x$ -tree  $\rightarrow O(\log n)$  time

query:  $[a_1, b_1] \times [a_2, b_2] \times [a_3, b_3]$   
direction:  $x \quad y \quad z$



# Back To The Range Queries

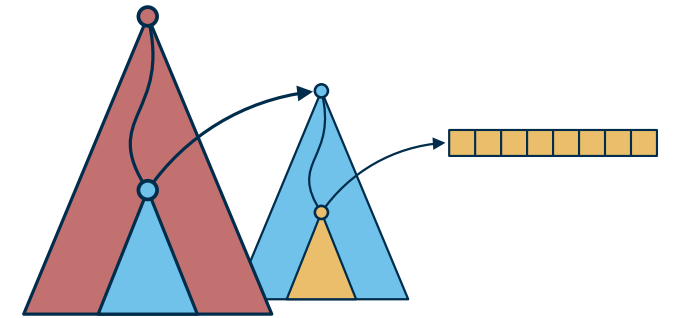
## Query In 3D Range Tree (Simple Variant)

- walk down the  $x$ -tree  $\rightarrow O(\log n)$
- walk down in  $O(\log n)$   $y$ -trees  $\rightarrow O(\log n \log n)$
- search in  $O(\log n \log n)$   $z$ -arrays  $\rightarrow O(\log n \log n \log n)$

## Last Lecture: Do $z$ -Search Earlier

- walk down the  $x$ -tree  $\rightarrow O(\log n)$  time
- search in  $z$ -arrays in roots of  $O(\log n)$   $y$ -trees  $\rightarrow O(\log n \log n)$

query:  $[a_1, b_1] \times [a_2, b_2] \times [a_3, b_3]$   
direction:  $\begin{matrix} \text{red box} & \text{blue box} & \text{yellow box} \\ x & y & z \end{matrix}$



# Back To The Range Queries

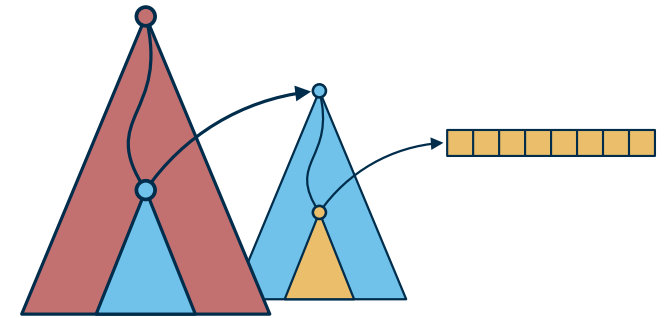
## Query In 3D Range Tree (Simple Variant)

- walk down the  $x$ -tree  $\rightarrow O(\log n)$
- walk down in  $O(\log n)$   $y$ -trees  $\rightarrow O(\log n \log n)$
- search in  $O(\log n \log n)$   $z$ -arrays  $\rightarrow O(\log n \log n \log n)$

## Last Lecture: Do $z$ -Search Earlier

- walk down the  $x$ -tree  $\rightarrow O(\log n)$  time
- search in  $z$ -arrays in roots of  $O(\log n)$   $y$ -trees  $\rightarrow O(\log n \log n)$
- walk down in  $O(\log n)$   $y$ -trees (and follow  $z$ -array pointers)  $\rightarrow O(\log n \log n)$

query:  $[a_1, b_1] \times [a_2, b_2] \times [a_3, b_3]$   
direction:  $\begin{matrix} \text{red box} & \text{blue box} & \text{yellow box} \\ x & y & z \end{matrix}$



# Back To The Range Queries

## Query In 3D Range Tree (Simple Variant)

- walk down the  $x$ -tree  $\rightarrow O(\log n)$
- walk down in  $O(\log n)$   $y$ -trees  $\rightarrow O(\log n \log n)$
- search in  $O(\log n \log n)$   $z$ -arrays  $\rightarrow O(\log n \log n \log n)$

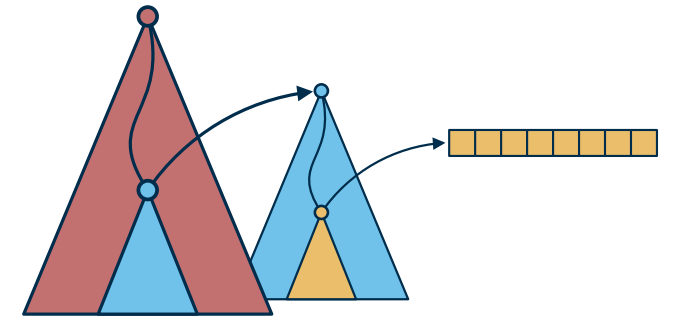
## Last Lecture: Do $z$ -Search Earlier

- walk down the  $x$ -tree  $\rightarrow O(\log n)$  time
- search in  $z$ -arrays in roots of  $O(\log n)$   $y$ -trees  $\rightarrow O(\log n \log n)$
- walk down in  $O(\log n)$   $y$ -trees (and follow  $z$ -array pointers)  $\rightarrow O(\log n \log n)$

## Idea: Do The $z$ -Search Even Earlier

- search  $z$ -array in root of  $x$ -tree  $\rightarrow O(\log n)$

query:  $[a_1, b_1] \times [a_2, b_2] \times [a_3, b_3]$   
direction:  $\begin{matrix} \text{red box} & \text{blue box} & \text{yellow box} \\ x & y & z \end{matrix}$



# Back To The Range Queries

## Query In 3D Range Tree (Simple Variant)

- walk down the  $x$ -tree  $\rightarrow O(\log n)$
- walk down in  $O(\log n)$   $y$ -trees  $\rightarrow O(\log n \log n)$
- search in  $O(\log n \log n)$   $z$ -arrays  $\rightarrow O(\log n \log n \log n)$

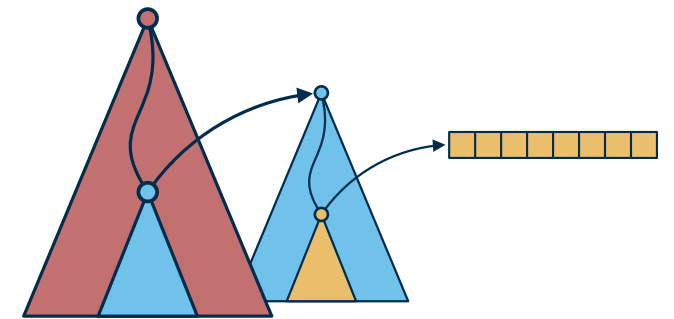
## Last Lecture: Do $z$ -Search Earlier

- walk down the  $x$ -tree  $\rightarrow O(\log n)$  time
- search in  $z$ -arrays in roots of  $O(\log n)$   $y$ -trees  $\rightarrow O(\log n \log n)$
- walk down in  $O(\log n)$   $y$ -trees (and follow  $z$ -array pointers)  $\rightarrow O(\log n \log n)$

## Idea: Do The $z$ -Search Even Earlier

- search  $z$ -array in root of  $x$ -tree  $\rightarrow O(\log n)$
- walk down the  $x$ -tree  $\rightarrow O(\log n)$  time

query:  $[a_1, b_1] \times [a_2, b_2] \times [a_3, b_3]$   
direction:  $\begin{matrix} \text{red box} & \text{blue box} & \text{yellow box} \\ x & y & z \end{matrix}$





# Back To The Range Queries

## Query In 3D Range Tree (Simple Variant)

- walk down the  $x$ -tree  $\rightarrow O(\log n)$
- walk down in  $O(\log n)$   $y$ -trees  $\rightarrow O(\log n \log n)$
- search in  $O(\log n \log n)$   $z$ -arrays  $\rightarrow O(\log n \log n \log n)$

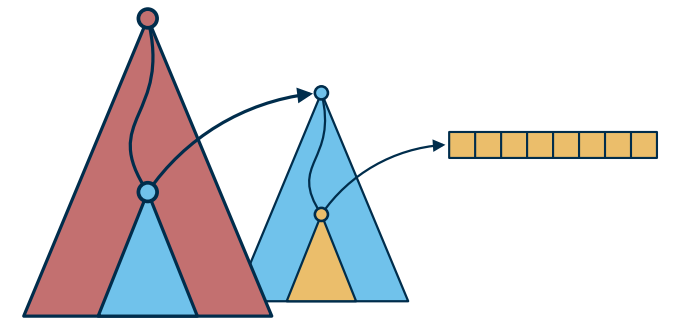
## Last Lecture: Do $z$ -Search Earlier

- walk down the  $x$ -tree  $\rightarrow O(\log n)$  time
- search in  $z$ -arrays in roots of  $O(\log n)$   $y$ -trees  $\rightarrow O(\log n \log n)$
- walk down in  $O(\log n)$   $y$ -trees (and follow  $z$ -array pointers)  $\rightarrow O(\log n \log n)$

## Idea: Do The $z$ -Search Even Earlier

- search  $z$ -array in root of  $x$ -tree  $\rightarrow O(\log n)$
- walk down the  $x$ -tree  $\rightarrow O(\log n)$  time
- walk down in  $O(\log n)$   $y$ -trees  $\rightarrow O(\log n \log n)$

query:  $[a_1, b_1] \times [a_2, b_2] \times [a_3, b_3]$   
direction:  $x \quad y \quad z$



# Back To The Range Queries

## Query In 3D Range Tree (Simple Variant)

- walk down the  $x$ -tree  $\rightarrow O(\log n)$
- walk down in  $O(\log n)$   $y$ -trees  $\rightarrow O(\log n \log n)$
- search in  $O(\log n \log n)$   $z$ -arrays  $\rightarrow O(\log n \log n \log n)$

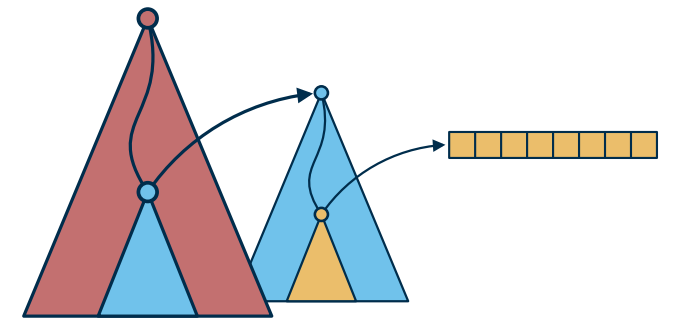
## Last Lecture: Do $z$ -Search Earlier

- walk down the  $x$ -tree  $\rightarrow O(\log n)$  time
- search in  $z$ -arrays in roots of  $O(\log n)$   $y$ -trees  $\rightarrow O(\log n \log n)$
- walk down in  $O(\log n)$   $y$ -trees (and follow  $z$ -array pointers)  $\rightarrow O(\log n \log n)$

## Idea: Do The $z$ -Search Even Earlier

- search  $z$ -array in root of  $x$ -tree  $\rightarrow O(\log n)$
- walk down the  $x$ -tree  $\rightarrow O(\log n)$  time
- walk down in  $O(\log n)$   $y$ -trees  $\rightarrow O(\log n \log n)$

query:  $[a_1, b_1] \times [a_2, b_2] \times [a_3, b_3]$   
direction:  $x \quad y \quad z$



## Observation

- getting rid of  $\log n$  seems easy
- getting rid of  $\log n$  seems hard

# Back To The Range Queries

## Query In 3D Range Tree (Simple Variant)

- walk down the  $x$ -tree  $\rightarrow O(\log n)$
- walk down in  $O(\log n)$   $y$ -trees  $\rightarrow O(\log n \log n)$
- search in  $O(\log n \log n)$   $z$ -arrays  $\rightarrow O(\log n \log n \log n)$

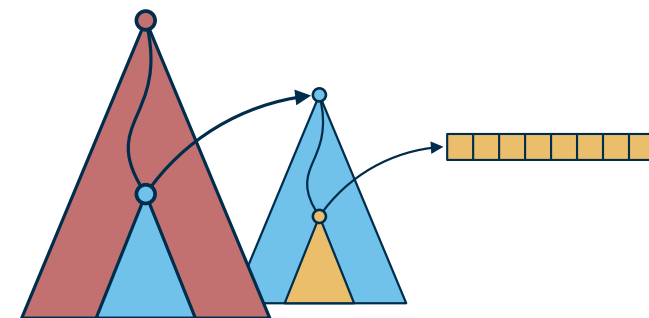
## Last Lecture: Do $z$ -Search Earlier

- walk down the  $x$ -tree  $\rightarrow O(\log n)$  time
- search in  $z$ -arrays in roots of  $O(\log n)$   $y$ -trees  $\rightarrow O(\log n \log n)$
- walk down in  $O(\log n)$   $y$ -trees (and follow  $z$ -array pointers)  $\rightarrow O(\log n \log n)$

## Idea: Do The $z$ -Search Even Earlier

- search  $z$ -array in root of  $x$ -tree  $\rightarrow O(\log n)$
- walk down the  $x$ -tree  $\rightarrow O(\log n)$  time
- walk down in  $O(\log n)$   $y$ -trees  $\rightarrow O(\log n \log n)$

query:  $[a_1, b_1] \times [a_2, b_2] \times [a_3, b_3]$   
direction:  $x \quad y \quad z$



## Observation

- getting rid of  $\log n$  seems easy
- getting rid of  $\log n$  seems hard
- goal: 2D DS with query time  $O(\log n)$

# One-Sided 2D Range Queries

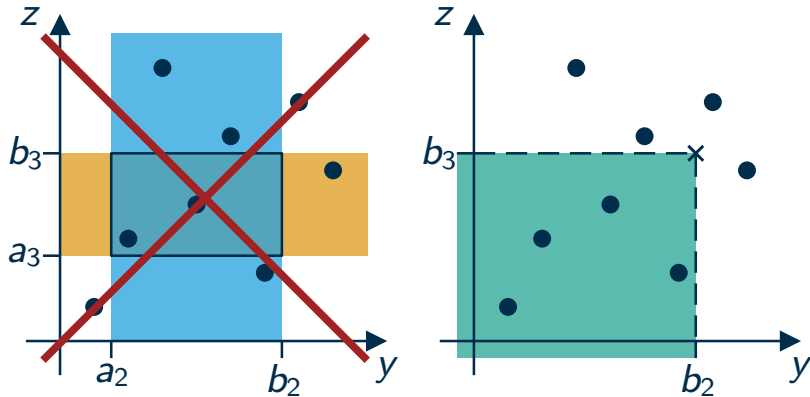
goal: 2D DS with query time  $O(\log n)$

# One-Sided 2D Range Queries

goal: 2D DS with query time  $O(\log n)$

## One-Sided Queries: Half The Sides, Half The Trouble

- goal: answer queries of the form  $(-\infty, b_2] \times (-\infty, b_3]$  (instead of  $[a_2, b_2] \times [a_3, b_3]$ )

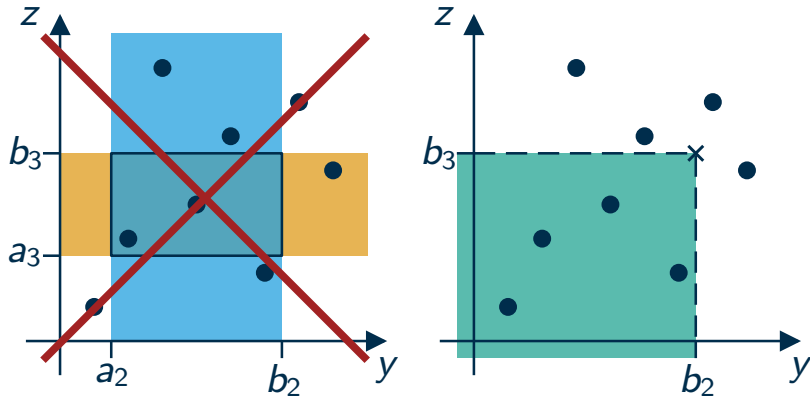


# One-Sided 2D Range Queries

goal: 2D DS with query time  $O(\log n)$

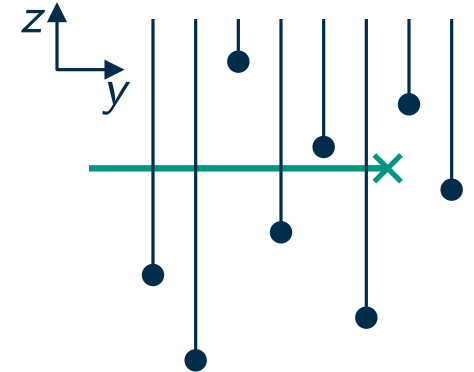
## One-Sided Queries: Half The Sides, Half The Trouble

- goal: answer queries of the form  $(-\infty, b_2] \times (-\infty, b_3]$  (instead of  $[a_2, b_2] \times [a_3, b_3]$ )



