LONGEST COMMON EXTENSIONS IN SUBLINEAR SPACE

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CPM 2015 June 29, 2015

THE LONGEST COMMON EXTENSION PROBLEM

Prepreprocess T of length n to support the query:

LCE(i,j): return the length of the longest common prefix of T[i...n] and T[j...n]

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Example

$$LCE(3,6)=5$$

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$$T = \begin{bmatrix} 1 & 2 & 3 & 4 & 5 & 6 & 7 & 8 & 9 & 10 & 11 \\ A & C & A & C & B & A & C & B & A & C & C \end{bmatrix}$$
Suffix 3 A C B A C B A C C

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Suffix 3 A C B A C C Suffix 6 A C B A C C

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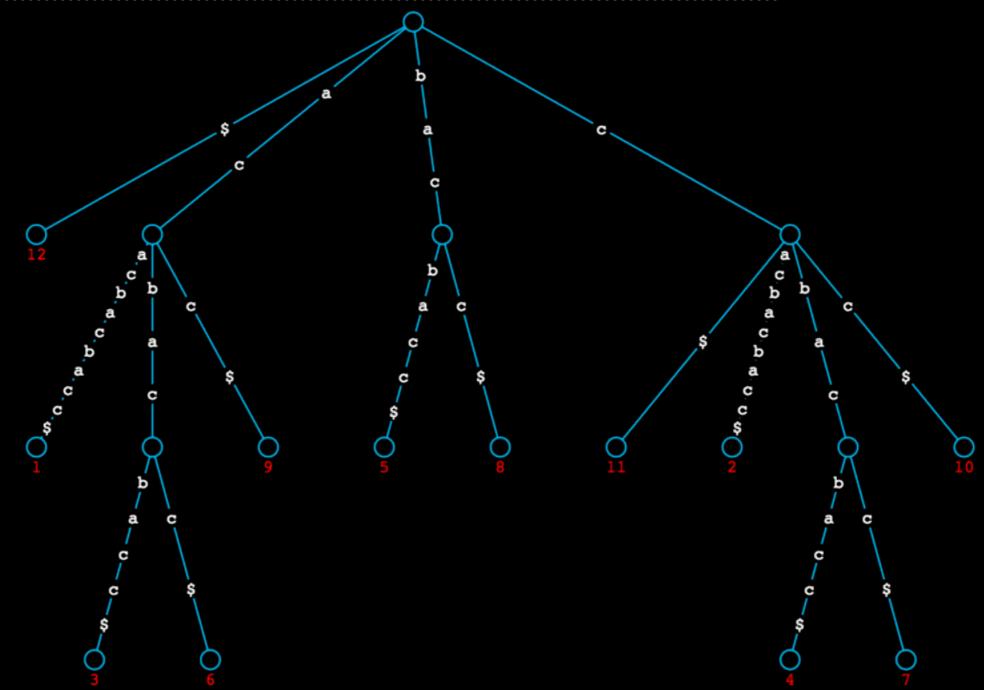
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		Space	Time
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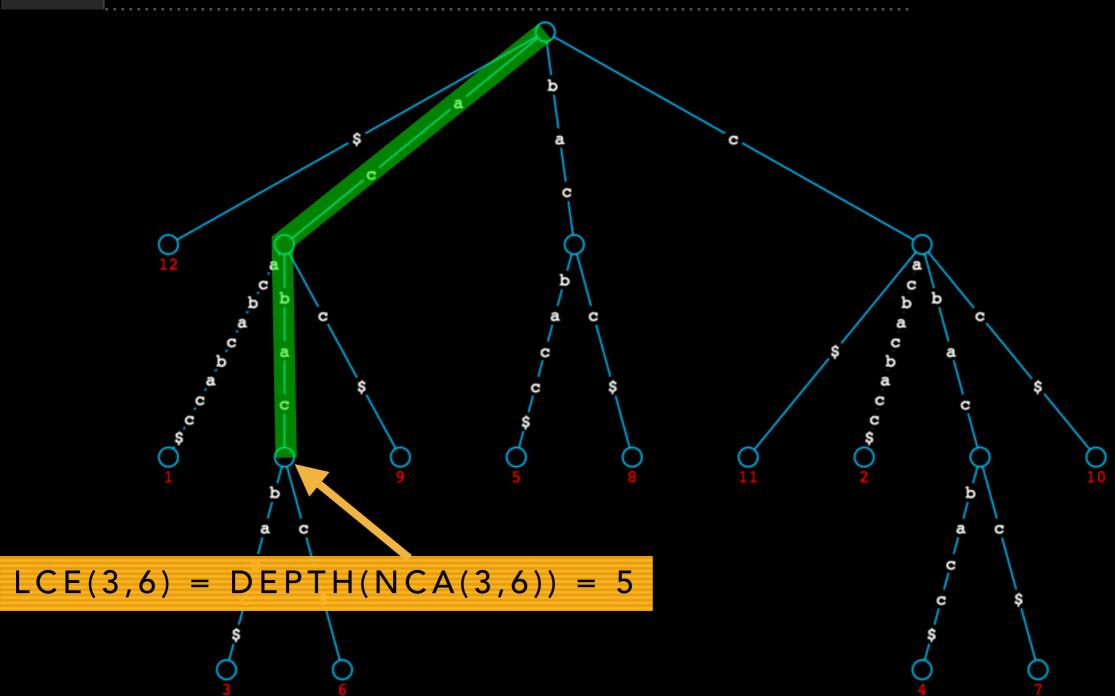
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OUR RESULTS

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CPM 2012 RESULTS*

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4	Randomized trade-off	$O(n/\tau)$	$O(\tau \log(\ell/\tau))$	1≤ <i>τ</i> ≤n

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CPM 2015 RESULTS

		Space	Time	Trade-off range
5	NEW deterministic trade-off	$O(n/\tau)$	$O(\tau log^2(n/\tau))$	1/logn≤τ≤n
6	NEW randomized trade-off	$O(n/\tau)$	O(au)	1≤ <i>τ</i> ≤n

