

A Further Improvement

- Parallel search first.
- Consider a sorted array A of n element and we want to search for an element x .
- Given p processors, we can always search at positions (indices) $1, n/p, 2n/p, \dots, n$.
- Record the result of each comparison as a 1 or 0 with 1 for position i indicating that $A[i] < x$ and 0 indicating that $A[i] \geq x$.
- The sequence of p results will have :
 - Either all 1's : x is not in A
 - Either all 0's : x is not in A
 - A shift from 1's to 0's : x is likely in the n/p segment corresponding to the shift from 1 to 0.

Search in Parallel

- We can identify the next step depending on the three cases.
 - Either all 1's : x is not in A
 - Either all 0's : x is not in A
 - A shift from 1's to 0's : x is likely in the n/p segment corresponding to the shift from 1 to 0.
 - Therefore, search recursively in the corresponding segment of size n/p while still using p processors.
- The recurrence relation for the time taken is
 - $T(n) = T(n/p) + O(1)$, for a solution of $T(n) = O(\log_p n)$.

Search in Parallel

- Consider typical values of p .
- For $p = O(1)$, no change in time taken asymptotically.
- For $p = O(\log n)$, the time taken is $O(\log n / \log \log n)$.
- For $p = O(n^{1/2})$, the time taken is $O(\log n / \log n^{1/2}) = O(1)$!
 - Of course, looks like wasteful from a work point of view.
 - Let us see what it is good for!

$$0 < \epsilon < 1$$

$$p = n^\epsilon, T(n) = O\left(\frac{1}{\epsilon}\right), W(n) = O(n^\epsilon)$$

From Parallel Search to Merge

- Recall our idea to arrive at an optimal algorithm to merge two sorted arrays A and B.
- We rank a few elements of A in B to partition B into sub-arrays.
- Let us consider ranking $n^{1/2}$ elements of A in B.
- We have n processors, so each search can use $n^{1/2}$ processors!
- Each search now finishes in $O(1)$ time.

$$T(n) = O(\log_p n)$$

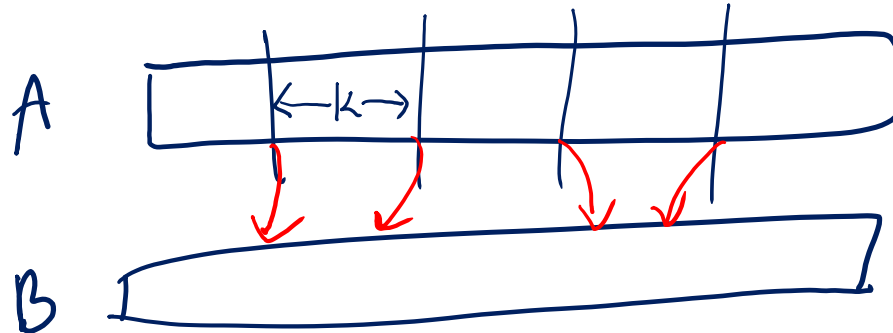
$$W(n) = O(p \log_p n)$$

$$\begin{aligned} p = \sqrt{n} : T(n) &= O(1) \\ p = O(1) : T(n) &= O(\log n) \end{aligned}$$

$$\begin{aligned} W(n) &= O(\sqrt{n}) \\ W(n) &= O(\log n) \end{aligned} \quad ||$$

From Parallel Search to Merge

- Let us consider ranking $n^{1/2}$ elements of A in B.
- We have n processors, so each search can use $n^{1/2}$ processors!
- Each search now finishes in $O(1)$ time.
- There is a downside however.
- The partitions of A are now much longer at $n^{1/2}$ each.
- The partitions of B are like in the earlier case, unknown.