## Alternative Perspective

- shoot a ray from each point upwards
- ray from  $\langle b_2, b_3 \rangle$  to the left

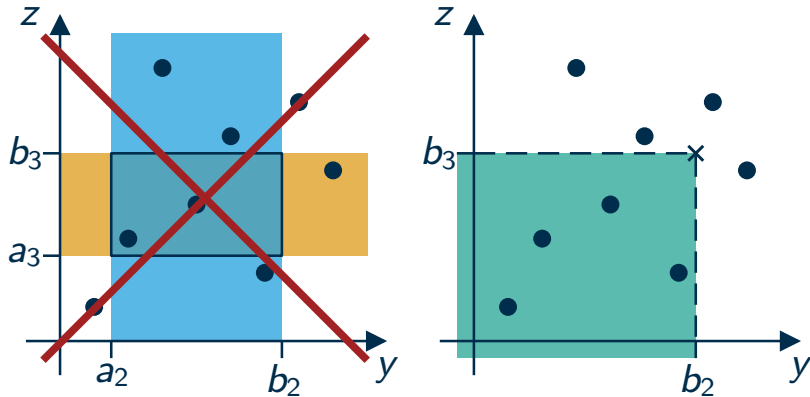


# One-Sided 2D Range Queries

goal: 2D DS with query time  $O(\log n)$

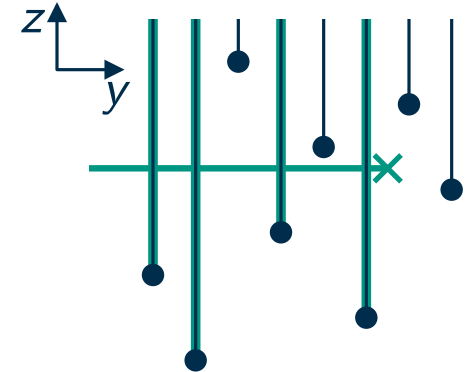
## One-Sided Queries: Half The Sides, Half The Trouble

- goal: answer queries of the form  $(-\infty, b_2] \times (-\infty, b_3]$  (instead of  $[a_2, b_2] \times [a_3, b_3]$ )



## Alternative Perspective

- shoot a ray from each point upwards
- ray from  $\langle b_2, b_3 \rangle$  to the left
- intersecting rays yield desired points

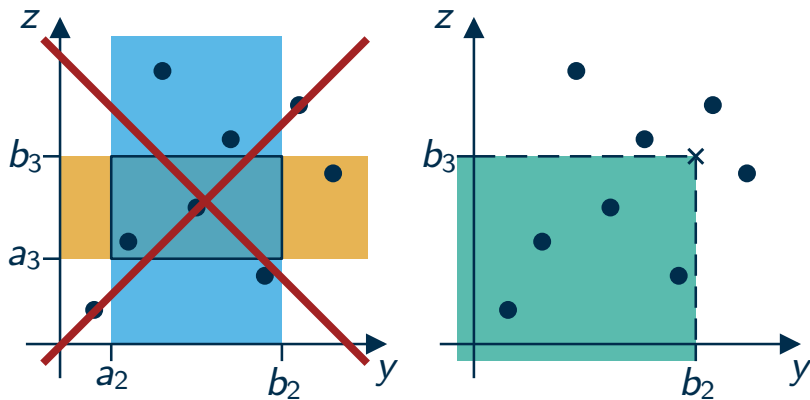


# One-Sided 2D Range Queries

goal: 2D DS with query time  $O(\log n)$

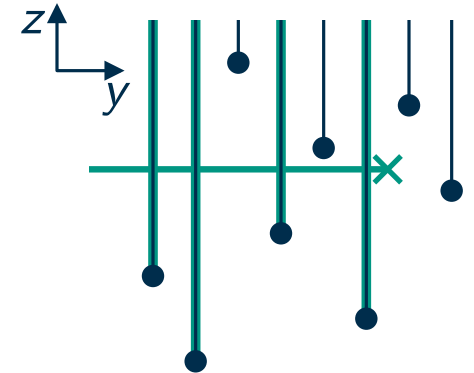
## One-Sided Queries: Half The Sides, Half The Trouble

- goal: answer queries of the form  $(-\infty, b_2] \times (-\infty, b_3]$  (instead of  $[a_2, b_2] \times [a_3, b_3]$ )



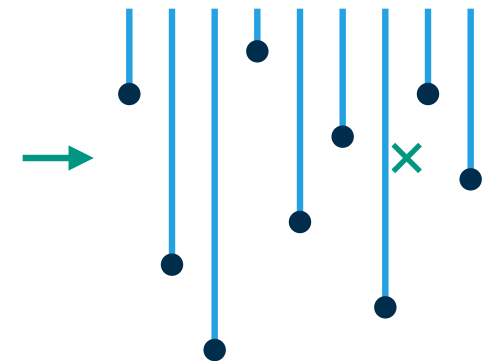
## Alternative Perspective

- shoot a ray from each point upwards
- ray from  $\langle b_2, b_3 \rangle$  to the left
- intersecting rays yield desired points



## Find All Intersecting Rays

- collect the intersecting rays from left to right



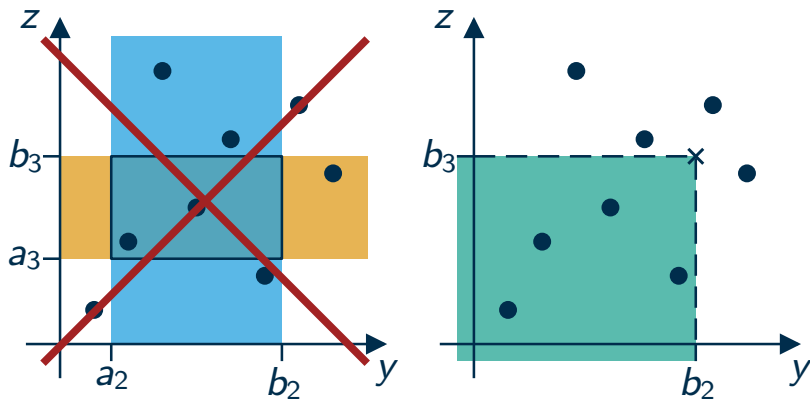


# One-Sided 2D Range Queries

goal: 2D DS with query time  $O(\log n)$

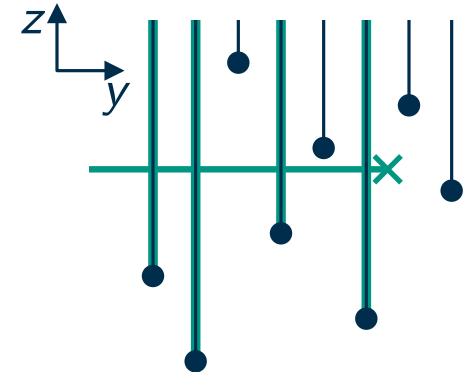
## One-Sided Queries: Half The Sides, Half The Trouble

- goal: answer queries of the form  $(-\infty, b_2] \times (-\infty, b_3]$  (instead of  $[a_2, b_2] \times [a_3, b_3]$ )



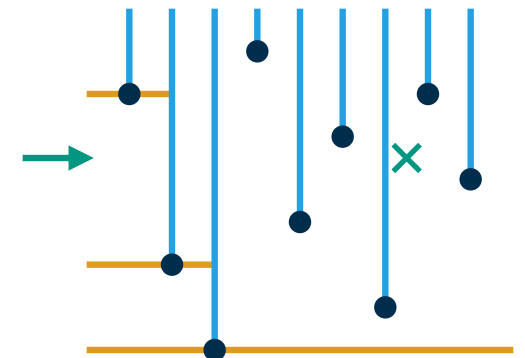
## Alternative Perspective

- shoot a ray from each point upwards
- ray from  $\langle b_2, b_3 \rangle$  to the left
- intersecting rays yield desired points



## Find All Intersecting Rays

- collect the intersecting rays from left to right

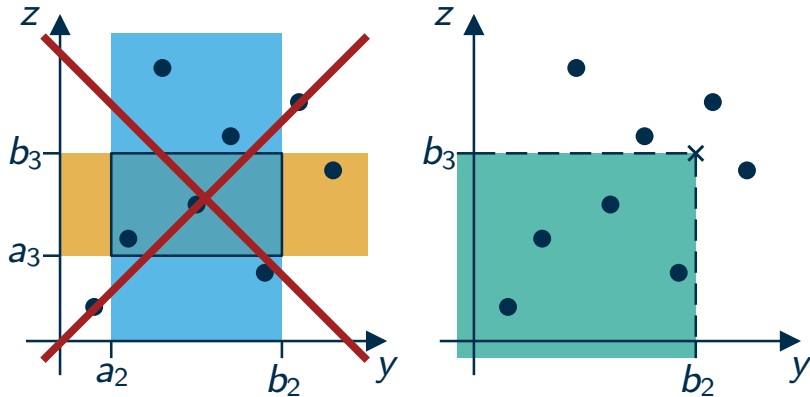


# One-Sided 2D Range Queries

goal: 2D DS with query time  $O(\log n)$

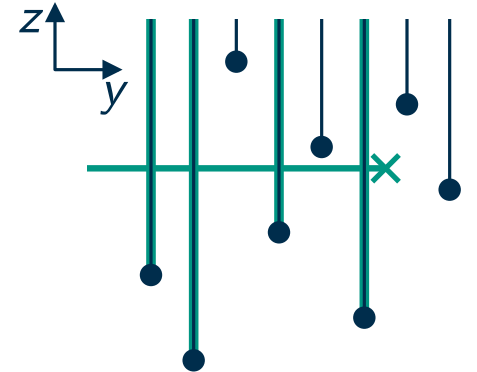
## One-Sided Queries: Half The Sides, Half The Trouble

- goal: answer queries of the form  $(-\infty, b_2] \times (-\infty, b_3]$  (instead of  $[a_2, b_2] \times [a_3, b_3]$ )



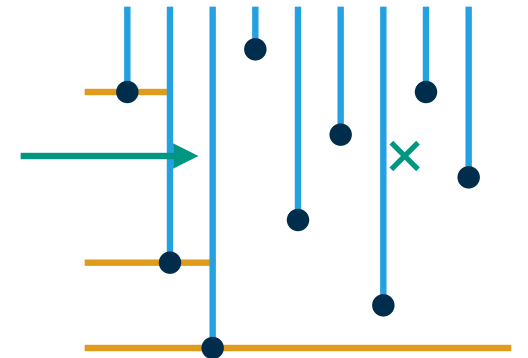
## Alternative Perspective

- shoot a ray from each point upwards
- ray from  $\langle b_2, b_3 \rangle$  to the left
- intersecting rays yield desired points



## Find All Intersecting Rays

- collect the intersecting rays from left to right

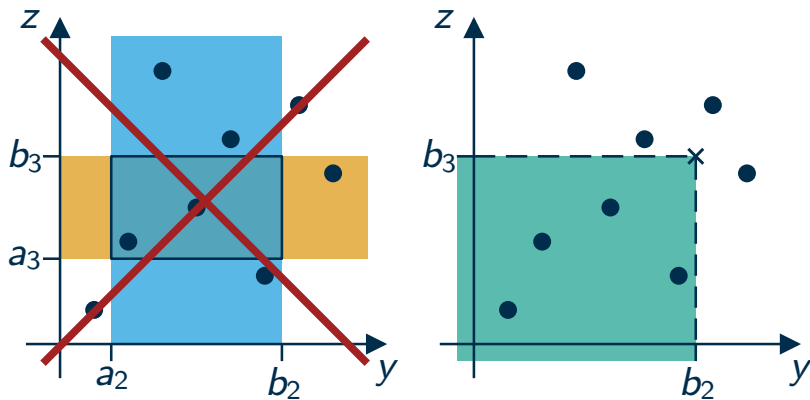


# One-Sided 2D Range Queries

goal: 2D DS with query time  $O(\log n)$

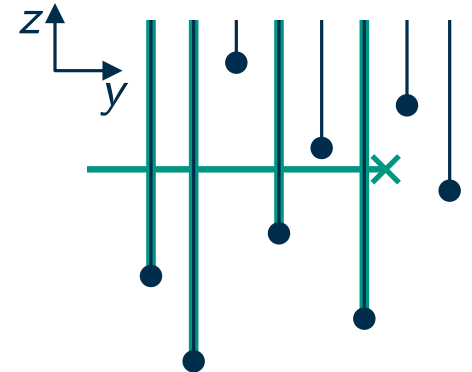
## One-Sided Queries: Half The Sides, Half The Trouble

- goal: answer queries of the form  $(-\infty, b_2] \times (-\infty, b_3]$  (instead of  $[a_2, b_2] \times [a_3, b_3]$ )



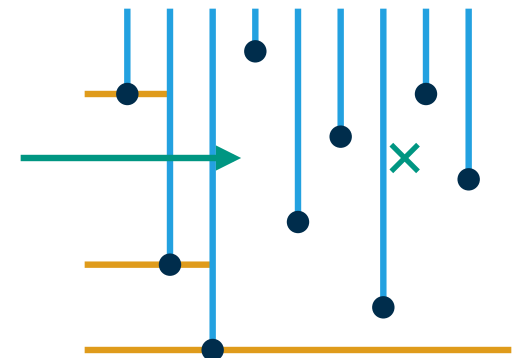
## Alternative Perspective

- shoot a ray from each point upwards
- ray from  $\langle b_2, b_3 \rangle$  to the left
- intersecting rays yield desired points



## Find All Intersecting Rays

- collect the intersecting rays from left to right

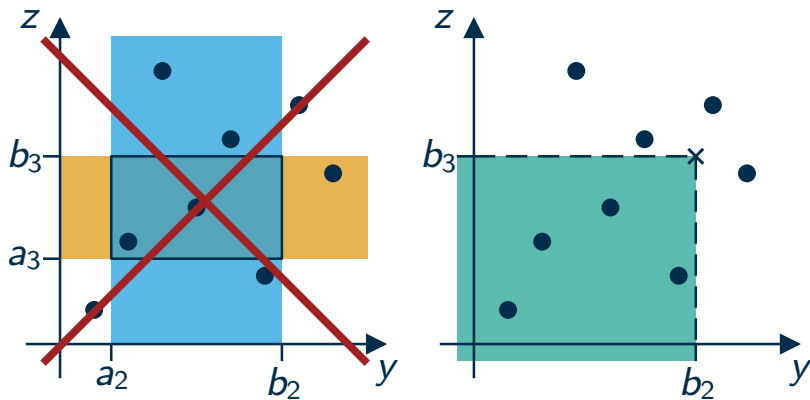


# One-Sided 2D Range Queries

goal: 2D DS with query time  $O(\log n)$

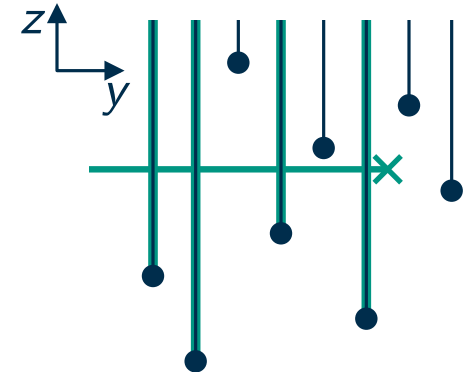
## One-Sided Queries: Half The Sides, Half The Trouble

- goal: answer queries of the form  $(-\infty, b_2] \times (-\infty, b_3]$  (instead of  $[a_2, b_2] \times [a_3, b_3]$ )



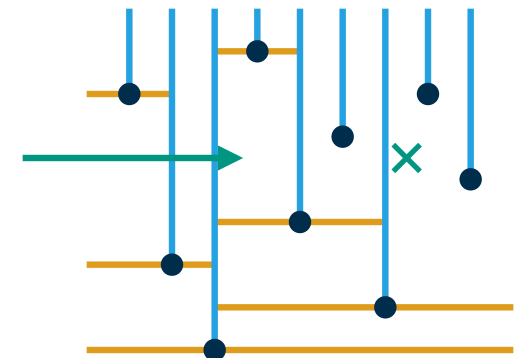
## Alternative Perspective

- shoot a ray from each point upwards
- ray from  $\langle b_2, b_3 \rangle$  to the left
- intersecting rays yield desired points