*Philip Bille, Inge Li Gørtz, Benjamin Sach, Hjalte Wedel Vildhøj, Time-Space Trade-Offs for Longest Common Extensions, CPM 2012

THE NEW DETERMINISTIC TRADE-0FF

TWO STRUCTURES

Data Structure 1: O(n/ τ) space and O(τ) time, but works only if $|i-j| < \tau$

Data Structure 2: $O(n/\tau)$ space and $O(\tau \log^2(n/\tau))$ time:

Reduces an LCE(i,j) query to another query LCE(i',j') s.t. $|i'-j'| < \tau$



Lemma

An LCE(i,j) query where i and j are in separate halves of T can be reduced to another LCE(i',j') query such that i' and j' are in the same half of T



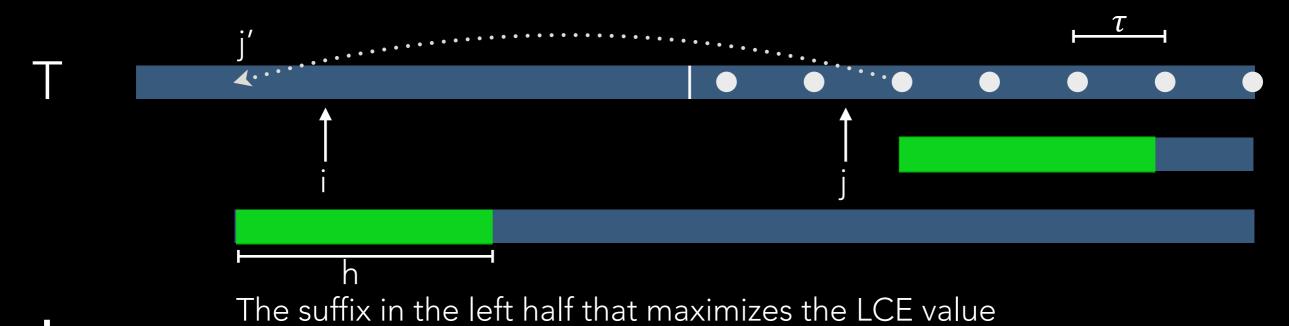
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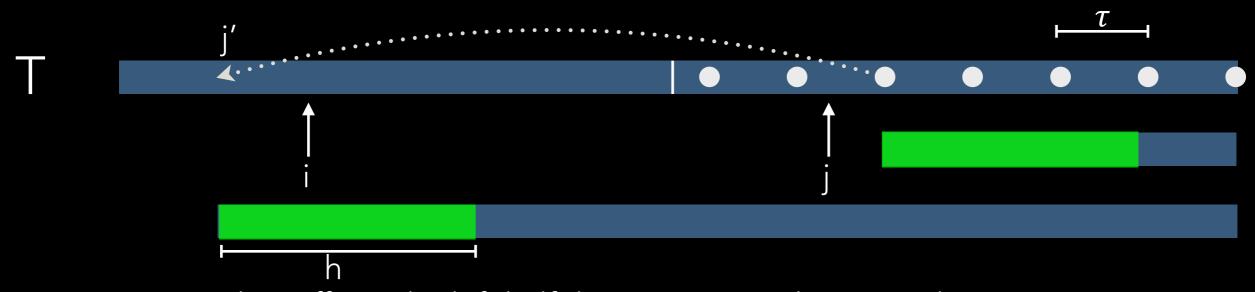
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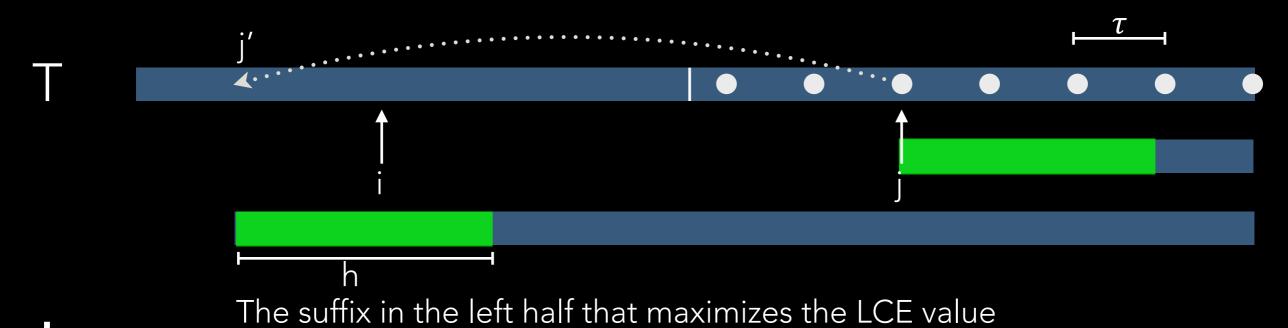