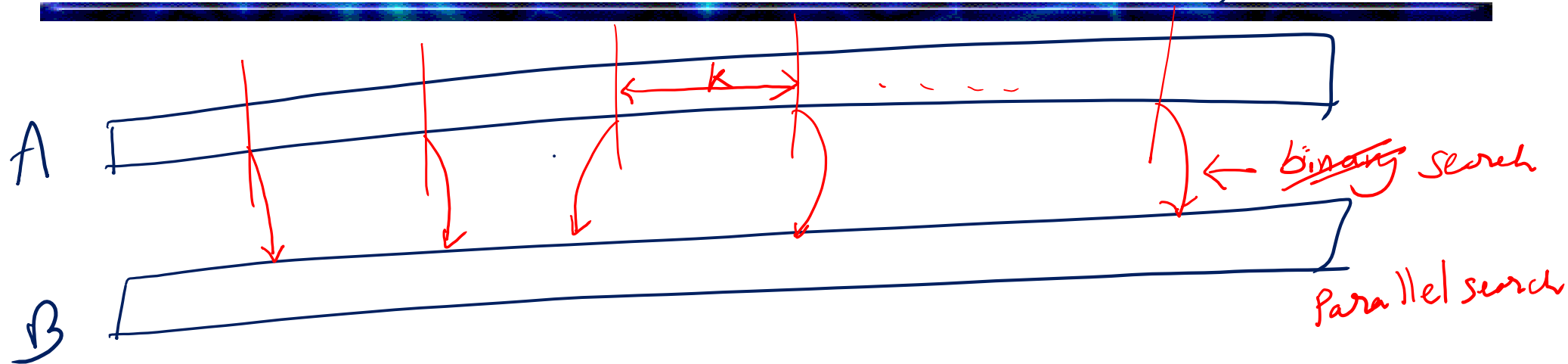
$$k = \sqrt{n}$$

$$\# \text{Proc} / \text{search} = \sqrt{n}$$

$$\# \text{tasks} = \sqrt{n}$$

p processors / search : Time = \log_p^n //

work = $p //$



Merge

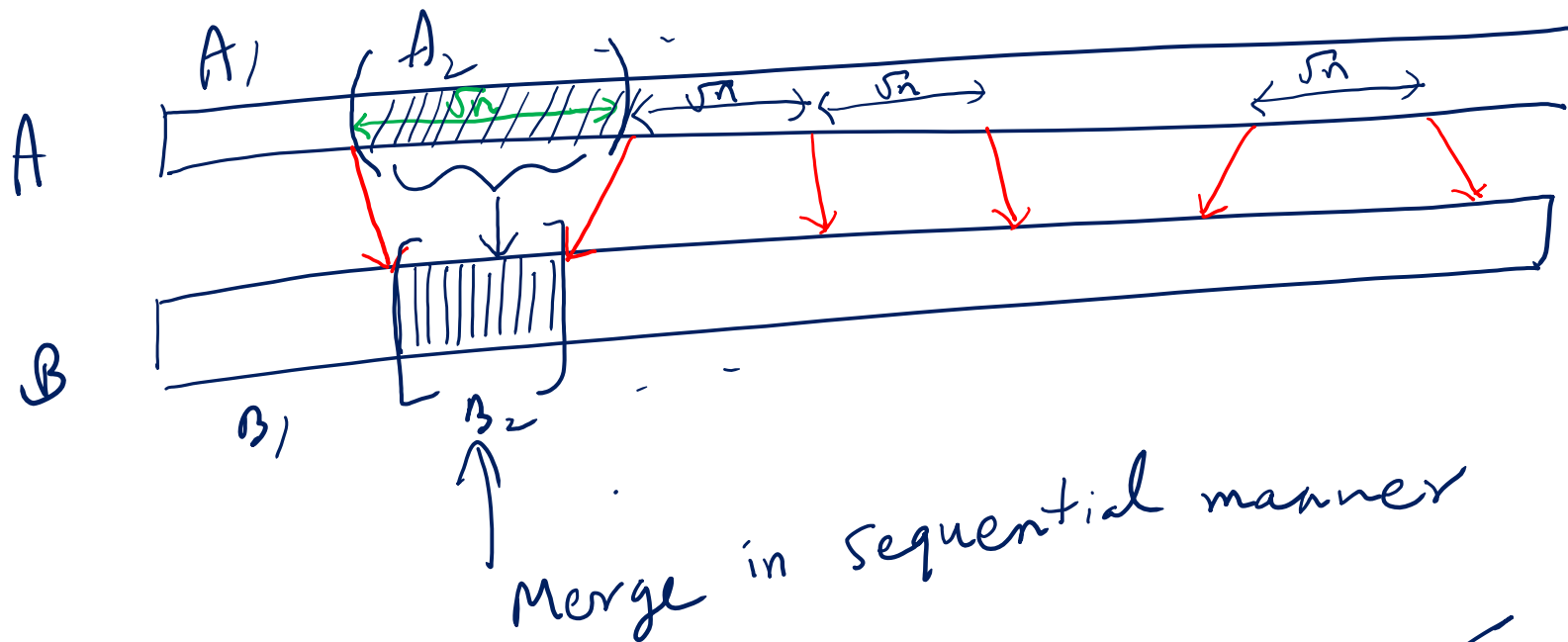
Rank $\left(\frac{n}{k}\right)$ elements of A into B