## Find All Intersecting Rays

- collect the intersecting rays from left to right

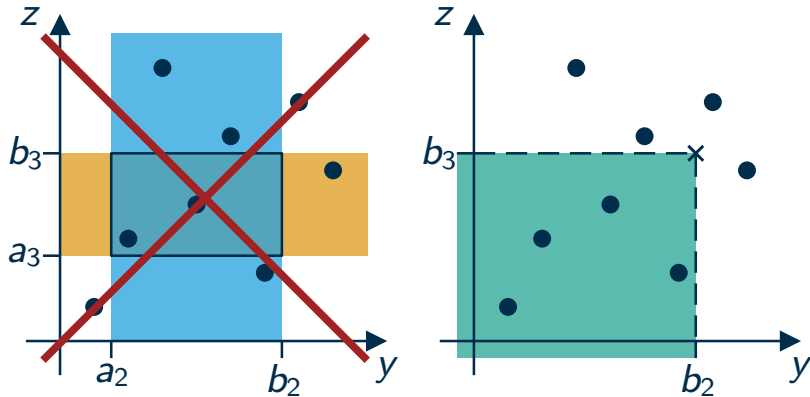


# One-Sided 2D Range Queries

goal: 2D DS with query time  $O(\log n)$

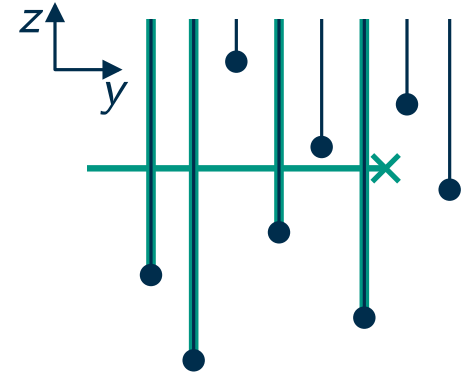
## One-Sided Queries: Half The Sides, Half The Trouble

- goal: answer queries of the form  $(-\infty, b_2] \times (-\infty, b_3]$  (instead of  $[a_2, b_2] \times [a_3, b_3]$ )



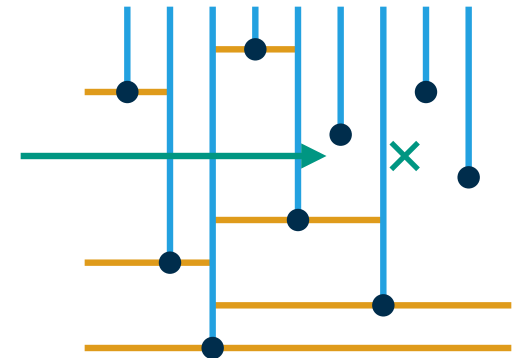
## Alternative Perspective

- shoot a ray from each point upwards
- ray from  $\langle b_2, b_3 \rangle$  to the left
- intersecting rays yield desired points



## Find All Intersecting Rays

- collect the intersecting rays from left to right

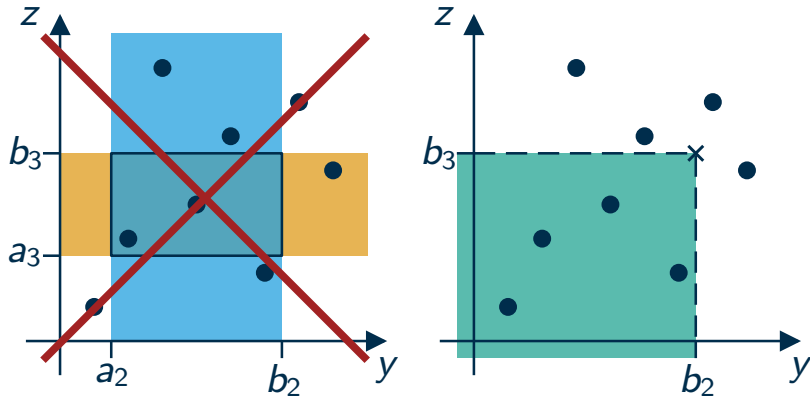


# One-Sided 2D Range Queries

goal: 2D DS with query time  $O(\log n)$

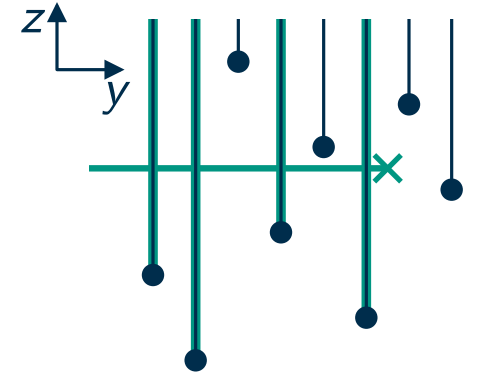
## One-Sided Queries: Half The Sides, Half The Trouble

- goal: answer queries of the form  $(-\infty, b_2] \times (-\infty, b_3]$  (instead of  $[a_2, b_2] \times [a_3, b_3]$ )



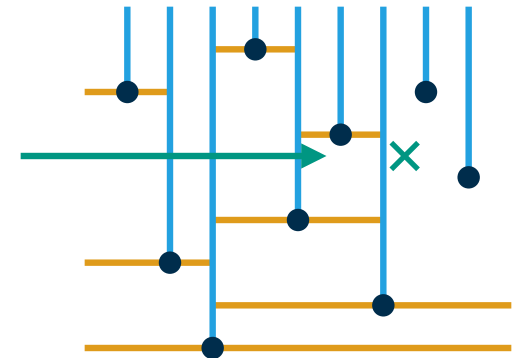
## Alternative Perspective

- shoot a ray from each point upwards
- ray from  $\langle b_2, b_3 \rangle$  to the left
- intersecting rays yield desired points



## Find All Intersecting Rays

- collect the intersecting rays from left to right

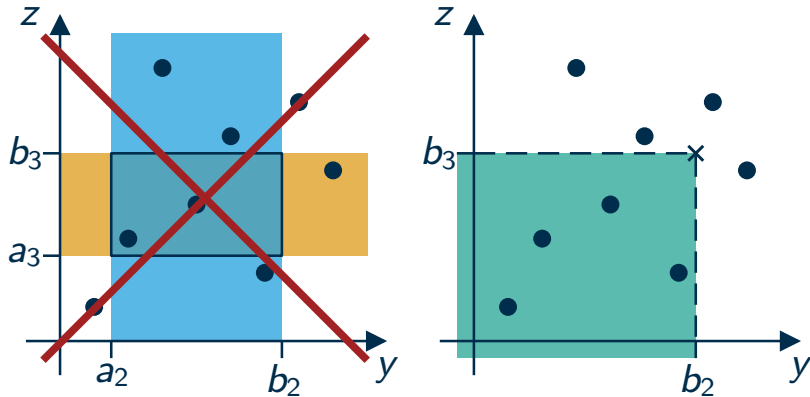


# One-Sided 2D Range Queries

goal: 2D DS with query time  $O(\log n)$

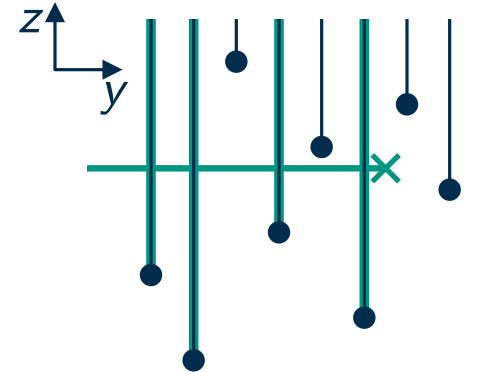
## One-Sided Queries: Half The Sides, Half The Trouble

- goal: answer queries of the form  $(-\infty, b_2] \times (-\infty, b_3]$  (instead of  $[a_2, b_2] \times [a_3, b_3]$ )



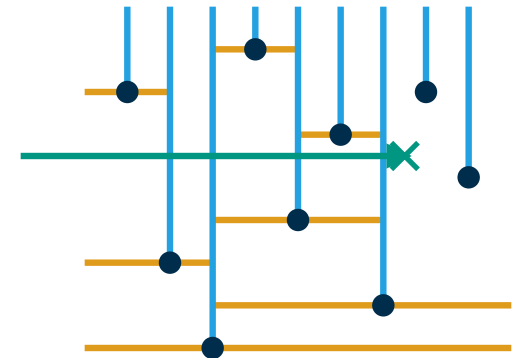
## Alternative Perspective

- shoot a ray from each point upwards
- ray from  $\langle b_2, b_3 \rangle$  to the left
- intersecting rays yield desired points



## Find All Intersecting Rays

- collect the intersecting rays from left to right

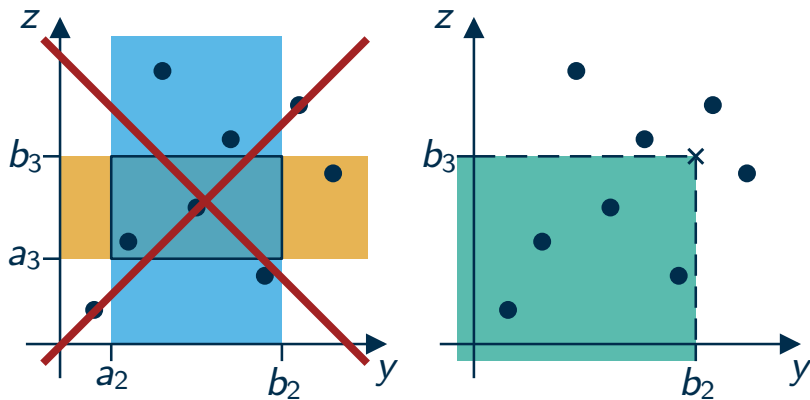


# One-Sided 2D Range Queries

goal: 2D DS with query time  $O(\log n)$

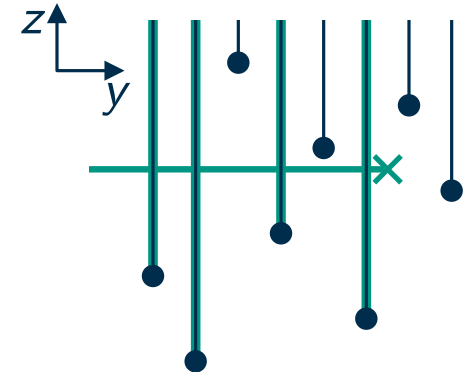
## One-Sided Queries: Half The Sides, Half The Trouble

- goal: answer queries of the form  $(-\infty, b_2] \times (-\infty, b_3]$  (instead of  $[a_2, b_2] \times [a_3, b_3]$ )



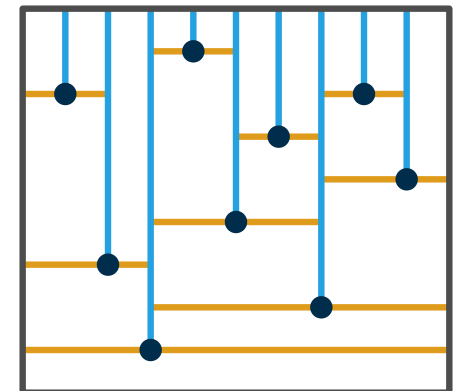
## Alternative Perspective

- shoot a ray from each point upwards
- ray from  $\langle b_2, b_3 \rangle$  to the left
- intersecting rays yield desired points



## Find All Intersecting Rays

- collect the intersecting rays from left to right
- we basically walk from cell to cell



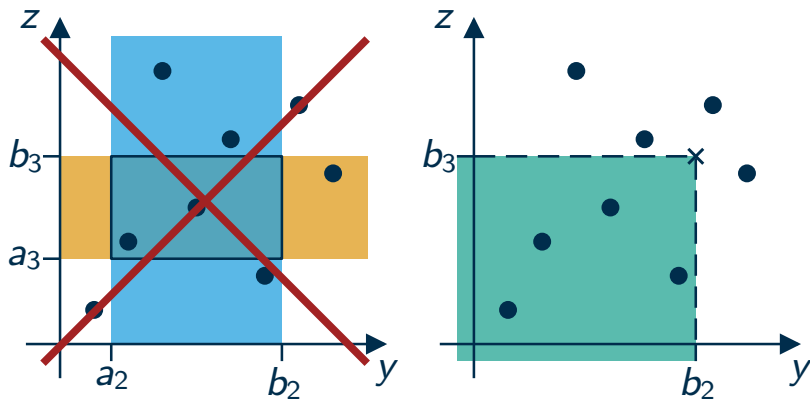


# One-Sided 2D Range Queries

goal: 2D DS with query time  $O(\log n)$

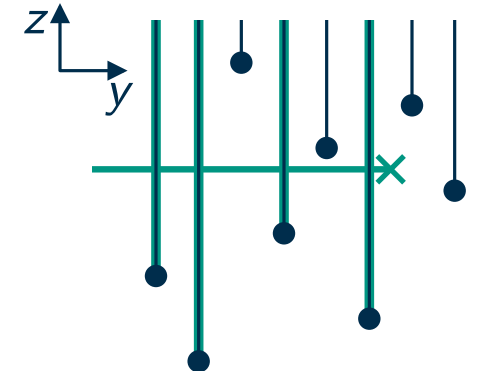
## One-Sided Queries: Half The Sides, Half The Trouble

- goal: answer queries of the form  $(-\infty, b_2] \times (-\infty, b_3]$  (instead of  $[a_2, b_2] \times [a_3, b_3]$ )



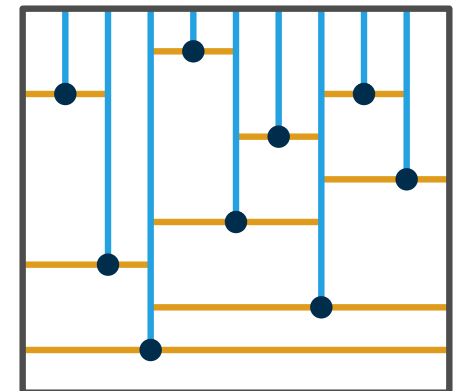
## Alternative Perspective

- shoot a ray from each point upwards
- ray from  $\langle b_2, b_3 \rangle$  to the left
- intersecting rays yield desired points



## Find All Intersecting Rays

- collect the intersecting rays from left to right
- we basically walk from cell to cell
- each cell knows its right neighbors sorted by  $z \Rightarrow O(k \log n)$

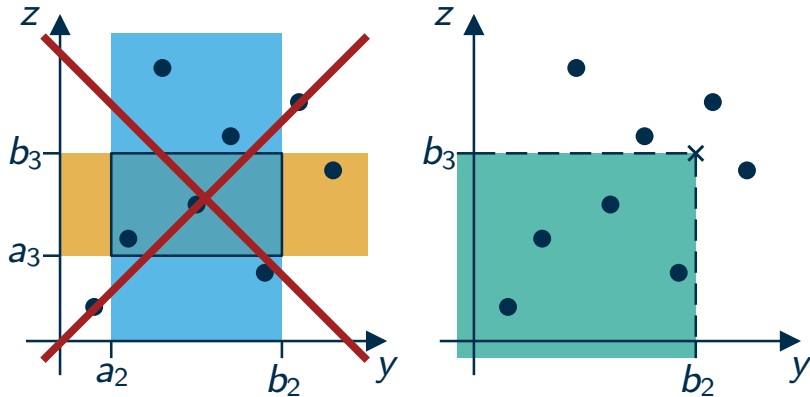


# One-Sided 2D Range Queries

goal: 2D DS with query time  $O(\log n)$

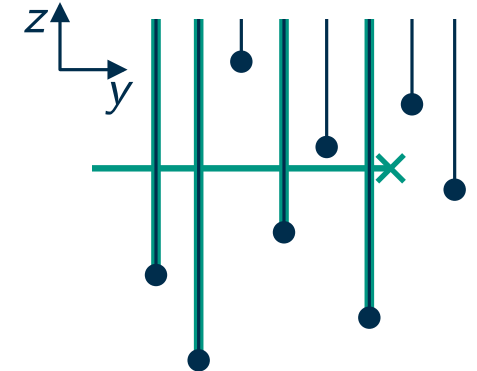
## One-Sided Queries: Half The Sides, Half The Trouble

- goal: answer queries of the form  $(-\infty, b_2] \times (-\infty, b_3]$  (instead of  $[a_2, b_2] \times [a_3, b_3]$ )



## Alternative Perspective

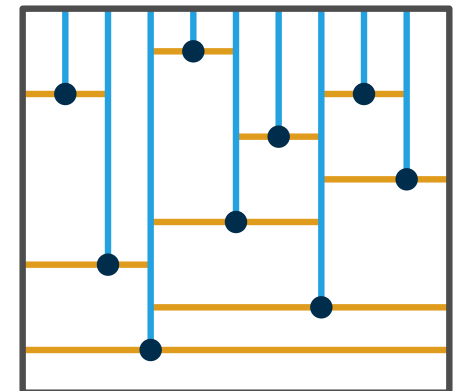
- shoot a ray from each point upwards
- ray from  $\langle b_2, b_3 \rangle$  to the left
- intersecting rays yield desired points



## Find All Intersecting Rays

- collect the intersecting rays from left to right
- we basically walk from cell to cell
- each cell knows its right neighbors sorted by  $z \Rightarrow O(k \log n)$

Can we do  $\log n + k$ ?