The suffix in the left half that maximizes the LCE value

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Proof

Assume that j is a sampled position

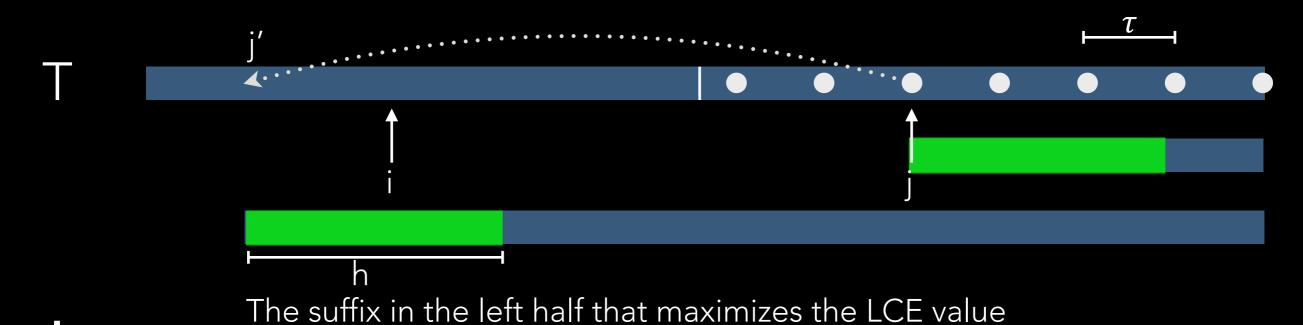


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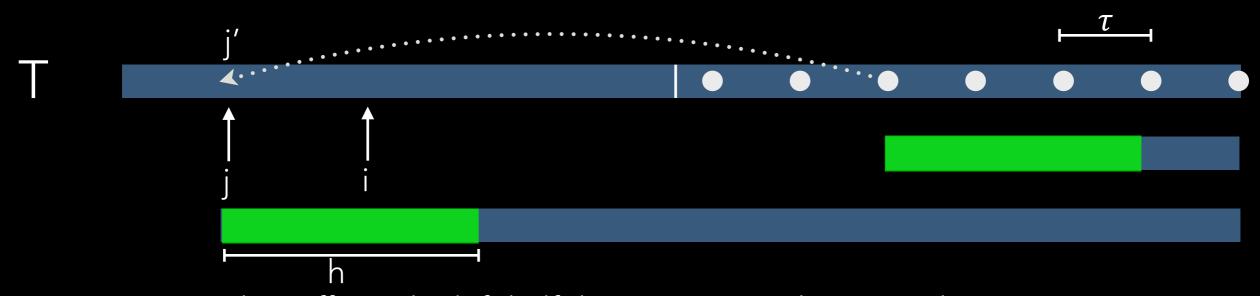
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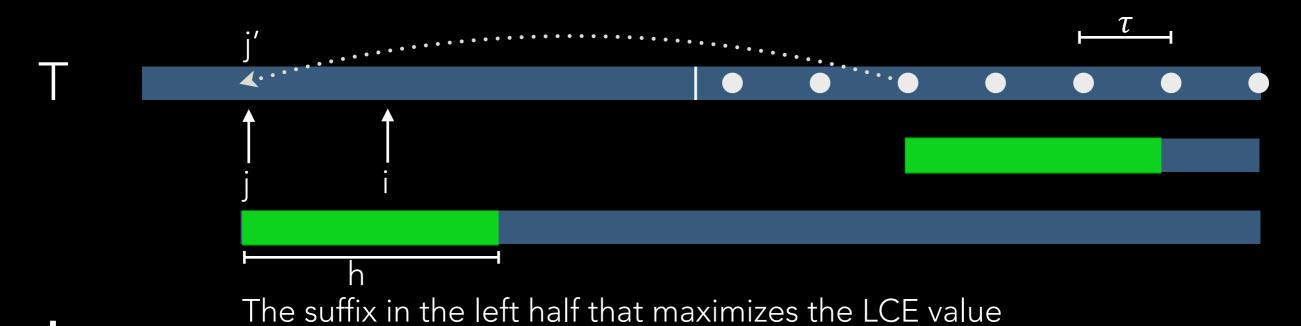


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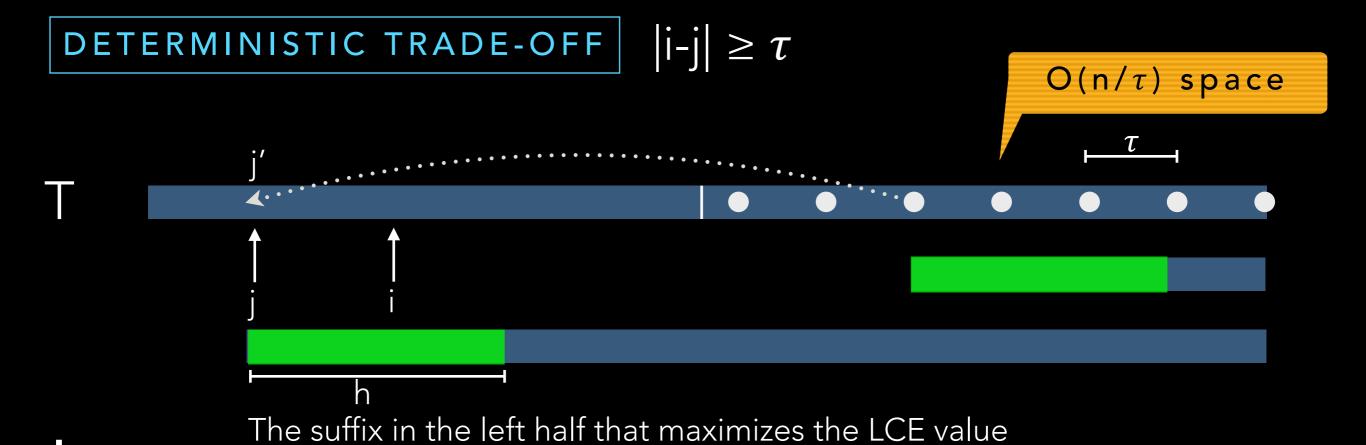


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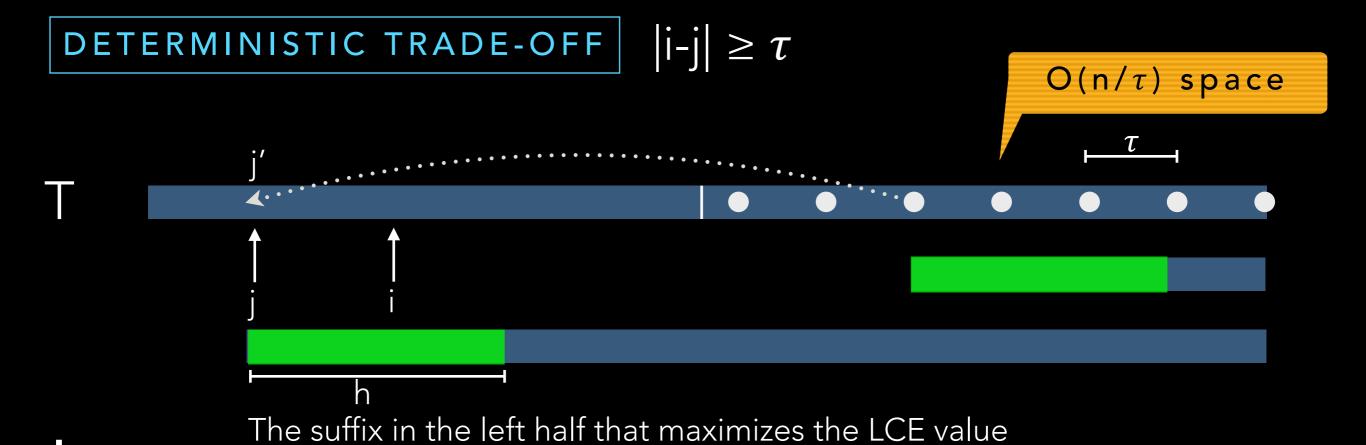