Total work = $\frac{n}{k} \times p$, Total Time = \log_p^n

find a k, p
 s.t. $\log_p^n = O(1)$,
 work = $O(n)$

Processors used = $p \times \frac{n}{k}$
 across all ranks

$p = \sqrt{n}$, $k = \sqrt{n}$
 $p = n^\epsilon$, $k = n^\epsilon$



Reduce $|B_2|$ to $O(\sqrt{n})$

Time = $O(1)$ for searching/ranking

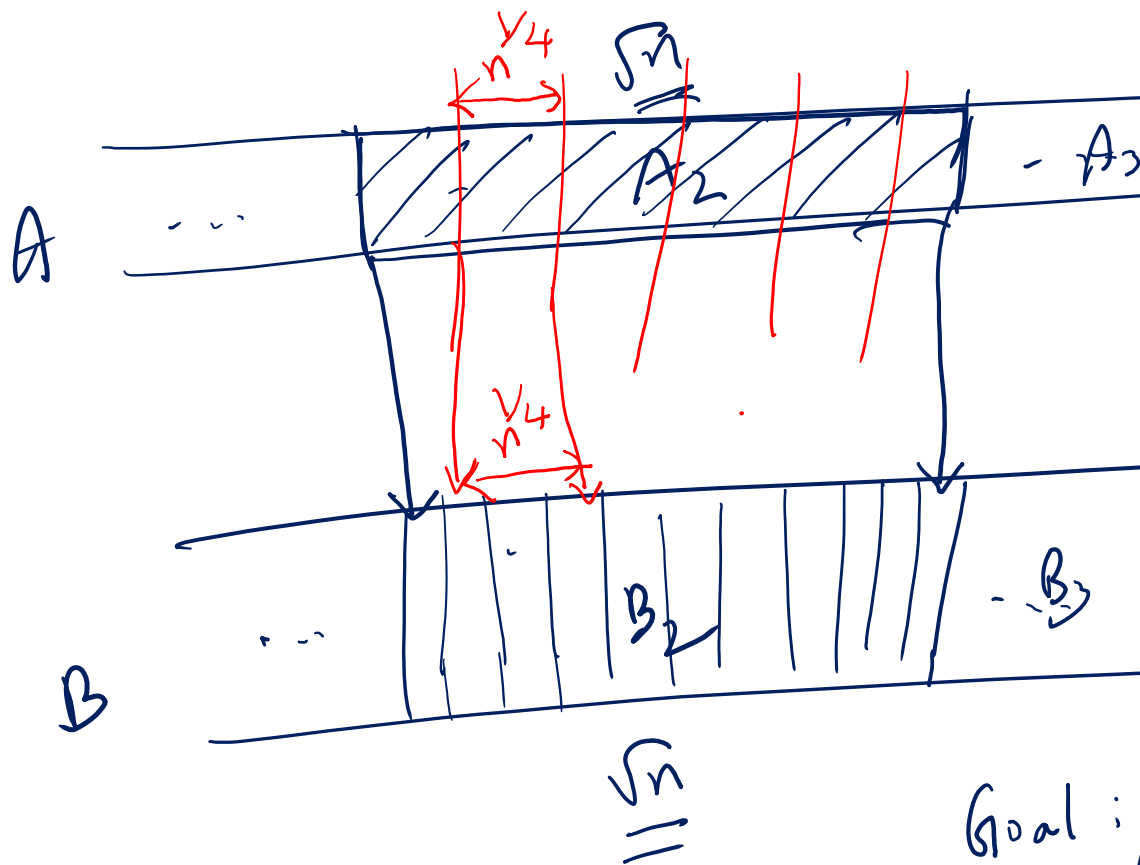
$O(\text{length of } A_2 + \text{length of } B_2) = O(\sqrt{n})$