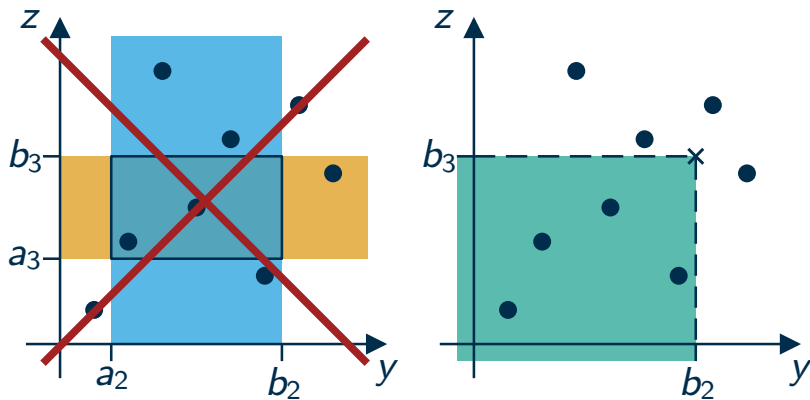


# One-Sided 2D Range Queries

goal: 2D DS with query time  $O(\log n)$

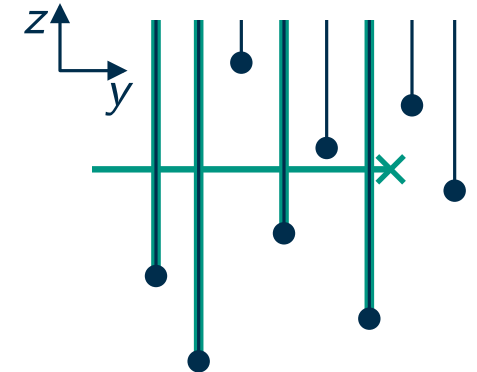
## One-Sided Queries: Half The Sides, Half The Trouble

- goal: answer queries of the form  $(-\infty, b_2] \times (-\infty, b_3]$  (instead of  $[a_2, b_2] \times [a_3, b_3]$ )



## Alternative Perspective

- shoot a ray from each point upwards
- ray from  $\langle b_2, b_3 \rangle$  to the left
- intersecting rays yield desired points

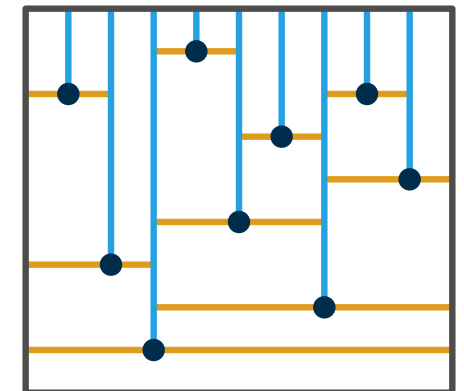


## Find All Intersecting Rays

- collect the intersecting rays from left to right
- we basically walk from cell to cell
- each cell knows its right neighbors sorted by  $z \Rightarrow O(k \log n)$

Can we do  $\log n + k$ ?

Fractional Cascading!

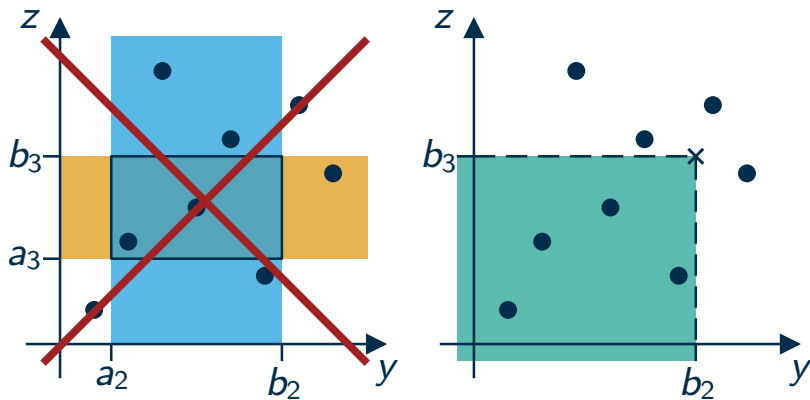


# One-Sided 2D Range Queries

goal: 2D DS with query time  $O(\log n)$

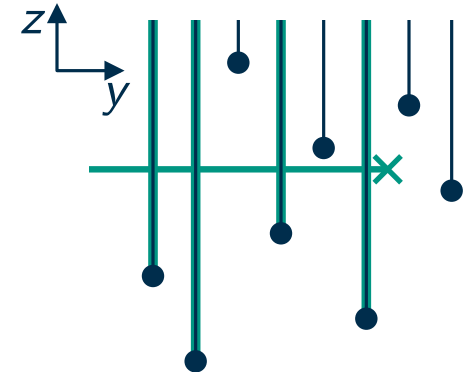
## One-Sided Queries: Half The Sides, Half The Trouble

- goal: answer queries of the form  $(-\infty, b_2] \times (-\infty, b_3]$  (instead of  $[a_2, b_2] \times [a_3, b_3]$ )



## Alternative Perspective

- shoot a ray from each point upwards
- ray from  $\langle b_2, b_3 \rangle$  to the left
- intersecting rays yield desired points

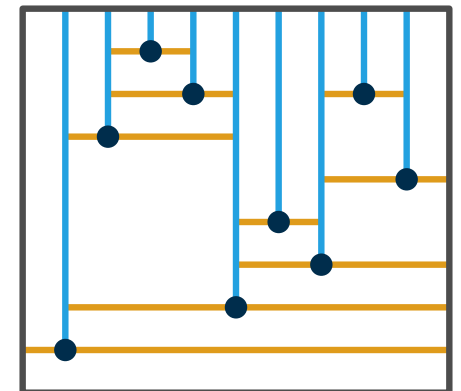


## Find All Intersecting Rays

- collect the intersecting rays from left to right
- we basically walk from cell to cell
- each cell knows its right neighbors sorted by  $z \Rightarrow O(k \log n)$

Can we do  $\log n + k$ ?

**Fractional Cascading!**

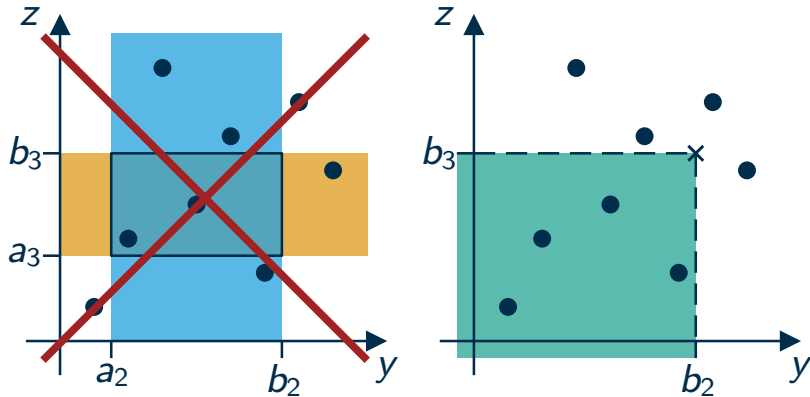


# One-Sided 2D Range Queries

goal: 2D DS with query time  $O(\log n)$

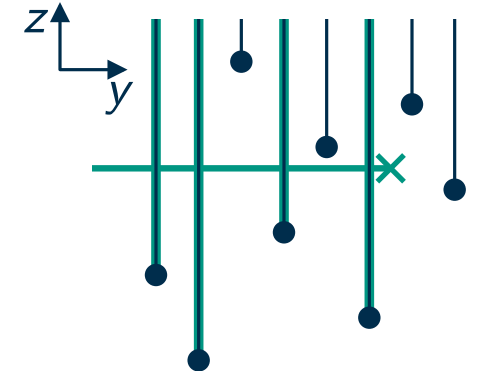
## One-Sided Queries: Half The Sides, Half The Trouble

- goal: answer queries of the form  $(-\infty, b_2] \times (-\infty, b_3]$  (instead of  $[a_2, b_2] \times [a_3, b_3]$ )



## Alternative Perspective

- shoot a ray from each point upwards
- ray from  $\langle b_2, b_3 \rangle$  to the left
- intersecting rays yield desired points

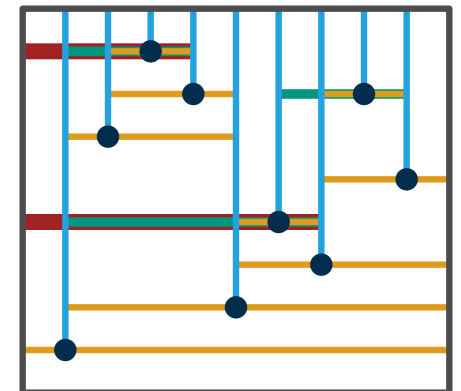


## Find All Intersecting Rays

- collect the intersecting rays from left to right
- we basically walk from cell to cell
- each cell knows its right neighbors sorted by  $z \Rightarrow O(k \log n)$

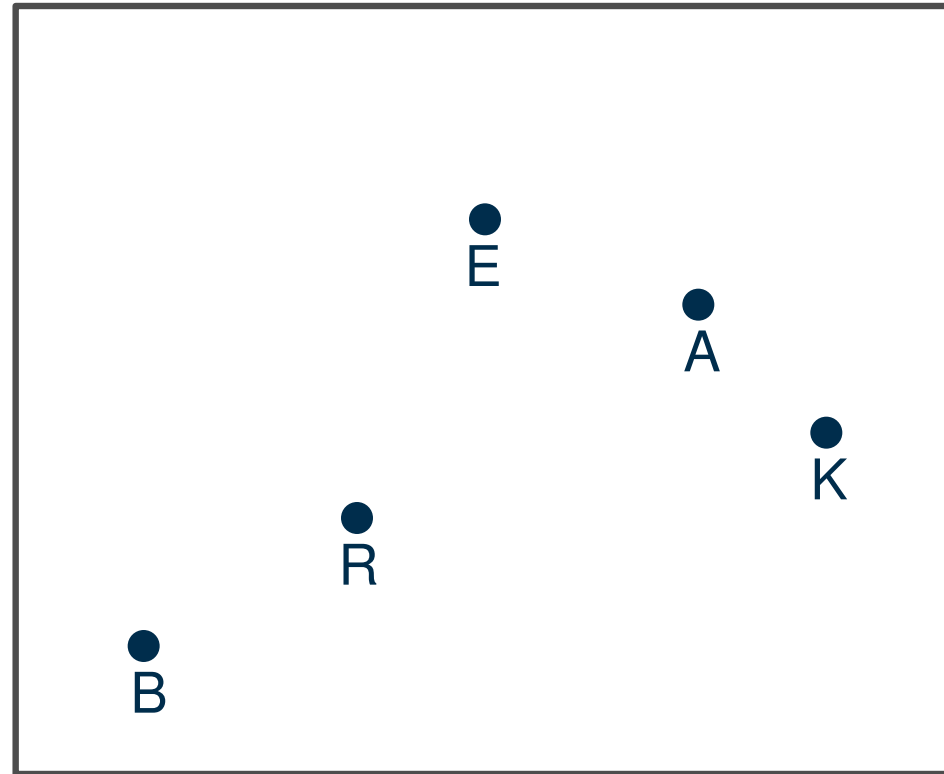
Can we do  $\log n + k$ ?

Fractional Cascading!



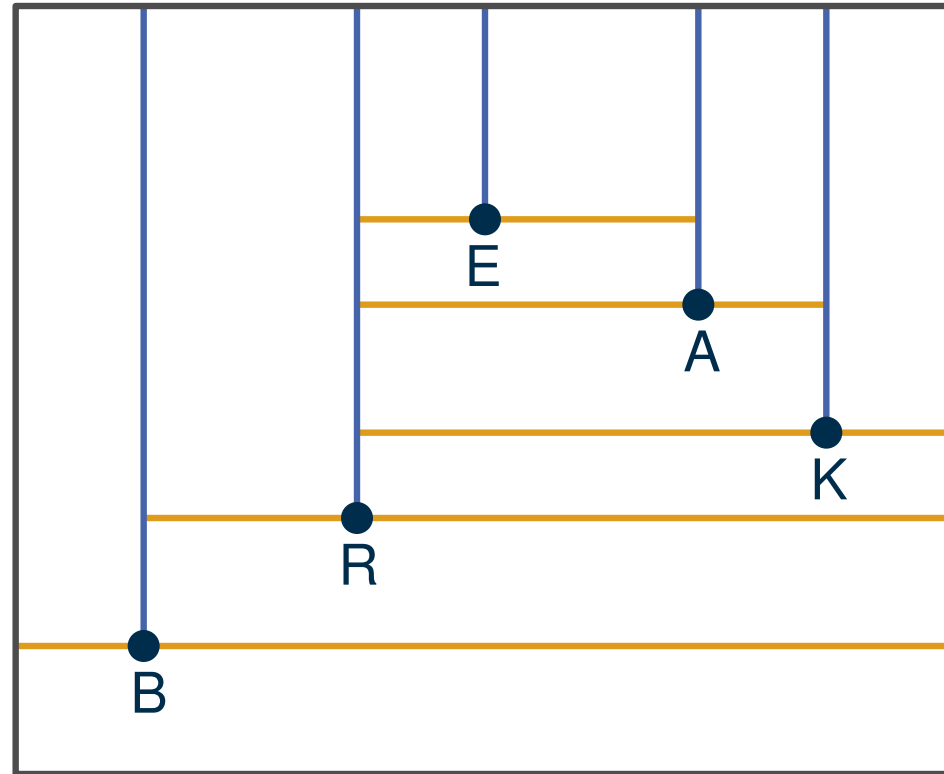
# Count The Cells

How many cells do we get (with and without fractional cascading)?



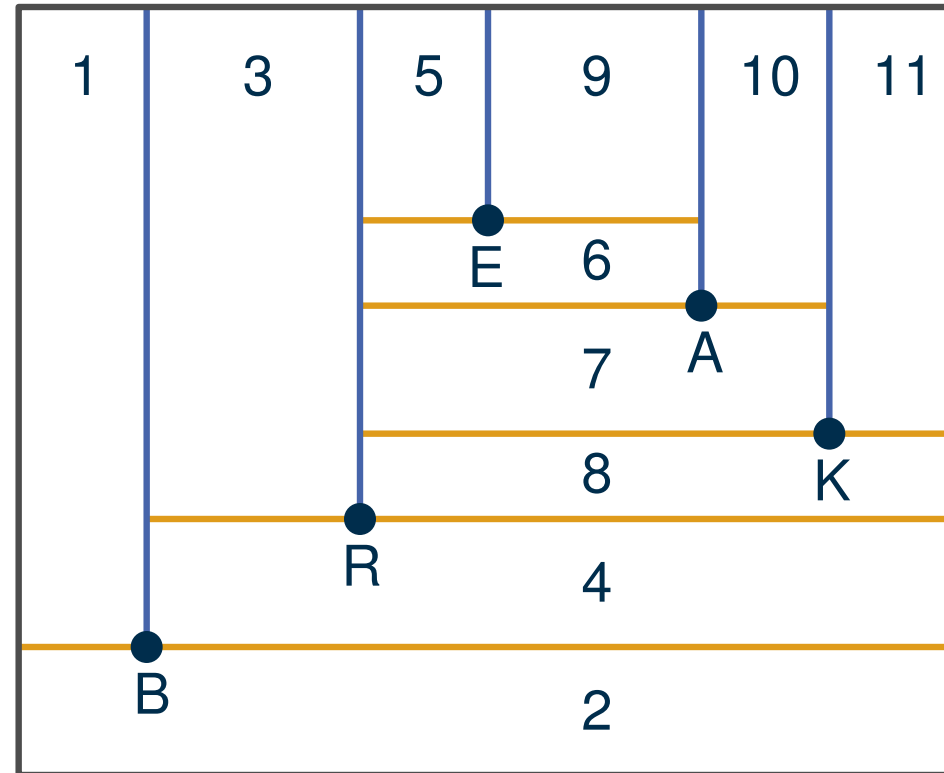
# Count The Cells

How many cells do we get (with and without fractional cascading)?