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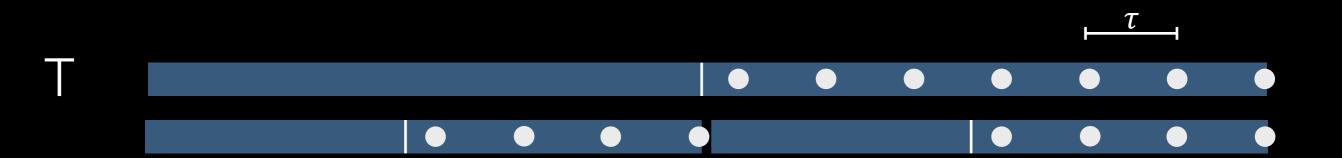
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 $O(\tau)$ time

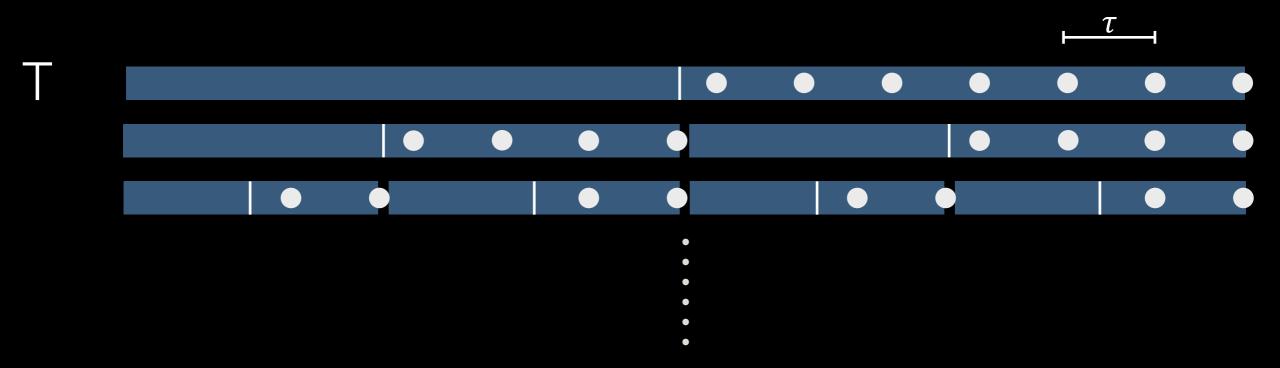
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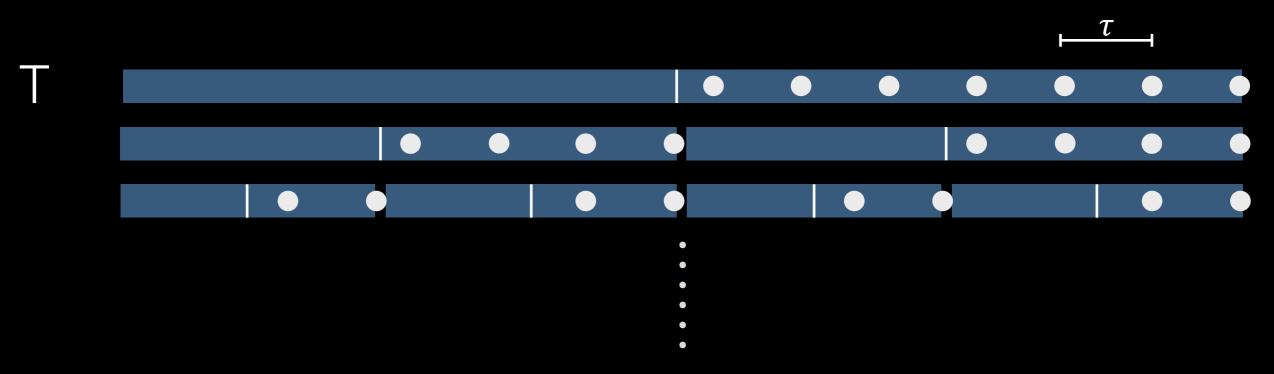
Build data structure recursively for left and right half of T