$\rightarrow \text{length of } A_2 = \sqrt{n}$

$\rightarrow \text{Don't know} = \sqrt{n}$

\sqrt{n} Processors

Rank & elements of A_2 in B_2 .



$$\text{Time} = \log_{P=\sqrt{n}/t} \sqrt{n} / \text{search} = \frac{\log \sqrt{n}}{\log \sqrt{n} - \log t}$$

total of \sqrt{n} processors available

$$\# \text{Proc/search} = \frac{\sqrt{n}}{t}$$

$$\text{work/search} = p = \sqrt{n}/t$$

$$\text{total work} = \frac{\sqrt{n}}{t} \times t = \sqrt{n}$$

Goal: Merge time \sqrt{n} $\downarrow \downarrow$ $n^{1/4}$
 \rightarrow lengths of $|A_2|, |B_2|$

$$t = n^{\frac{k-1}{2}}$$

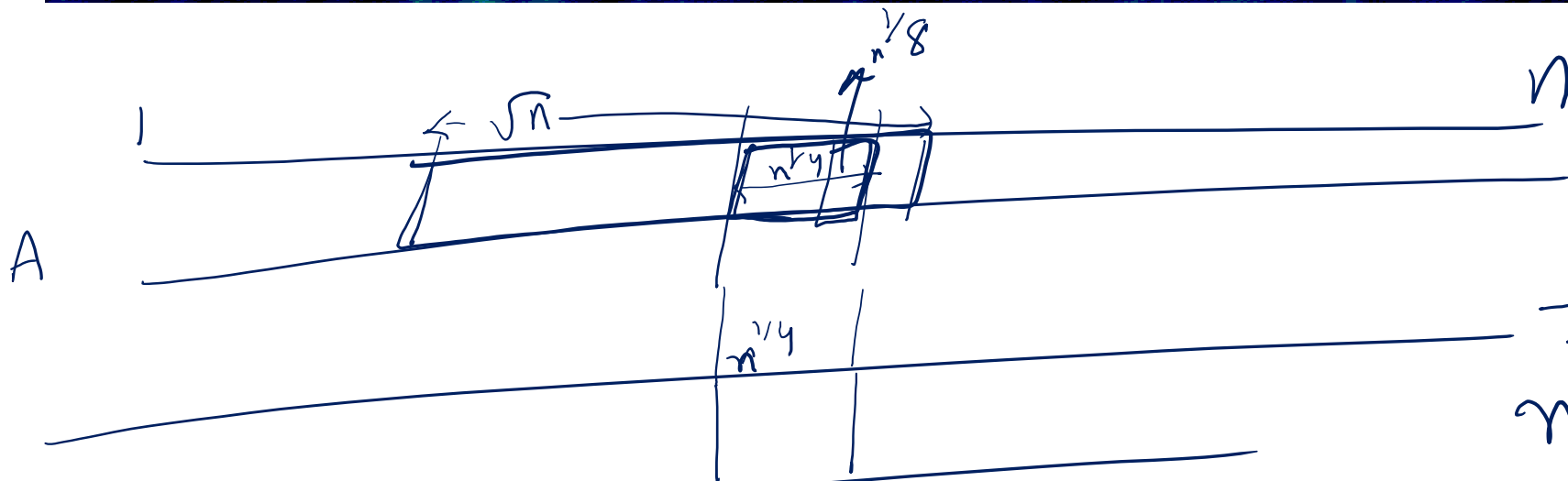
$$t = n^{1/4}$$

$$\log \sqrt{n} = 2 \log \sqrt{n} - 2 \log t$$

$$2 \log t = \log \sqrt{n}$$

$$\log t = \log \sqrt{\sqrt{n}}$$

$$\frac{\log \sqrt{n}}{\log \sqrt{n} - \log t} = O(1) \leftarrow$$



$$\frac{1}{2^i} n = O(1)$$

$i = ?$

B

$$n \xrightarrow{i} \sqrt{n} \xrightarrow{2} n^{1/4} \xrightarrow{3} n^{1/8} \xrightarrow{4} n^{1/16} \xrightarrow{5} n^{1/32} \dots \xrightarrow{i} n^{1/2^i} \rightarrow O(1)$$

$\# \text{ steps} = O(\log \log n)$

$= n^{1/2^i}$

recurs.