# Count The Cells

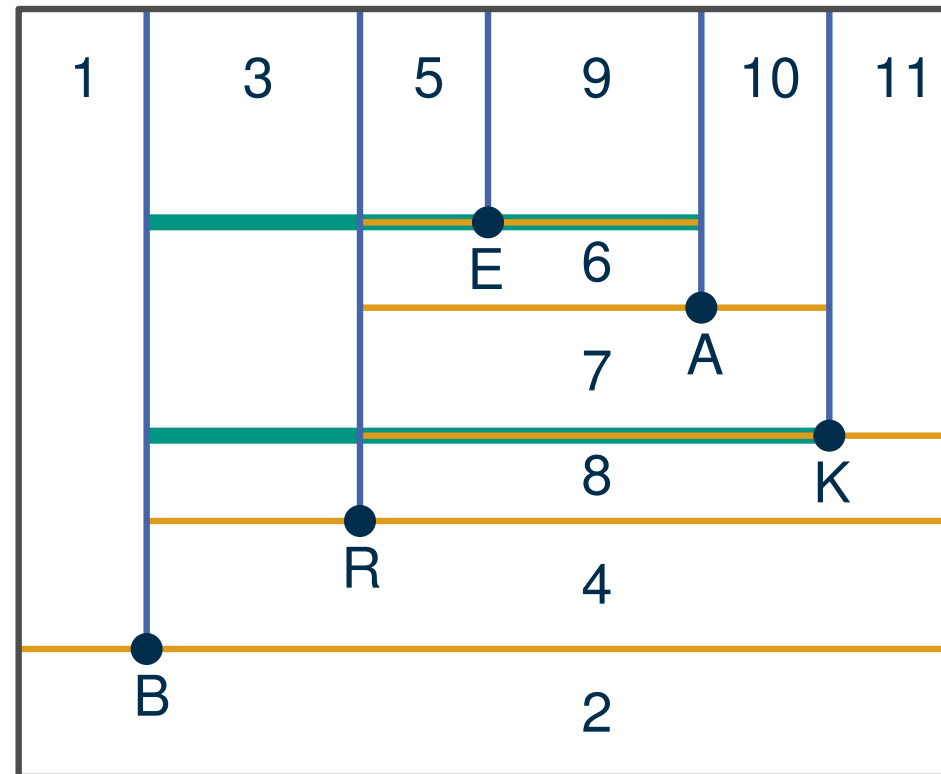
How many cells do we get (with and without fractional cascading)?





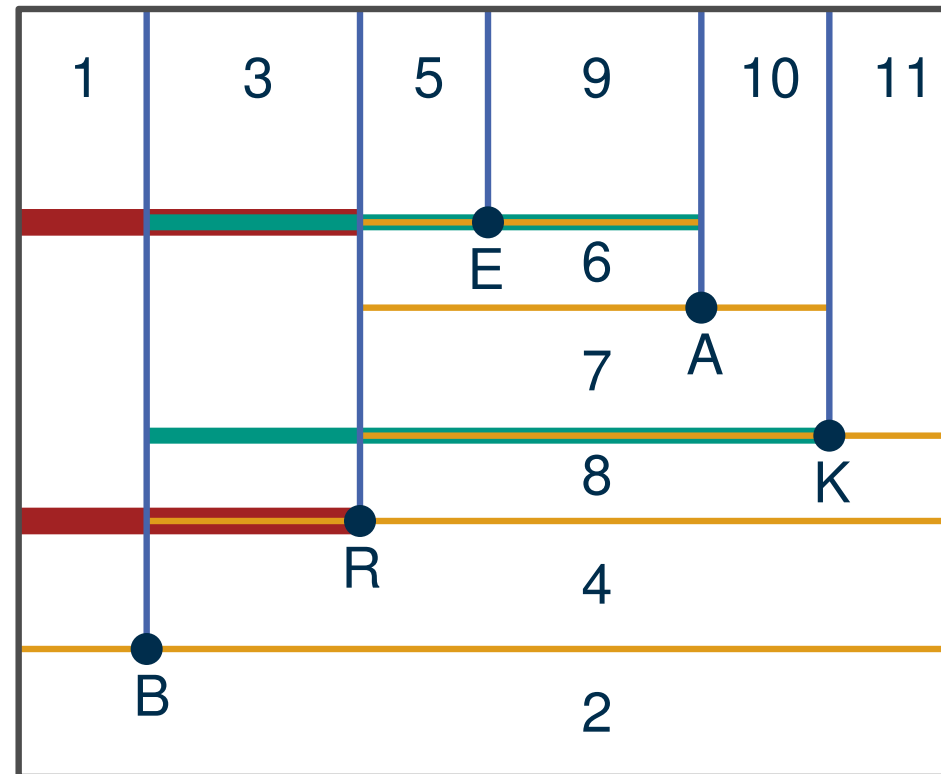
# Count The Cells

How many cells do we get (with and without fractional cascading)?



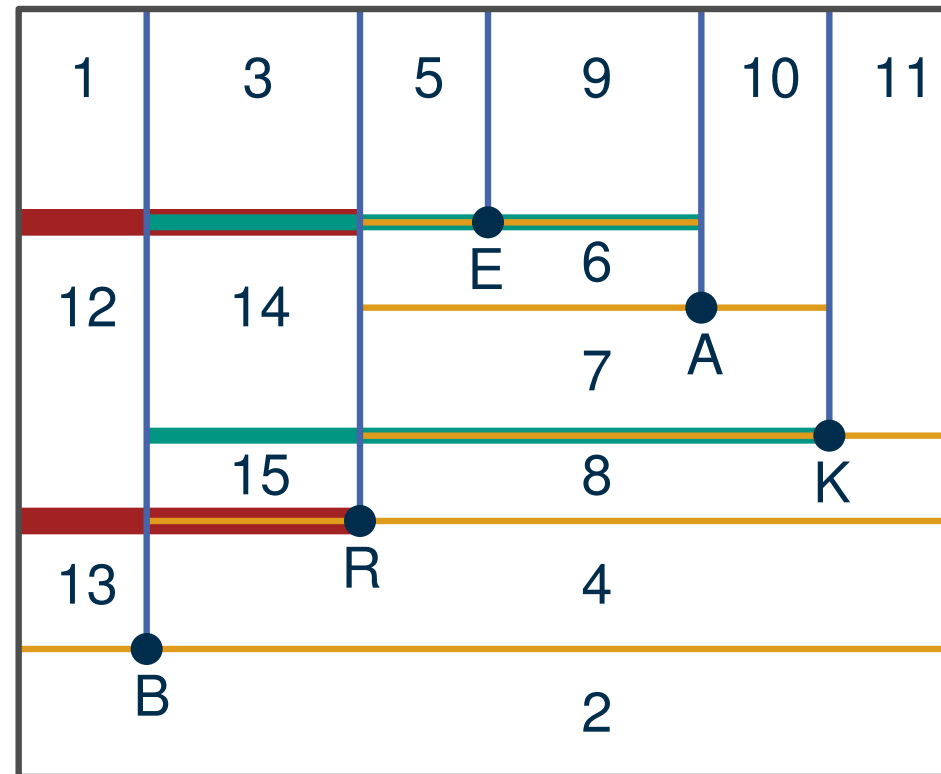
# Count The Cells

How many cells do we get (with and without fractional cascading)?



# Count The Cells

## How many cells do we get (with and without fractional cascading)?



# General Framework vs. Specific Situation

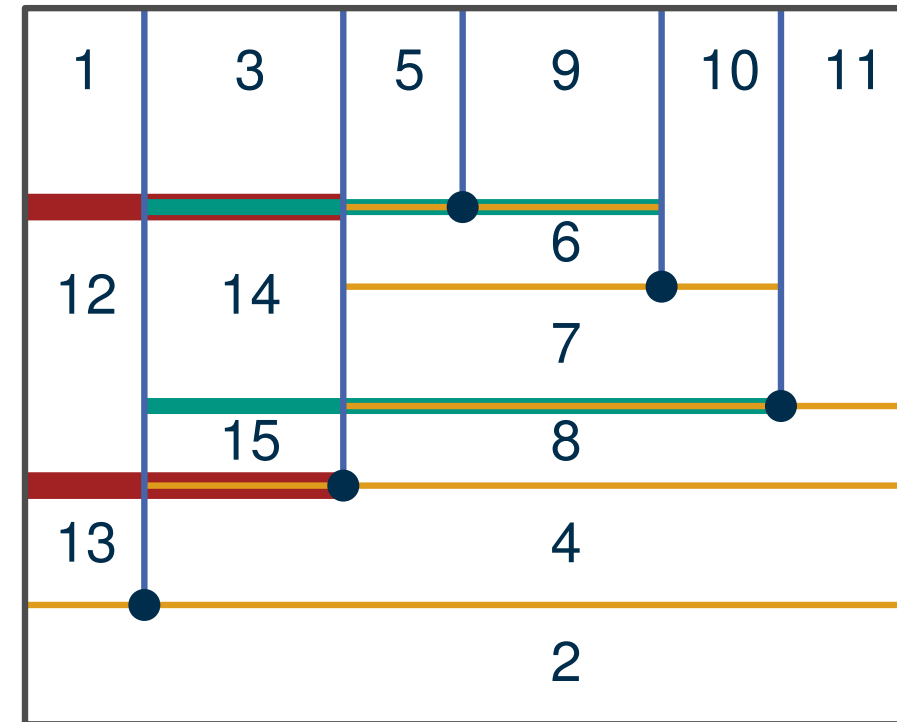
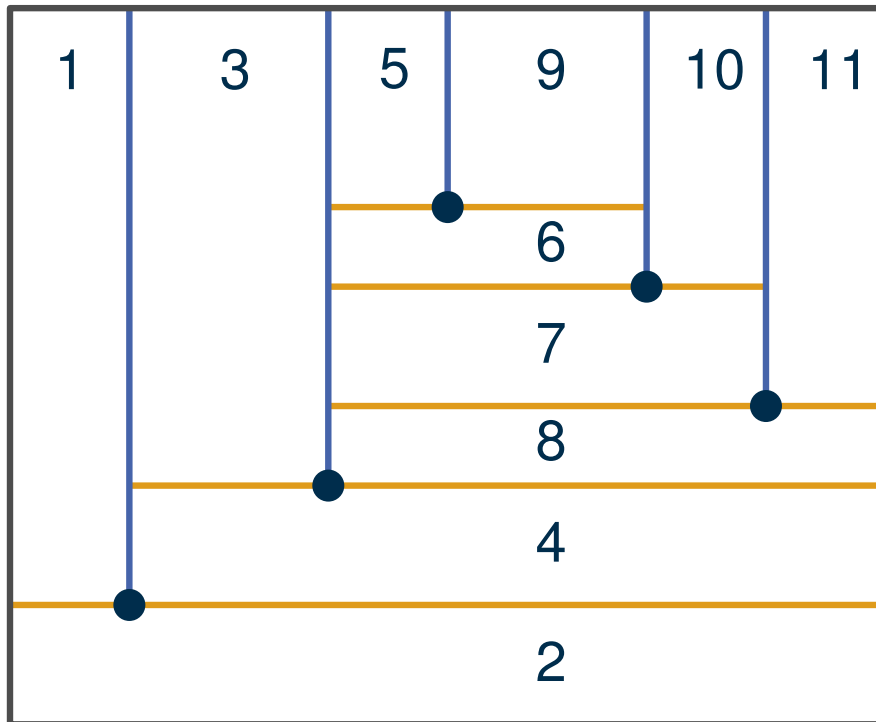
## Useful Way Of Thinking

- mental shortcut: multiple searches for the same number → fractional cascading probably helps
- specific situation: problem-specific argument often easier than pressing it into the framework

# General Framework vs. Specific Situation

## Useful Way Of Thinking

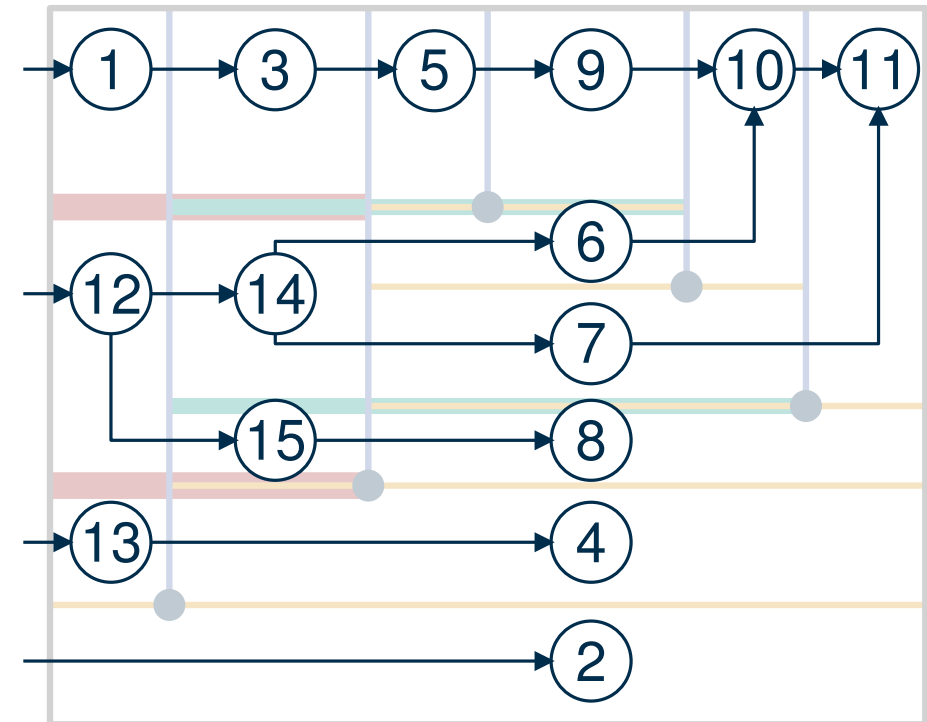
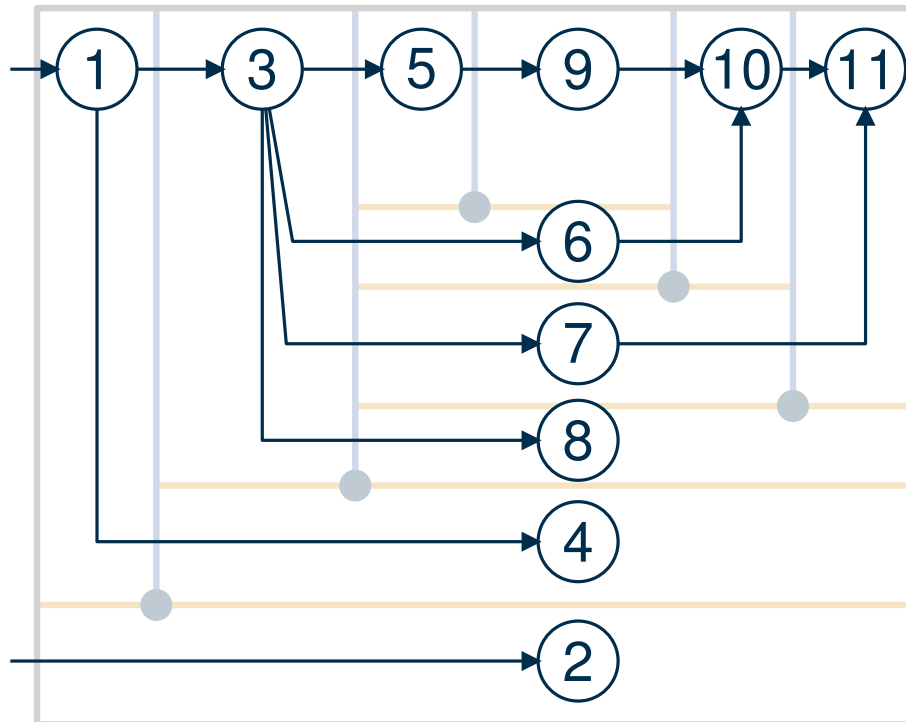
- mental shortcut: multiple searches for the same number → fractional cascading probably helps
- specific situation: problem-specific argument often easier than pressing it into the framework



# General Framework vs. Specific Situation

## Useful Way Of Thinking

- mental shortcut: multiple searches for the same number → fractional cascading probably helps
- specific situation: problem-specific argument often easier than pressing it into the framework



# One-Sided 3D Range Queries

**Seen So Far:** queries  $(-\infty, b_2] \times (-\infty, b_3]$  can be answered in  $O(\log n + k)$  **(DS1)**

one search in z direction

output size

# One-Sided 3D Range Queries

**Seen So Far:** queries  $(-\infty, b_2] \times (-\infty, b_3]$  can be answered in  $O(\log n + k)$  **(DS1)**

one search in z direction

output size

**New Goal:** answer queries of the form  $[a_1, b_1] \times (-\infty, b_2] \times (-\infty, b_3]$



# One-Sided 3D Range Queries

**Seen So Far:** queries  $(-\infty, b_2] \times (-\infty, b_3]$  can be answered in  $O(\log n + k)$  **(DS1)**

one search in z direction

output size

**New Goal:** answer queries of the form  $[a_1, b_1] \times (-\infty, b_2] \times (-\infty, b_3]$

**We Already Know How To Do This ...**

# One-Sided 3D Range Queries

**Seen So Far:** queries  $(-\infty, b_2] \times (-\infty, b_3]$  can be answered in  $O(\log n + k)$  (DS1)

one search in z direction  
output size

**New Goal:** answer queries of the form  $[a_1, b_1] \times (-\infty, b_2] \times (-\infty, b_3]$

**We Already Know How To Do This ...**

- binary search tree for x-direction

# One-Sided 3D Range Queries

**Seen So Far:** queries  $(-\infty, b_2] \times (-\infty, b_3]$  can be answered in  $O(\log n + k)$  **(DS1)**

one search in z direction  
output size

**New Goal:** answer queries of the form  $[a_1, b_1] \times (-\infty, b_2] \times (-\infty, b_3]$

**We Already Know How To Do This ...**

- binary search tree for x-direction
- every node stores **(DS1)** for the corresponding points