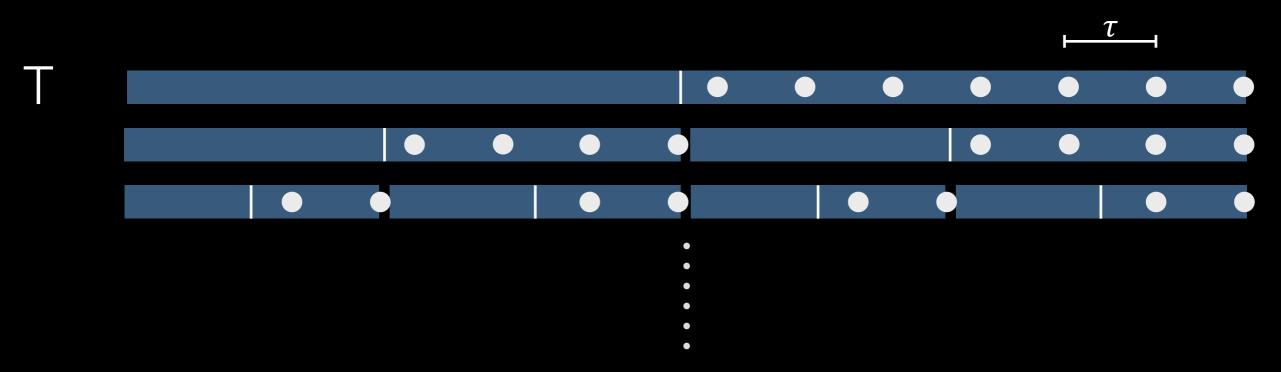
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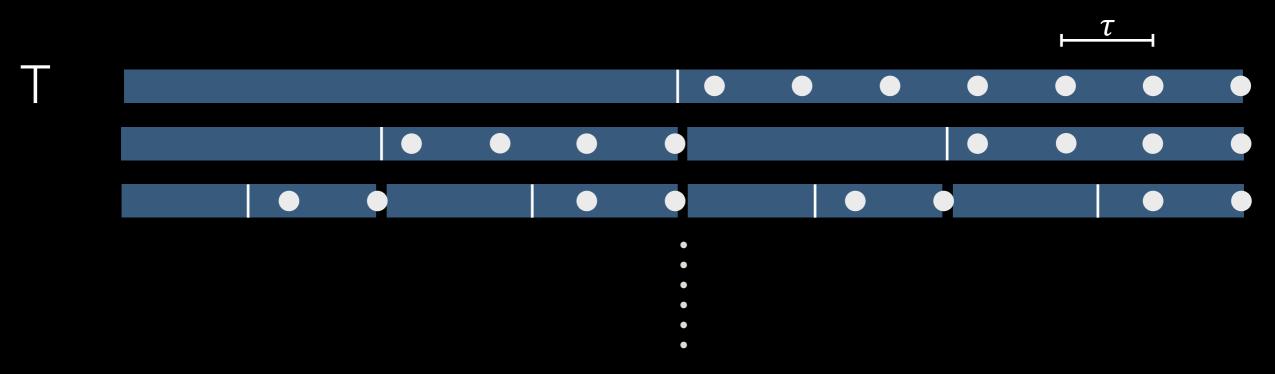
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- $n/(2\tau)$ sampled positions on each level
- $\log(n/\tau)$ levels
- $O(\tau)$ time on each level

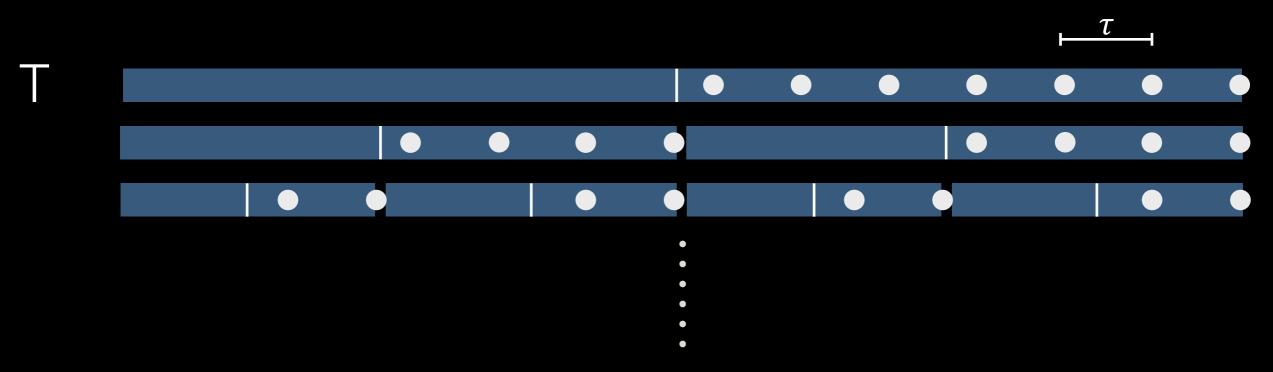


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 $O((n/\tau)\log(n/\tau))$ space $O(\tau\log(n/\tau))$ time



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SHAVING TWO LOGS

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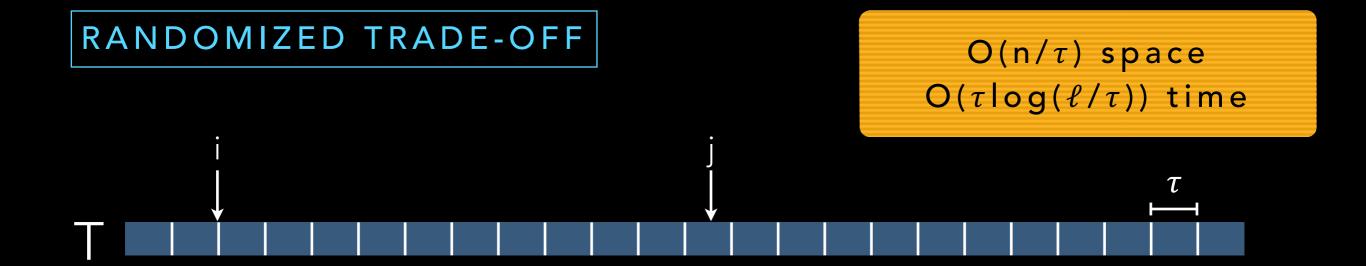