From Parallel Search to Merge

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- But, can use recursion to make further progress.

From Parallel Search to Merge

- The partitions of A are now much longer at $n^{1/2}$ each.
- The partitions of B are like in the earlier case, unknown.
- But, can use recursion to make further progress.
- Recursively apply the same procedure on each partition of A into the corresponding partition of B.
- Notice that each part of A is only $n^{1/2}$ in size.
- We want to rank $n^{1/4}$ element of each part of A into the corresponding B.

From Parallel Search to Merge

- The recurrence relation guiding this process is captured by $T(n, m) = \max_i T(n^{1/2}, m_i) + O(1)$.
 - In the above, n and m refer to the length of A and B respectively.
 - And, m_i refers to the length of the i^{th} partition of B .
- Can show that $T(n, m) = O(\log \log n)$.
- Once recursion ends, each partition of A and partitions of B will be $O(\log \log n)$ long, and we merge them sequentially.

0 (1)

$$\text{Time} = O(\log \log n)$$

$$\text{Work} = O(\ln(\log \log n))$$

non optimal

$$n = 10^{100} \quad \log \log n \approx 2$$

$$n = 10^{1000} \quad \log \log n = 3$$

$$O(\log \log n)$$

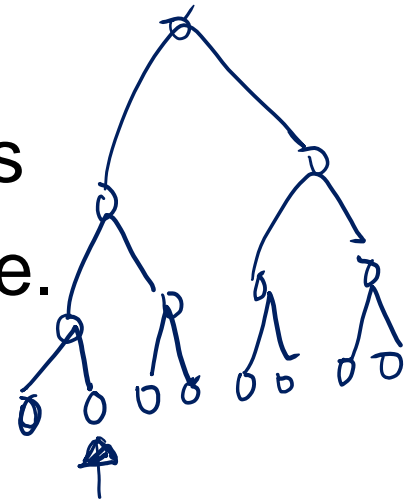
$$\cancel{O(n)}$$

fun ↑↑

→ solve a smaller problem

The Power of CRCW – Minima

- Two points of interest
 - Illustrate the power of CRCW models
 - Illustrate another optimality technique.
- Find the minima of n elements.
 - Input: An array A of n elements
 - Output: The minimum element in A .
- From what we already know:
 - Standard sequential algorithm not good enough
 - Can use an upward traversal, with min as the operator at each internal node. Time = $O(\log n)$, work = $O(n)$.



$O(n)$ time

The Power of CRCW – Minima

- Our solution steps:
 - Design a $O(n^2)$ work, $O(1)$ time algorithm.
 - Gain optimality by sacrificing runtime to $O(\log \log n)$.