# One-Sided 3D Range Queries

**Seen So Far:** queries  $(-\infty, b_2] \times (-\infty, b_3]$  can be answered in  $O(\log n + k)$  **(DS1)**

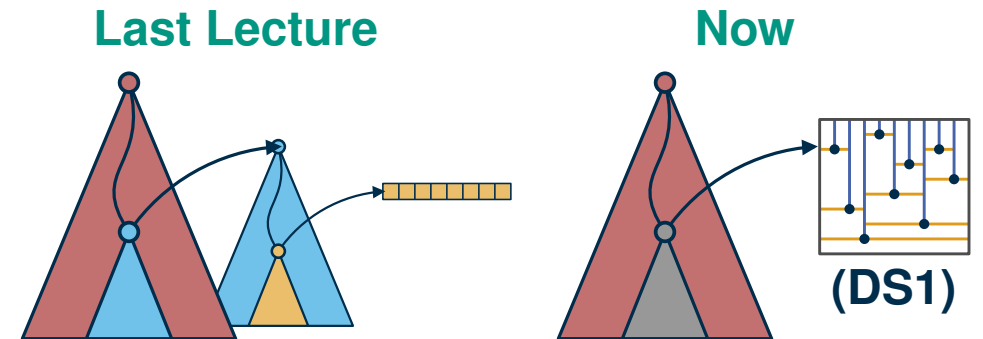
one search in z direction

output size

**New Goal:** answer queries of the form  $[a_1, b_1] \times (-\infty, b_2] \times (-\infty, b_3]$

**We Already Know How To Do This ...**

- binary search tree for x-direction
- every node stores **(DS1)** for the corresponding points



# One-Sided 3D Range Queries

**Seen So Far:** queries  $(-\infty, b_2] \times (-\infty, b_3]$  can be answered in  $O(\log n + k)$  **(DS1)**

one search in  $z$  direction

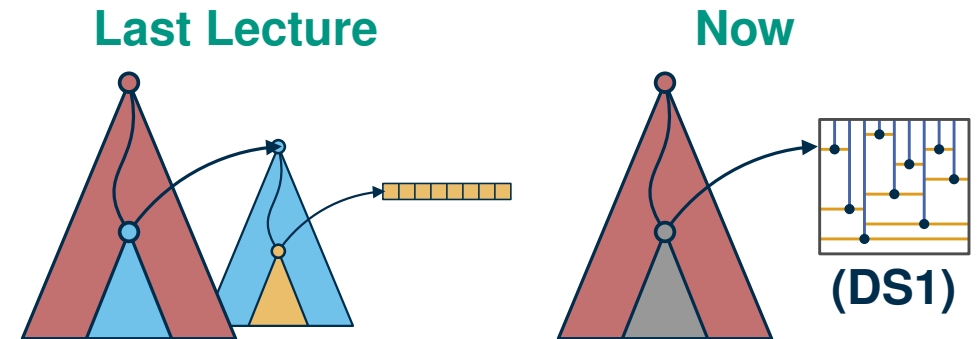
output size

**New Goal:** answer queries of the form  $[a_1, b_1] \times (-\infty, b_2] \times (-\infty, b_3]$

**We Already Know How To Do This ...**

- binary search tree for  $x$ -direction
- every node stores **(DS1)** for the corresponding points

**Don't We Have To Search In  $O(\log n)$  Many (DS1)?**



# One-Sided 3D Range Queries

**Seen So Far:** queries  $(-\infty, b_2] \times (-\infty, b_3]$  can be answered in  $O(\log n + k)$  **(DS1)**

one search in z direction

output size

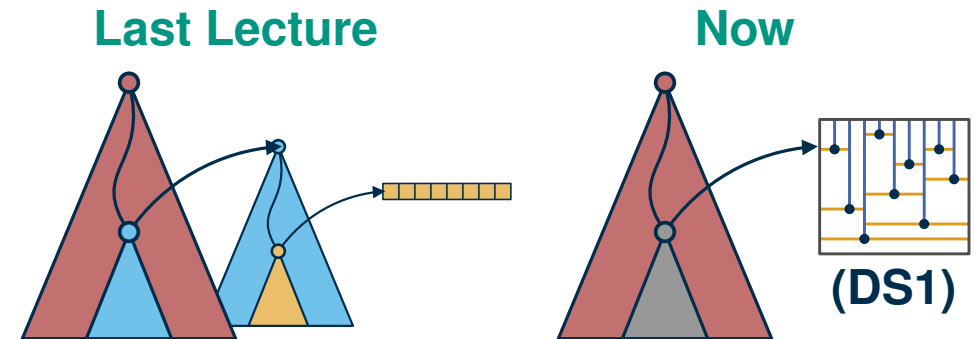
**New Goal:** answer queries of the form  $[a_1, b_1] \times (-\infty, b_2] \times (-\infty, b_3]$

**We Already Know How To Do This ...**

- binary search tree for x-direction
- every node stores **(DS1)** for the corresponding points

**Don't We Have To Search In  $O(\log n)$  Many (DS1)?**

- yes, but ...



# One-Sided 3D Range Queries

**Seen So Far:** queries  $(-\infty, b_2] \times (-\infty, b_3]$  can be answered in  $O(\log n + k)$  **(DS1)**

one search in z direction  
output size

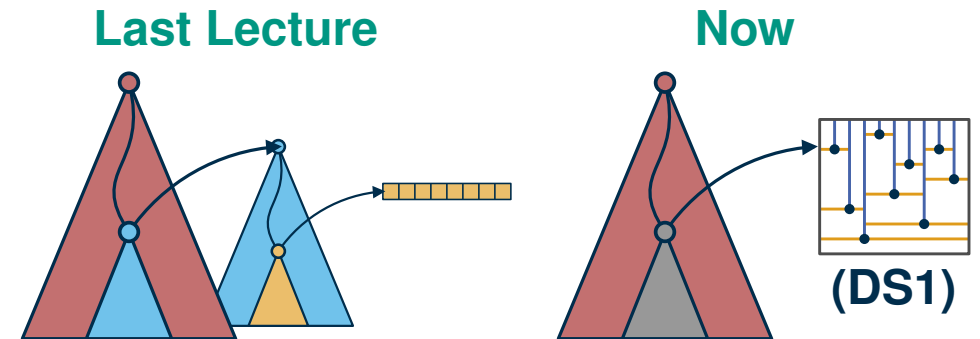
**New Goal:** answer queries of the form  $[a_1, b_1] \times (-\infty, b_2] \times (-\infty, b_3]$

**We Already Know How To Do This ...**

- binary search tree for x-direction
- every node stores **(DS1)** for the corresponding points

**Don't We Have To Search In  $O(\log n)$  Many (DS1)?**

- yes, but ... **Fractional Cascading!**



# One-Sided 3D Range Queries

**Seen So Far:** queries  $(-\infty, b_2] \times (-\infty, b_3]$  can be answered in  $O(\log n + k)$  **(DS1)**

one search in  $z$  direction

output size

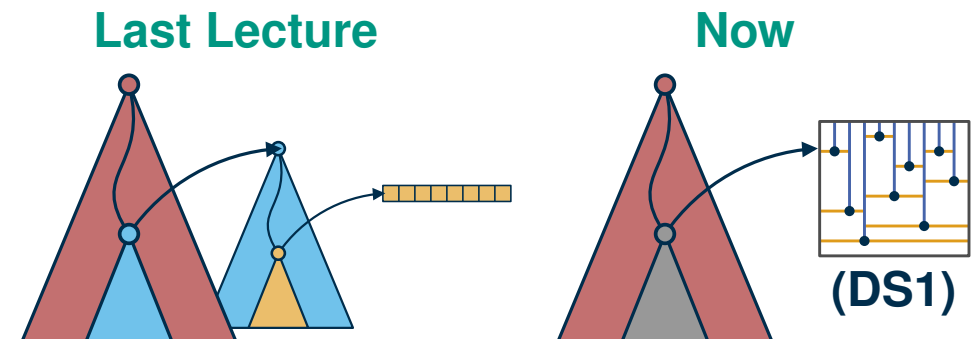
**New Goal:** answer queries of the form  $[a_1, b_1] \times (-\infty, b_2] \times (-\infty, b_3]$

**We Already Know How To Do This ...**

- binary search tree for  $x$ -direction
- every node stores **(DS1)** for the corresponding points

**Don't We Have To Search In  $O(\log n)$  Many (DS1)?**

- yes, but ... **Fractional Cascading!**
- search once in  $z$ -direction in the root of the  $x$ -tree
- follow pointers for the  $z$ -positions while walking down the  $x$ -tree





# One-Sided 3D Range Queries

**Seen So Far:** queries  $(-\infty, b_2] \times (-\infty, b_3]$  can be answered in  $O(\log n + k)$  **(DS1)**

one search in z direction

output size

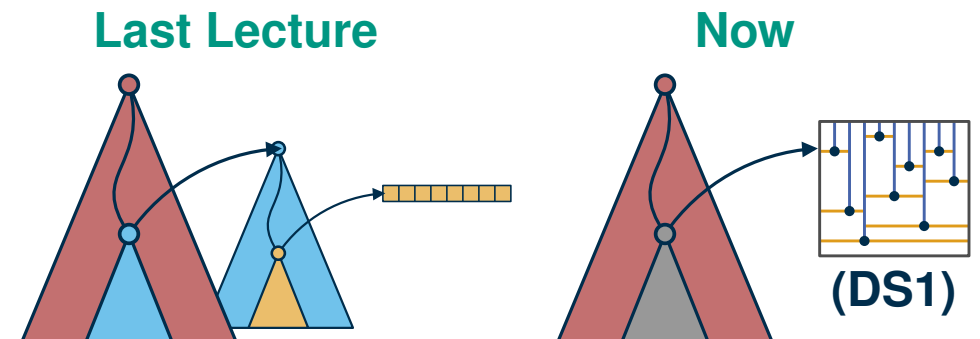
**New Goal:** answer queries of the form  $[a_1, b_1] \times (-\infty, b_2] \times (-\infty, b_3]$

**We Already Know How To Do This ...**

- binary search tree for x-direction
- every node stores **(DS1)** for the corresponding points

**Don't We Have To Search In  $O(\log n)$  Many (DS1)?**

- yes, but ... **Fractional Cascading!**
- search once in z-direction in the root of the x-tree
- follow pointers for the z-positions while walking down the x-tree
- save the first search in **(DS1)**  $\Rightarrow$  total running time  $O(\log n + k)$



# One-Sided $\rightarrow$ Two-Sided

## Lemma

(DS2)

For  $n$  points in  $\mathbb{R}^3$ , we can answer queries of the form  $[a_1, b_1] \times (-\infty, b_2] \times (-\infty, b_3]$  in  $O(\log n + k)$  time after  $O(n \log n)$  preprocessing with  $O(n \log n)$  memory.

# One-Sided $\rightarrow$ Two-Sided

## Lemma

(DS2)

For  $n$  points in  $\mathbb{R}^3$ , we can answer queries of the form  $[a_1, b_1] \times (-\infty, b_2] \times (-\infty, b_3]$  in  $O(\log n + k)$  time after  $O(n \log n)$  preprocessing with  $O(n \log n)$  memory.

## Plan

- use (DS2) as black box

# One-Sided $\rightarrow$ Two-Sided

## Lemma

(DS2)

For  $n$  points in  $\mathbb{R}^3$ , we can answer queries of the form  $[a_1, b_1] \times (-\infty, b_2] \times (-\infty, b_3]$  in  $O(\log n + k)$  time after  $O(n \log n)$  preprocessing with  $O(n \log n)$  memory.

## Plan

- use (DS2) as black box
- $y$ -inverted variant  $\rightarrow [a_2, \infty)$  queries
- query  $[a_2, \infty)$  and  $(-\infty, b_2]$  to get  $[a_2, b_2]$

# One-Sided $\rightarrow$ Two-Sided

## Lemma

(DS2)

For  $n$  points in  $\mathbb{R}^3$ , we can answer queries of the form  $[a_1, b_1] \times (-\infty, b_2] \times (-\infty, b_3]$  in  $O(\log n + k)$  time after  $O(n \log n)$  preprocessing with  $O(n \log n)$  memory.

## Plan

- use (DS2) as black box
- y-inverted variant  $\rightarrow [a_2, \infty)$  queries
- query  $[a_2, \infty)$  and  $(-\infty, b_2]$  to get  $[a_2, b_2]$

Why can't we just use the intersection of two queries?

$$\begin{array}{ccccccc} [a_1, b_1] & \times & [a_2, b_2] & \times & [a_3, b_3] & = & \\ [a_1, b_1] & \times & (-\infty, b_2] & \times & (-\infty, b_3] & \cap & \\ [a_1, b_1] & \times & [a_2, \infty) & \times & [a_3, \infty) & & \end{array}$$

# One-Sided $\rightarrow$ Two-Sided

## Lemma

(DS2)

For  $n$  points in  $\mathbb{R}^3$ , we can answer queries of the form  $[a_1, b_1] \times (-\infty, b_2] \times (-\infty, b_3]$  in  $O(\log n + k)$  time after  $O(n \log n)$  preprocessing with  $O(n \log n)$  memory.

## Plan

- use (DS2) as black box
- y-inverted variant  $\rightarrow [a_2, \infty)$  queries
- query  $[a_2, \infty)$  and  $(-\infty, b_2]$  to get  $[a_2, b_2]$

Why can't we just use the intersection of two queries?

$$\begin{array}{ccccccc} [a_1, b_1] & \times & [a_2, b_2] & \times & [a_3, b_3] & = \\ [a_1, b_1] & \times & (-\infty, b_2] & \times & (-\infty, b_3] & \cap \\ [a_1, b_1] & \times & [a_2, \infty) & \times & [a_3, \infty) & \end{array}$$

## Lemma

(DS3)

For  $n$  point in  $\mathbb{R}^3$ , we can answer queries of the form  $[a_1, b_1] \times [a_2, b_2] \times (-\infty, b_3]$  in  $O(\log n + k)$  time after  $O(n \log^2 n)$  preprocessing with  $O(n \log^2 n)$  memory.

# One-Sided $\rightarrow$ Two-Sided

## Lemma

(DS2)

For  $n$  points in  $\mathbb{R}^3$ , we can answer queries of the form  $[a_1, b_1] \times (-\infty, b_2] \times (-\infty, b_3]$  in  $O(\log n + k)$  time after  $O(n \log n)$  preprocessing with  $O(n \log n)$  memory.

## Plan

- use (DS2) as black box
- y-inverted variant  $\rightarrow [a_2, \infty)$  queries
- query  $[a_2, \infty)$  and  $(-\infty, b_2]$  to get  $[a_2, b_2]$

Why can't we just use the intersection of two queries?

$$\begin{array}{ccccccc} [a_1, b_1] & \times & [a_2, b_2] & \times & [a_3, b_3] & = & \\ [a_1, b_1] & \times & (-\infty, b_2] & \times & (-\infty, b_3] & \cap & \\ [a_1, b_1] & \times & [a_2, \infty) & \times & [a_3, \infty) & & \end{array}$$

## Theorem

(DS4)

For  $n$  point in  $\mathbb{R}^3$ , we can answer queries of the form  $[a_1, b_1] \times [a_2, b_2] \times [a_3, b_3]$  in  $O(\log n + k)$  time after  $O(n \log^3 n)$  preprocessing with  $O(n \log^3 n)$  memory.