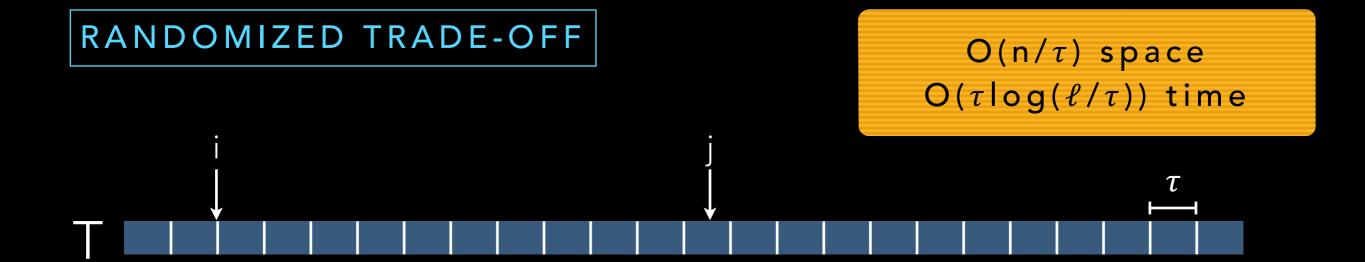
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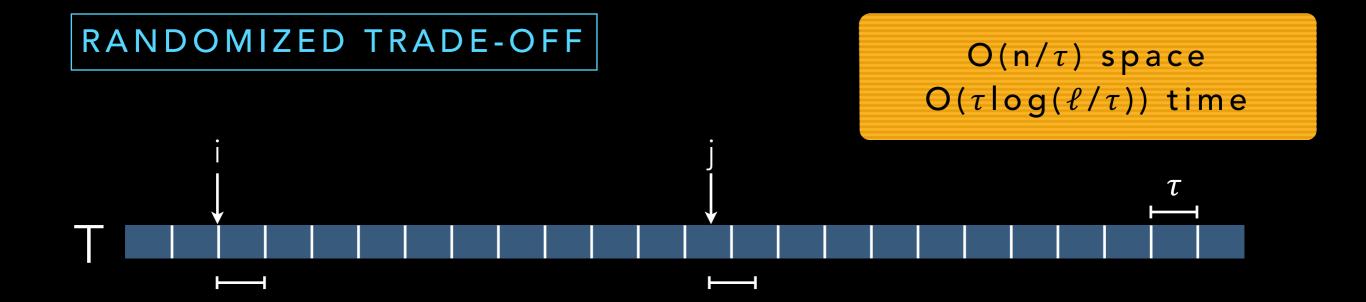
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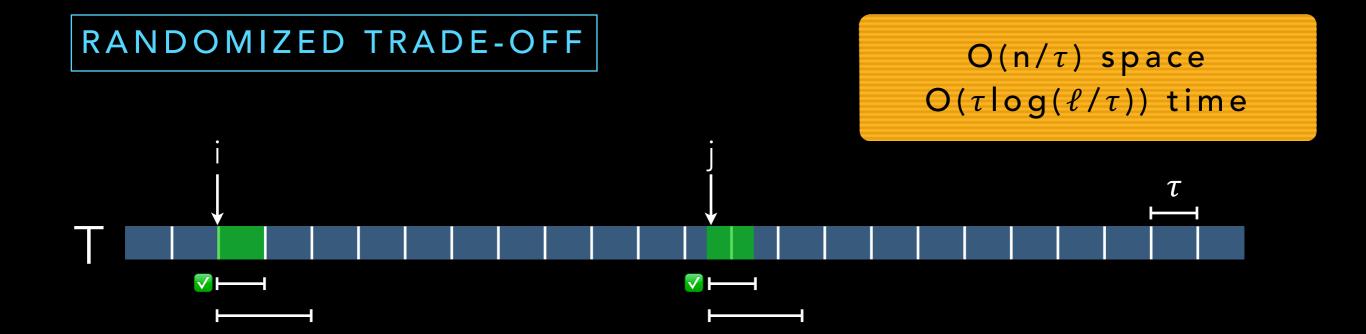
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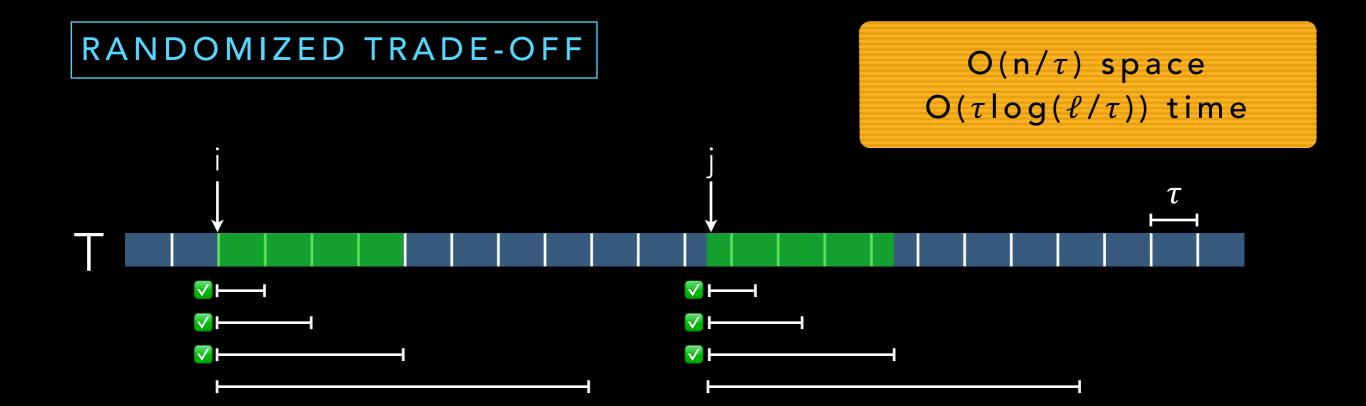