Friday

An $O(1)$ Time Algorithm

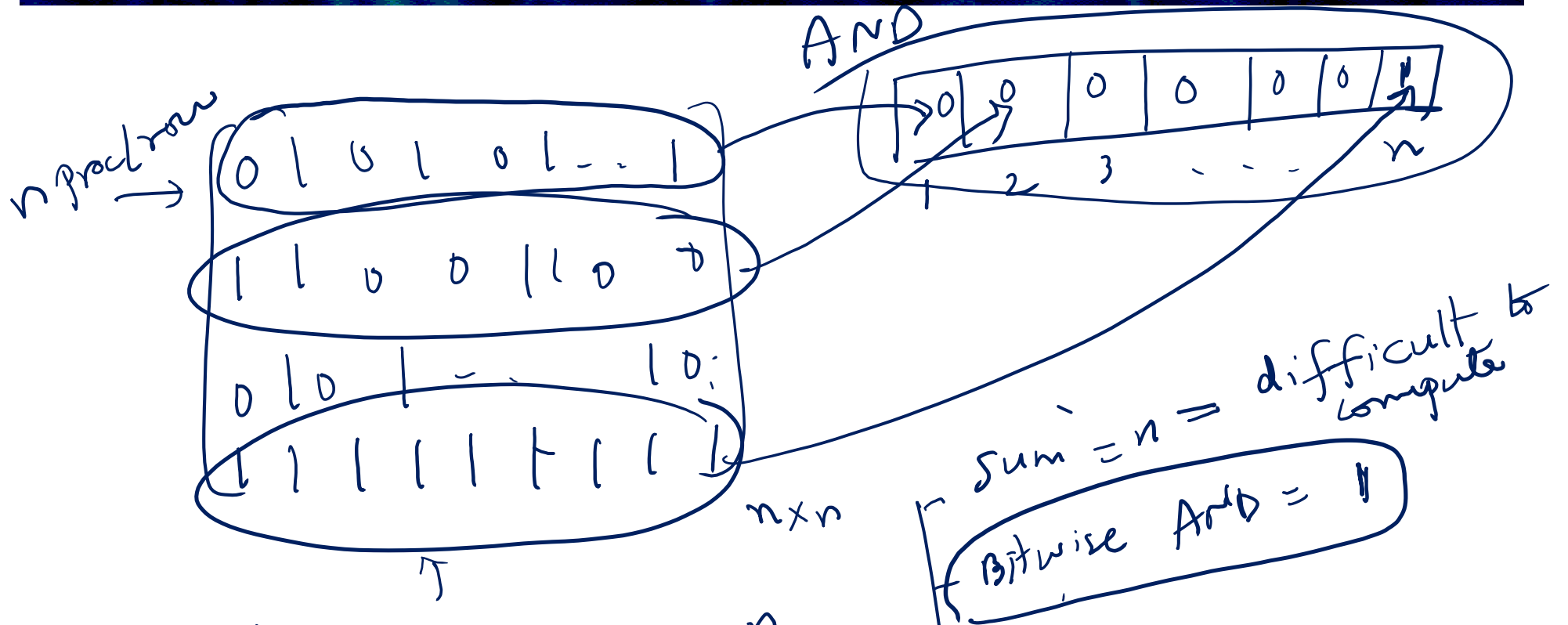
<i>A</i>	12	17	8	18	26
12	--	1	0	1	1
17	0	--	0	1	1
8	1	1	--	1	1
18	0	0	0	--	1
26	0	0	0	0	--

n x n

- Use n^2 processors.
- Compare $A[i]$ with $A[j]$ for each i and j .
- Now can identify the minimum.

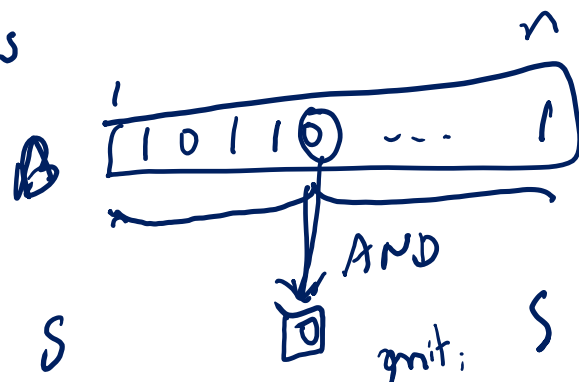
$$\underline{\underline{A(i,j) = 0 \text{ if } A(i,i) > A(j,j)}}$$

n^2 Processes



Sum = n = difficult to compute
 Bitwise AND = 1

CRCW helps



if $B(i) = 0$ write 0 to S
 $S = \begin{cases} 1 & \text{if all } B(i) = 1 \\ 0 & \text{if any } B(i) = 0 \end{cases}$
 // for all i in parallel

An $O(1)$ Time Algorithm

	12	17	8	18	26
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17	0	--	0	1	1
8	1	1	--	1	1
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- Use n^2 processors.
- Compare $A[i]$ with $A[j]$ for each i and j .
- Now can identify the minimum.
 - How?

An $O(1)$ Time Algorithm

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- Use n^2 processors.
- Compare $A[i]$ with $A[j]$ for each i and j .
- Now can identify the minimum.
 - How?
- Where did we need the CRCW model?

work = n^2 $\downarrow \downarrow$
time $\geq O(1)$

Towards Optimality

- The earlier algorithm is heavy on work.
- To reduce the work, we proceed as follows.
- We derive an $O(n \log \log n)$ work algorithm running in $O(\log \log n)$ time.
- For this, use a doubly logarithmic tree.
 - Defined in the following.