# Two-Sided Query In $y$ -Direction

## Simplified Perspective: Ignore $x$ And $z$ -Direction

- **(DS2)** allows  $[a_2, \infty)$  and  $(-\infty, b_2]$  queries
- goal: build data structure, that allows  $[a_2, b_2]$  queries

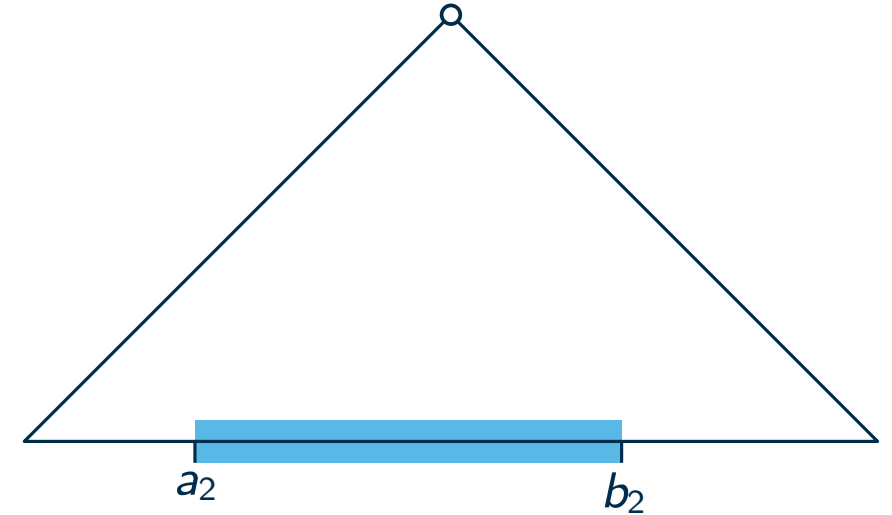


# Two-Sided Query In $y$ -Direction

## Simplified Perspective: Ignore $x$ And $z$ -Direction

- **(DS2)** allows  $[a_2, \infty)$  and  $(-\infty, b_2]$  queries
- goal: build data structure, that allows  $[a_2, b_2]$  queries

## Binary Search Tree In $y$ -Direction



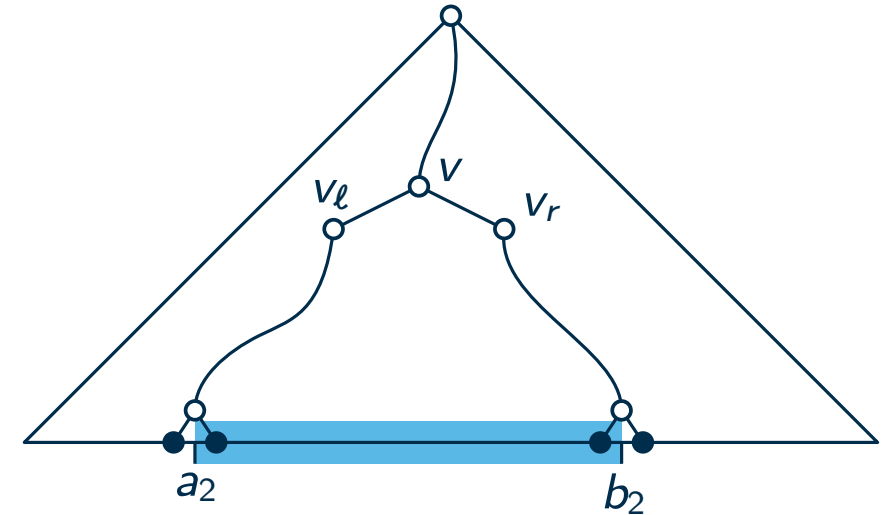
# Two-Sided Query In $y$ -Direction

## Simplified Perspective: Ignore $x$ And $z$ -Direction

- **(DS2)** allows  $[a_2, \infty)$  and  $(-\infty, b_2]$  queries
- goal: build data structure, that allows  $[a_2, b_2]$  queries

## Binary Search Tree In $y$ -Direction

- search for  $a_2$  and  $b_2$  splits at  $v$  to  $v_\ell$  and  $v_r$



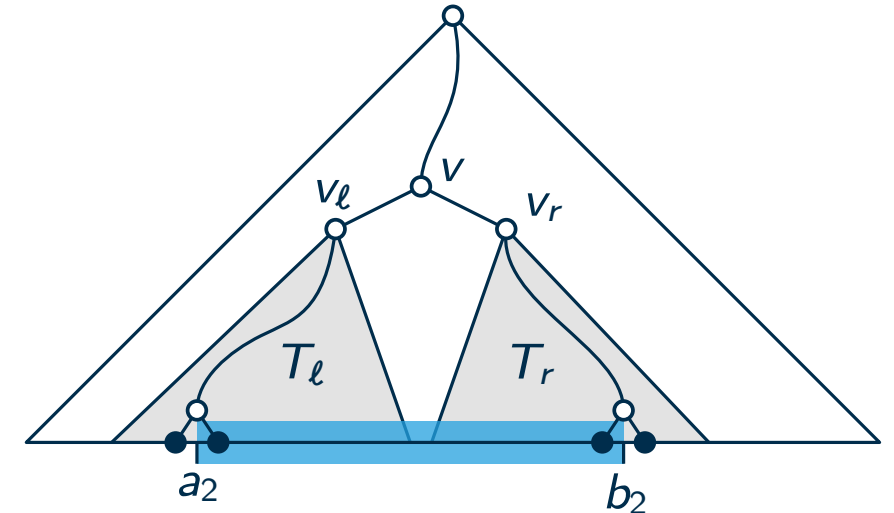
# Two-Sided Query In $y$ -Direction

## Simplified Perspective: Ignore $x$ And $z$ -Direction

- **(DS2)** allows  $[a_2, \infty)$  and  $(-\infty, b_2]$  queries
- goal: build data structure, that allows  $[a_2, b_2]$  queries

## Binary Search Tree In $y$ -Direction

- search for  $a_2$  and  $b_2$  splits at  $v$  to  $v_\ell$  and  $v_r$
- queries in instances of **(DS2)**:  $[a_2, \infty)$  on points in  $T_\ell$  and  $(-\infty, b_2]$  on points in  $T_r$



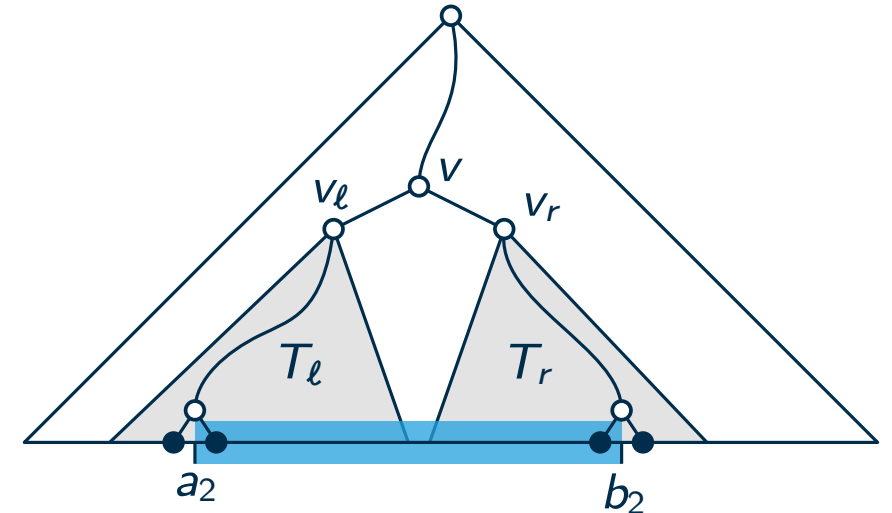
# Two-Sided Query In $y$ -Direction

## Simplified Perspective: Ignore $x$ And $z$ -Direction

- **(DS2)** allows  $[a_2, \infty)$  and  $(-\infty, b_2]$  queries
- goal: build data structure, that allows  $[a_2, b_2]$  queries

## Binary Search Tree In $y$ -Direction

- search for  $a_2$  and  $b_2$  splits at  $v$  to  $v_\ell$  and  $v_r$
- queries in instances of **(DS2)**:  $[a_2, \infty)$  on points in  $T_\ell$  and  $(-\infty, b_2]$  on points in  $T_r$
- running time:  $O(\log n)$  for search in  $y$ -tree plus  $O(\log n + k)$  for two queries in **(DS2)**



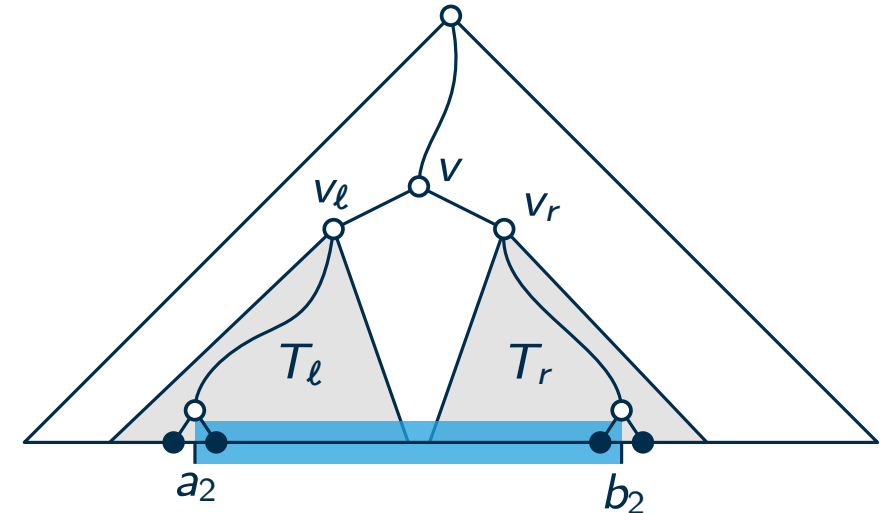
# Two-Sided Query In $y$ -Direction

## Simplified Perspective: Ignore $x$ And $z$ -Direction

- **(DS2)** allows  $[a_2, \infty)$  and  $(-\infty, b_2]$  queries
- goal: build data structure, that allows  $[a_2, b_2]$  queries

## Binary Search Tree In $y$ -Direction

- search for  $a_2$  and  $b_2$  splits at  $v$  to  $v_\ell$  and  $v_r$
- queries in instances of **(DS2)**:  $[a_2, \infty)$  on points in  $T_\ell$  and  $(-\infty, b_2]$  on points in  $T_r$
- running time:  $O(\log n)$  for search in  $y$ -tree plus  $O(\log n + k)$  for two queries in **(DS2)**
- memory:  $O(\log n) \cdot (\text{memory for } \mathbf{DS2})$



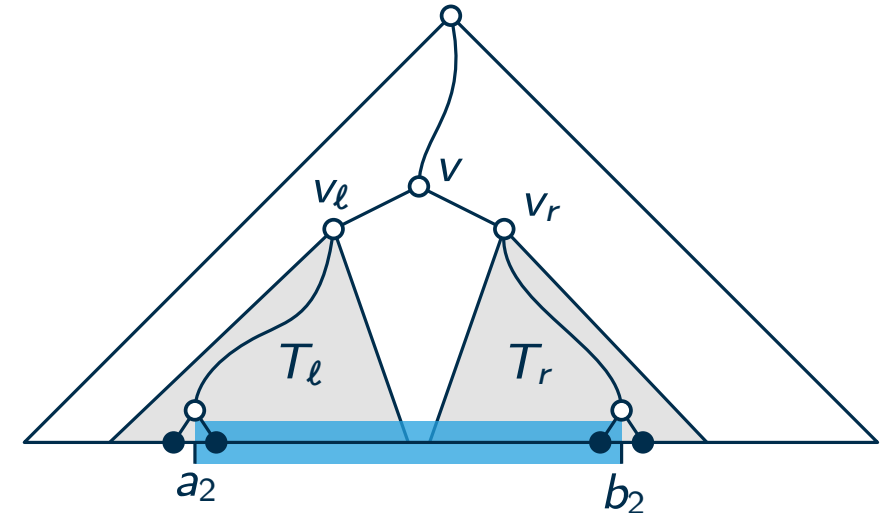
# Two-Sided Query In $y$ -Direction

## Simplified Perspective: Ignore $x$ And $z$ -Direction

- **(DS2)** allows  $[a_2, \infty)$  and  $(-\infty, b_2]$  queries
- goal: build data structure, that allows  $[a_2, b_2]$  queries

## Binary Search Tree In $y$ -Direction

- search for  $a_2$  and  $b_2$  splits at  $v$  to  $v_\ell$  and  $v_r$
- queries in instances of **(DS2)**:  $[a_2, \infty)$  on points in  $T_\ell$  and  $(-\infty, b_2]$  on points in  $T_r$
- running time:  $O(\log n)$  for search in  $y$ -tree plus  $O(\log n + k)$  for two queries in **(DS2)**
- memory:  $O(\log n) \cdot (\text{memory for } \mathbf{DS2})$



## Lemma

**(DS3)**

For  $n$  point in  $\mathbb{R}^3$ , we can answer queries of the form  $[a_1, b_1] \times [a_2, b_2] \times (-\infty, b_3]$  in  $O(\log n + k)$  time after  $O(n \log^2 n)$  preprocessing with  $O(n \log^2 n)$  memory.

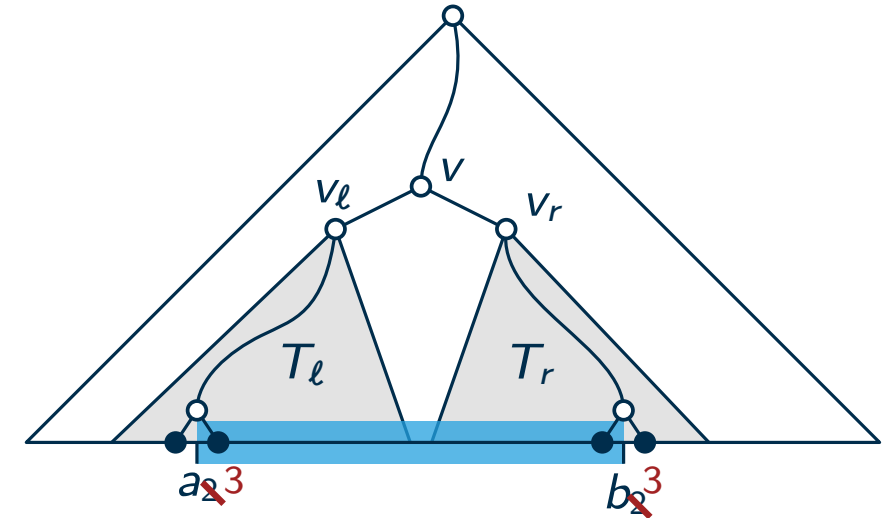
# Two-Sided Query In $y$ -Direction

## Simplified Perspective: Ignore $x$ And $z$ -Direction

- **(DS<sub>2</sub>)** allows  $[a_1^3, \infty)$  and  $(-\infty, b_1^3]$  queries
- goal: build data structure, that allows  $[a_1^3, b_1^3]$  queries

## Binary Search Tree In $y$ -Direction

- search for  $a_2^3$  and  $b_2^3$  splits at  $v$  to  $v_\ell$  and  $v_r$
- queries in instances of **(DS<sub>2</sub>)**:  $[a_2^3, \infty)$  on points in  $T_\ell$  and  $(-\infty, b_2^3]$  on points in  $T_r$
- running time:  $O(\log n)$  for search in  $y$ -tree plus  $O(\log n + k)$  for two queries in **(DS<sub>2</sub>)**
- memory:  $O(\log n) \cdot (\text{memory for DS}_2)$



## ~~Lemma~~ Theorem

For  $n$  point in  $\mathbb{R}^3$ , we can answer queries of the form  $[a_1, b_1] \times [a_2, b_2] \times (-\infty, b_3]$  in  $O(\log n + k)$  time after  $O(n \log^3 n)$  preprocessing with  $O(n \log^3 n)$  memory. **(DS<sub>3</sub>)**<sup>4</sup>

# The Big Picture

(DS4)

$[a_1, b_1] \times [a_2, b_2] \times [a_3, b_3]$

**precomp:**  $O(n \log^3 n)$

**memory:**  $O(n \log^3 n)$

**query:**  $O(\log n + k)$



# The Big Picture

(DS4)

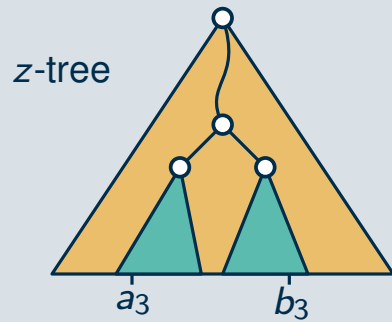
$[a_1, b_1] \times [a_2, b_2] \times [a_3, b_3]$

**precomp:**  $O(n \log^3 n)$

**memory:**  $O(n \log^3 n)$

**query:**  $O(\log n + k)$

- search for  $a_3, b_3$  in z-tree
- split  $\rightarrow$  two (DS3) queries



# The Big Picture

(DS4)

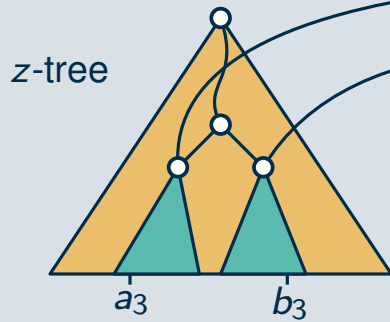
$[a_1, b_1] \times [a_2, b_2] \times [a_3, b_3]$