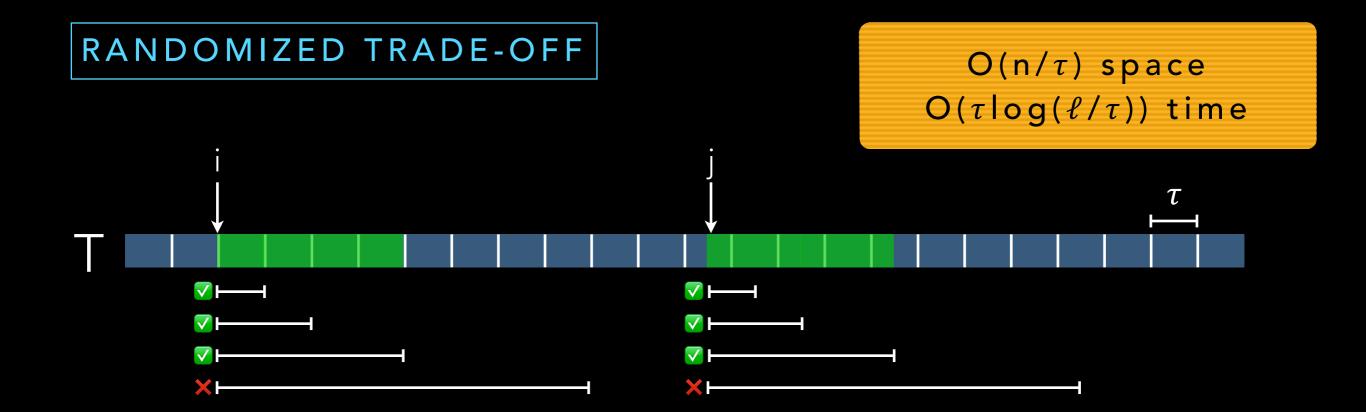




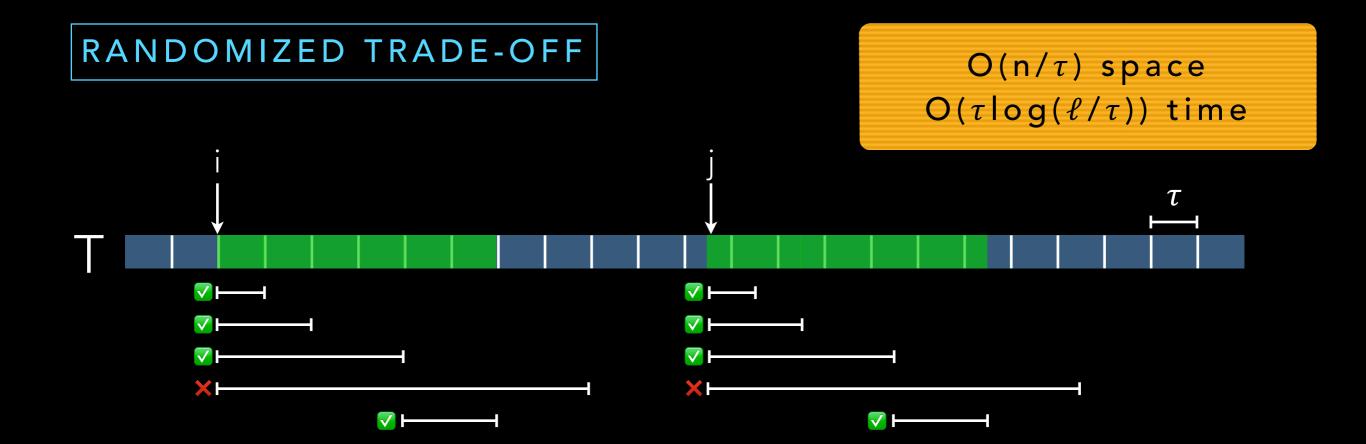


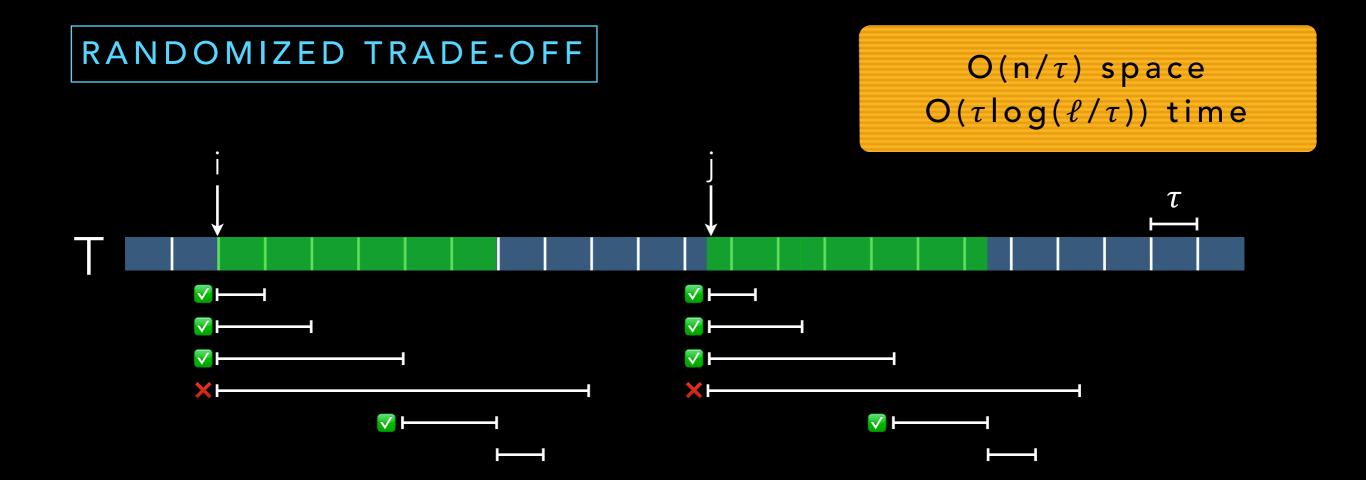