Work : $n^2 \rightarrow \underline{\underline{n \log \log n}}$ not optimal

Time : $O(1) \rightarrow \underline{\underline{O(\log \log n)}}$

↓

optimal

start with a smaller problem size

$$x = O(n/\log n)$$

$$x \log x = n$$

$$x = n$$

$$\log x + \log \log x = \log n$$

LHS $\uparrow\uparrow$

$$x < n$$

RHS $\uparrow\uparrow$

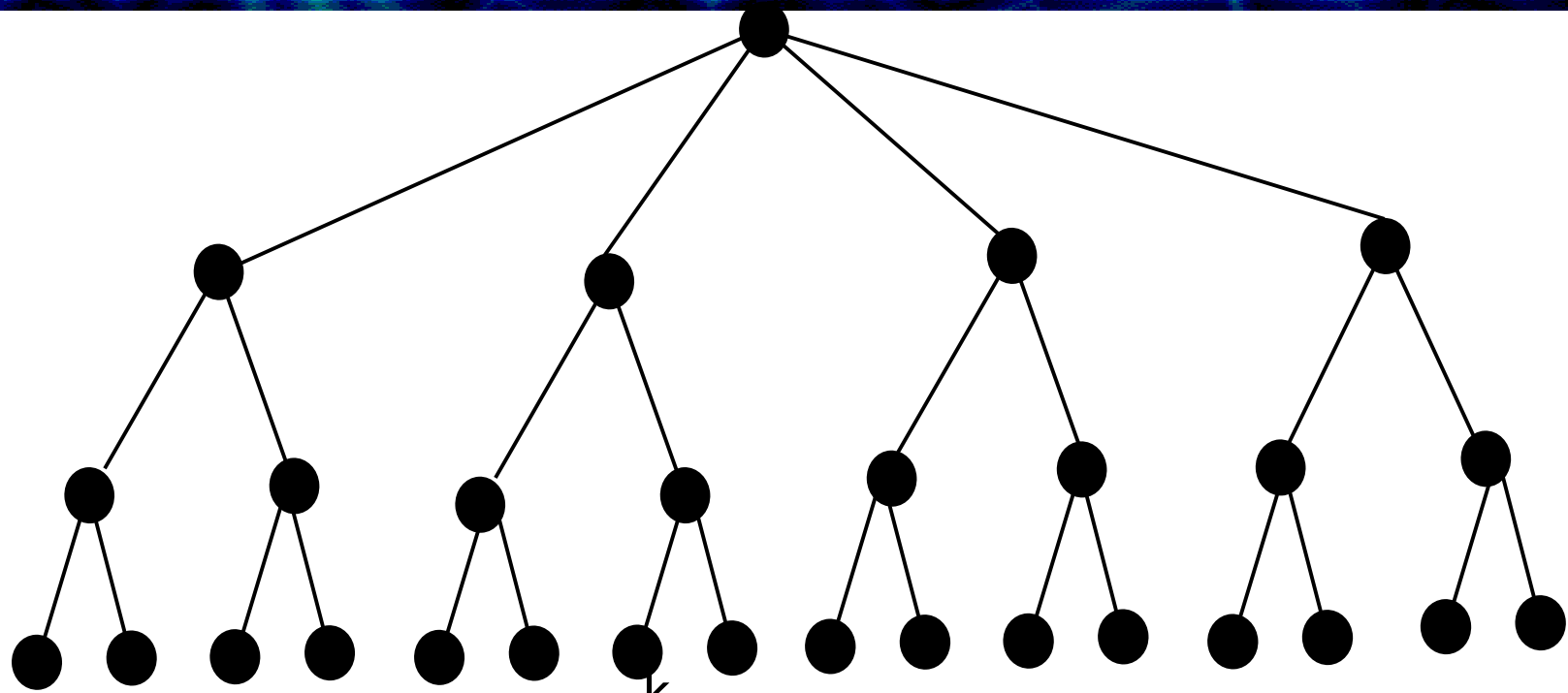
$$x = \frac{n}{\log n}$$

LHS:

$$\frac{n}{\log n} \times \log\left(\frac{n}{\log n}\right) = \frac{n}{\log n} (\log n - \log \log n)$$

$$= \cancel{n} - \frac{n \log \log n}{\log n}$$

Doubly Logarithmic Tree



- Let there be $n = 2^{2^k}$ leaves, the root is level 0. The root has $\sqrt{n} = 2^{2^{k-1}}$ children.
- In general, a node at level i has $2^{2^{k-i-1}}$ children, for $0 \leq i \leq k-1$.
- Each node at level k has two leaf nodes as children.