**precomp:**  $O(n \log^3 n)$

**memory:**  $O(n \log^3 n)$

**query:**  $O(\log n + k)$

- search for  $a_3, b_3$  in z-tree
- split  $\rightarrow$  two (DS3) queries



(DS3)

$[a_1, b_1] \times [a_2, b_2] \times (-\infty, b_3]$

**precomp:**  $O(n \log^2 n)$

**memory:**  $O(n \log^2 n)$

**query:**  $O(\log n + k)$

# The Big Picture

(DS4)

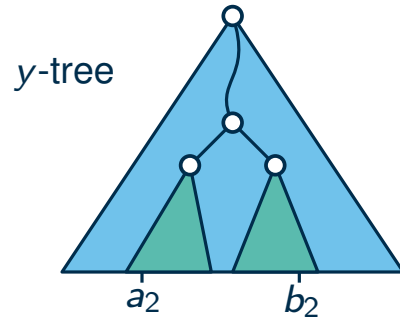
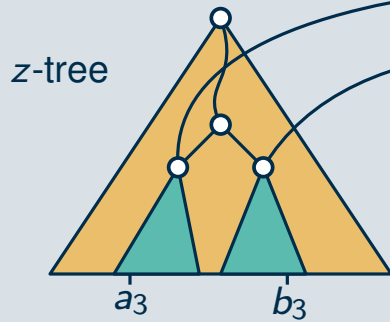
$[a_1, b_1] \times [a_2, b_2] \times [a_3, b_3]$

**precomp:**  $O(n \log^3 n)$

**memory:**  $O(n \log^3 n)$

**query:**  $O(\log n + k)$

- search for  $a_3, b_3$  in z-tree
- split  $\rightarrow$  two (DS3) queries



(DS3)

$[a_1, b_1] \times [a_2, b_2] \times (-\infty, b_3]$

**precomp:**  $O(n \log^2 n)$

**memory:**  $O(n \log^2 n)$

**query:**  $O(\log n + k)$

- search for  $a_2, b_2$  in y-tree
- splits  $\rightarrow$  two (DS2) queries

# The Big Picture

(DS4)

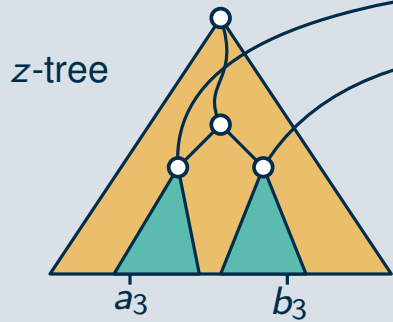
$[a_1, b_1] \times [a_2, b_2] \times [a_3, b_3]$

**precomp:**  $O(n \log^3 n)$

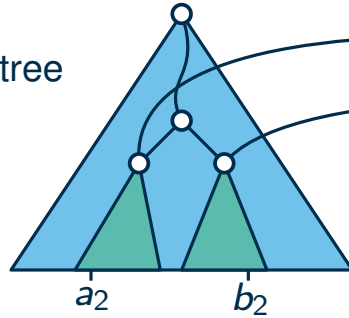
**memory:**  $O(n \log^3 n)$

**query:**  $O(\log n + k)$

- search for  $a_3, b_3$  in z-tree
- split  $\rightarrow$  two (DS3) queries



y-tree



(DS2)

$[a_1, b_1] \times (-\infty, b_2] \times (-\infty, b_3]$

**precomp:**  $O(n \log n)$

**memory:**  $O(n \log n)$

**query:**  $O(\log n + k)$

(DS3)

$[a_1, b_1] \times [a_2, b_2] \times (-\infty, b_3]$

**precomp:**  $O(n \log^2 n)$

**memory:**  $O(n \log^2 n)$

**query:**  $O(\log n + k)$

- search for  $a_2, b_2$  in y-tree
- splits  $\rightarrow$  two (DS2) queries

# The Big Picture

(DS4)

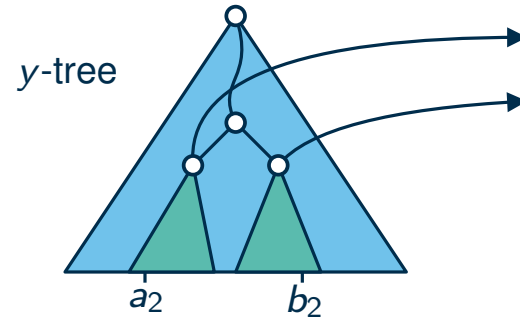
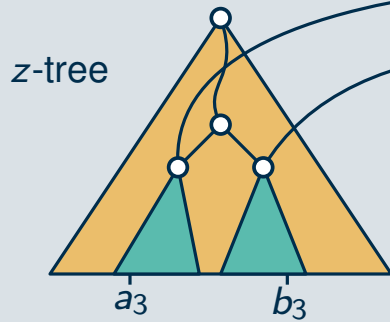
$[a_1, b_1] \times [a_2, b_2] \times [a_3, b_3]$

**precomp:**  $O(n \log^3 n)$

**memory:**  $O(n \log^3 n)$

**query:**  $O(\log n + k)$

- search for  $a_3, b_3$  in z-tree
- split  $\rightarrow$  two (DS3) queries



(DS3)

$[a_1, b_1] \times [a_2, b_2] \times (-\infty, b_3]$

**precomp:**  $O(n \log^2 n)$

**memory:**  $O(n \log^2 n)$

**query:**  $O(\log n + k)$

- search for  $a_2, b_2$  in y-tree
- splits  $\rightarrow$  two (DS2) queries

(DS2)

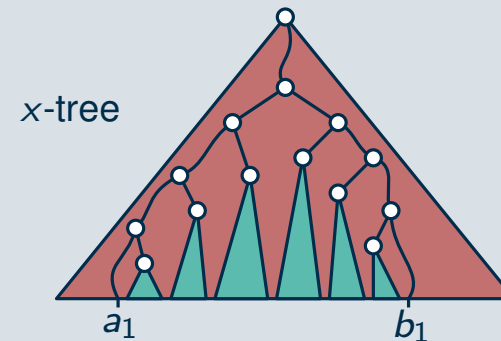
$[a_1, b_1] \times (-\infty, b_2] \times (-\infty, b_3]$

**precomp:**  $O(n \log n)$

**memory:**  $O(n \log n)$

**query:**  $O(\log n + k)$

- search for  $z$  in the root
- walk down x-tree
- follow z-pointers
- each x-subtree: (DS1) query (with initial z-pos)



# The Big Picture

(DS4)

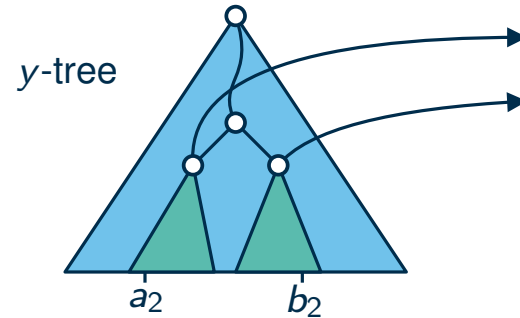
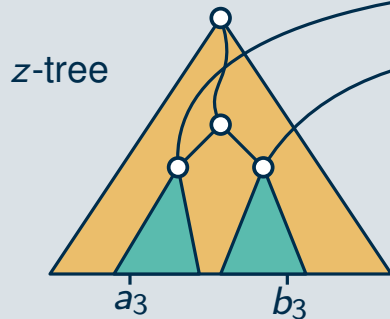
$[a_1, b_1] \times [a_2, b_2] \times [a_3, b_3]$

**precomp:**  $O(n \log^3 n)$

**memory:**  $O(n \log^3 n)$

**query:**  $O(\log n + k)$

- search for  $a_3, b_3$  in z-tree
- split  $\rightarrow$  two (DS3) queries



(DS3)

$[a_1, b_1] \times [a_2, b_2] \times (-\infty, b_3]$

**precomp:**  $O(n \log^2 n)$

**memory:**  $O(n \log^2 n)$

**query:**  $O(\log n + k)$

- search for  $a_2, b_2$  in y-tree
- splits  $\rightarrow$  two (DS2) queries

(DS2)

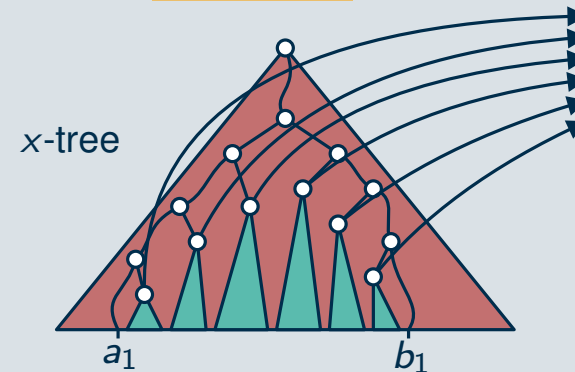
$[a_1, b_1] \times (-\infty, b_2] \times (-\infty, b_3]$

**precomp:**  $O(n \log n)$

**memory:**  $O(n \log n)$

**query:**  $O(\log n + k)$

- search for  $z$  in the root
- walk down x-tree
- follow z-pointers
- each x-subtree: (DS1) query (with initial z-pos)



(DS1)

$(-\infty, b_2] \times (-\infty, b_3]$

**query:**  $O(k)$

**precomp:**  $O(n)$  (if points are sorted)

**memory:**  $O(n)$

# The Big Picture

(DS4)

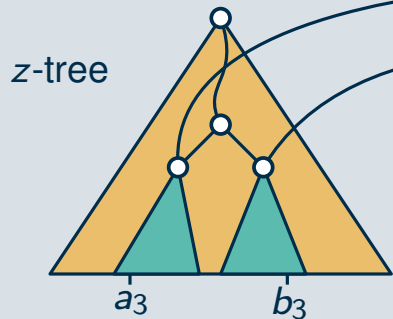
$[a_1, b_1] \times [a_2, b_2] \times [a_3, b_3]$

**precomp:**  $O(n \log^3 n)$

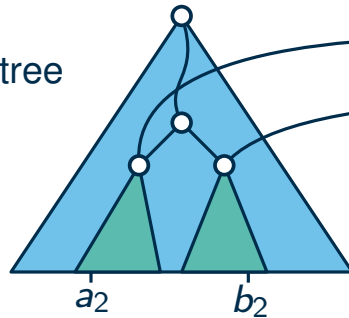
**memory:**  $O(n \log^3 n)$

**query:**  $O(\log n + k)$

- search for  $a_3, b_3$  in z-tree
- split  $\rightarrow$  two (DS3) queries



y-tree



(DS3)

$[a_1, b_1] \times [a_2, b_2] \times (-\infty, b_3]$

**precomp:**  $O(n \log^2 n)$

**memory:**  $O(n \log^2 n)$

**query:**  $O(\log n + k)$

- search for  $a_2, b_2$  in y-tree
- splits  $\rightarrow$  two (DS2) queries

(DS2)

$[a_1, b_1] \times (-\infty, b_2] \times (-\infty, b_3]$

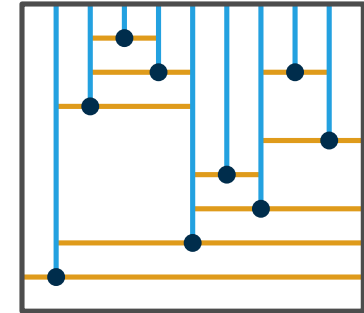
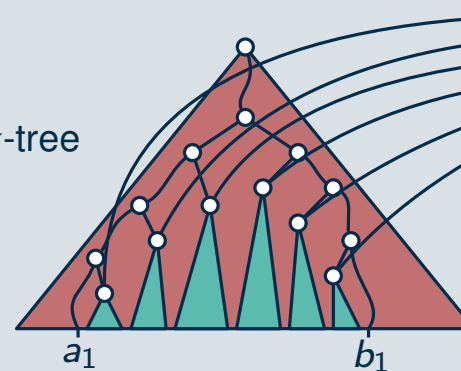
**precomp:**  $O(n \log n)$

**memory:**  $O(n \log n)$

**query:**  $O(\log n + k)$

- search for  $z$  in the root
- walk down x-tree
- follow z-pointers
- each x-subtree: (DS1) query (with initial z-pos)

x-tree



(DS1)

$(-\infty, b_2] \times (-\infty, b_3]$

**query:**  $O(k)$

**precomp:**  $O(n)$  (if points are sorted)

**memory:**  $O(n)$

- initial z-position known
- walk in y-direction
- decide for cell by z-query
- output intersected rays

# Wrap-Up

## What Have We Learned Today?

- fractional cascading: search only once and then follow pointers



# Wrap-Up

## What Have We Learned Today?

- fractional cascading: search only once and then follow pointers
- clever geometric solution for simplified queries  $(-\infty, b_2] \times (-\infty, b_3]$

# Wrap-Up

## What Have We Learned Today?

- fractional cascading: search only once and then follow pointers
- clever geometric solution for simplified queries  $(-\infty, b_2] \times (-\infty, b_3]$
- transformation from  $(-\infty, b]$  to  $[a, b]$

# Wrap-Up

## What Have We Learned Today?

- fractional cascading: search only once and then follow pointers
- clever geometric solution for simplified queries  $(-\infty, b_2] \times (-\infty, b_3]$
- transformation from  $(-\infty, b]$  to  $[a, b]$

### Theorem

(DS4)

For  $n$  point in  $\mathbb{R}^3$ , we can answer queries of the form  $[a_1, b_1] \times [a_2, b_2] \times [a_3, b_3]$  in  $O(\log n + k)$  time after  $O(n \log^3 n)$  preprocessing with  $O(n \log^3 n)$  memory.

# Wrap-Up

## What Have We Learned Today?

- fractional cascading: search only once and then follow pointers
- clever geometric solution for simplified queries  $(-\infty, b_2] \times (-\infty, b_3]$
- transformation from  $(-\infty, b]$  to  $[a, b]$

### Theorem

(DS4)

For  $n$  point in  $\mathbb{R}^3$ , we can answer queries of the form  $[a_1, b_1] \times [a_2, b_2] \times [a_3, b_3]$  in  $O(\log n + k)$  time after  $O(n \log^3 n)$  preprocessing with  $O(n \log^3 n)$  memory.

## What else is there?

- many applications of fractional cascading

# Wrap-Up

## What Have We Learned Today?

- fractional cascading: search only once and then follow pointers
- clever geometric solution for simplified queries  $(-\infty, b_2] \times (-\infty, b_3]$
- transformation from  $(-\infty, b]$  to  $[a, b]$

### Theorem

(DS4)

For  $n$  point in  $\mathbb{R}^3$ , we can answer queries of the form  $[a_1, b_1] \times [a_2, b_2] \times [a_3, b_3]$  in  $O(\log n + k)$  time after  $O(n \log^3 n)$  preprocessing with  $O(n \log^3 n)$  memory.

## What else is there?

- many applications of fractional cascading
- dynamic range queries: inserting and deleting points

# Wrap-Up

## What Have We Learned Today?

- fractional cascading: search only once and then follow pointers
- clever geometric solution for simplified queries  $(-\infty, b_2] \times (-\infty, b_3]$
- transformation from  $(-\infty, b]$  to  $[a, b]$

### Theorem

(DS4)

For  $n$  point in  $\mathbb{R}^3$ , we can answer queries of the form  $[a_1, b_1] \times [a_2, b_2] \times [a_3, b_3]$  in  $O(\log n + k)$  time after  $O(n \log^3 n)$  preprocessing with  $O(n \log^3 n)$  memory.

## What else is there?

- many applications of fractional cascading
- dynamic range queries: inserting and deleting points
- $O(\log n \cdot (\log n / \log \log n)^{d-3} + k)$  queries with  $O(n \cdot (\log n / \log \log n)^{d-3})$  memory

# Wrap-Up

## What Have We Learned Today?

- fractional cascading: search only once and then follow pointers
- clever geometric solution for simplified queries  $(-\infty, b_2] \times (-\infty, b_3]$
- transformation from  $(-\infty, b]$  to  $[a, b]$

### Theorem

(DS4)

For  $n$  point in  $\mathbb{R}^3$ , we can answer queries of the form  $[a_1, b_1] \times [a_2, b_2] \times [a_3, b_3]$  in  $O(\log n + k)$  time after  $O(n \log^3 n)$  preprocessing with  $O(n \log^3 n)$  memory.

## What else is there?

- many applications of fractional cascading
- dynamic range queries: inserting and deleting points
- $O(\log n \cdot (\log n / \log \log n)^{d-3} + k)$  queries with  $O(n \cdot (\log n / \log \log n)^{d-3})$  memory
- even better results with some bit-hacking in the word RAM model