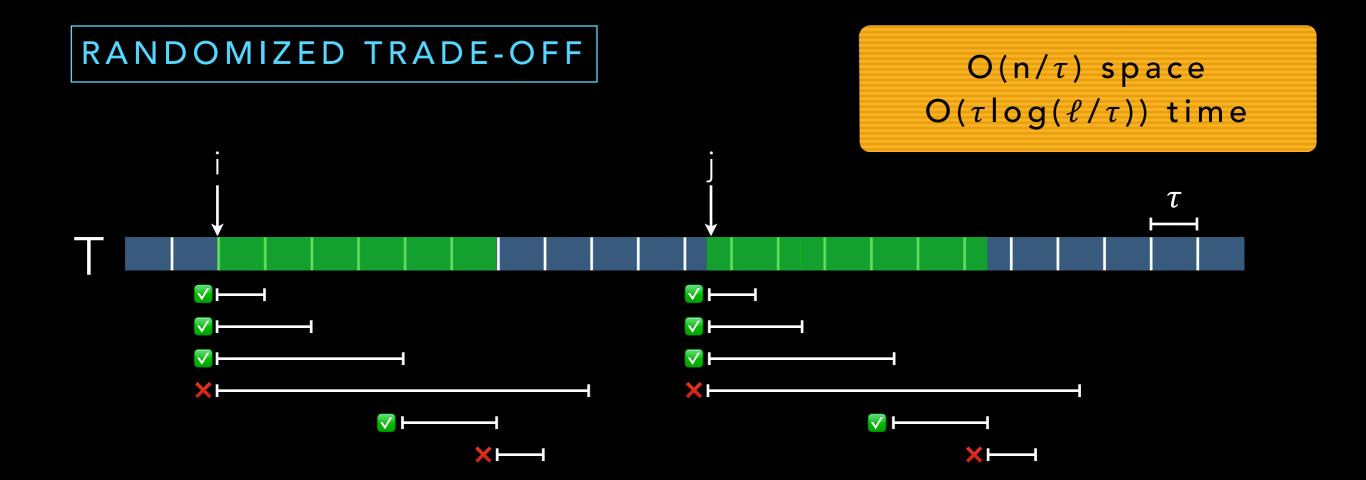


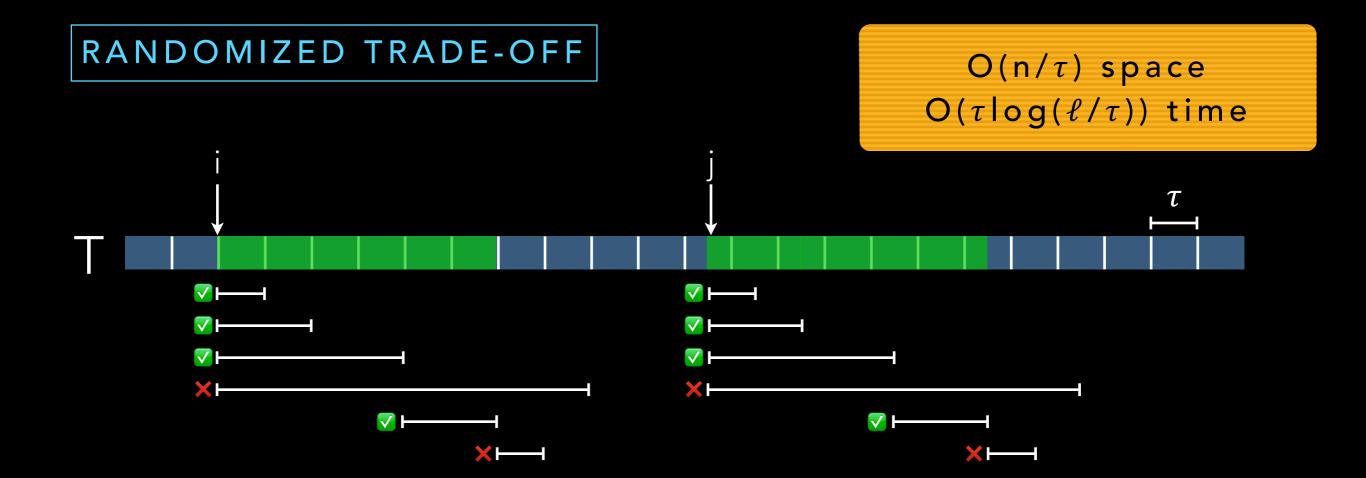




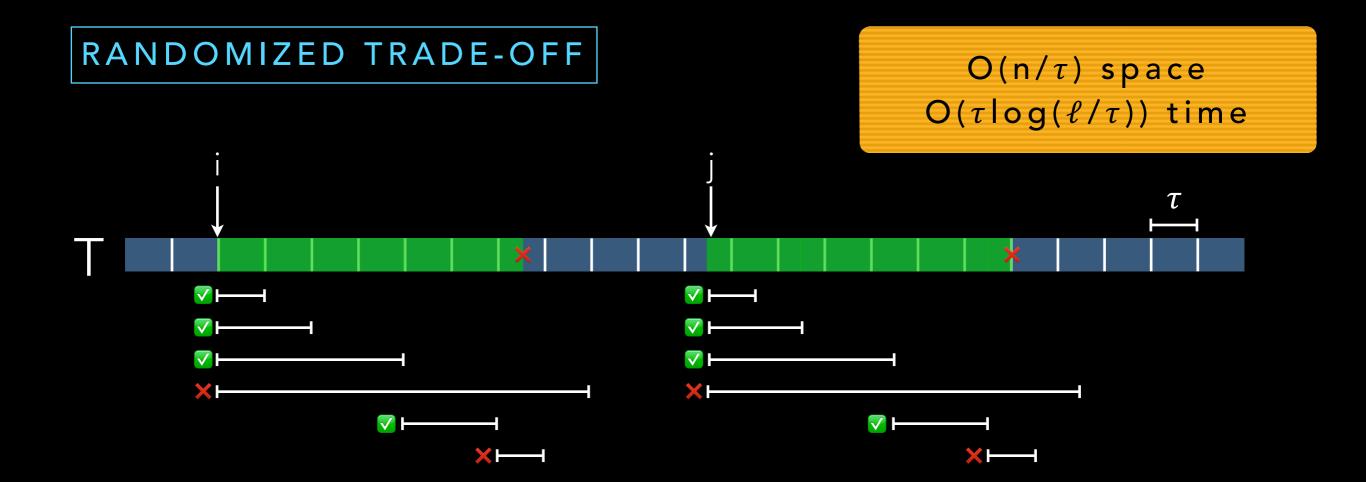




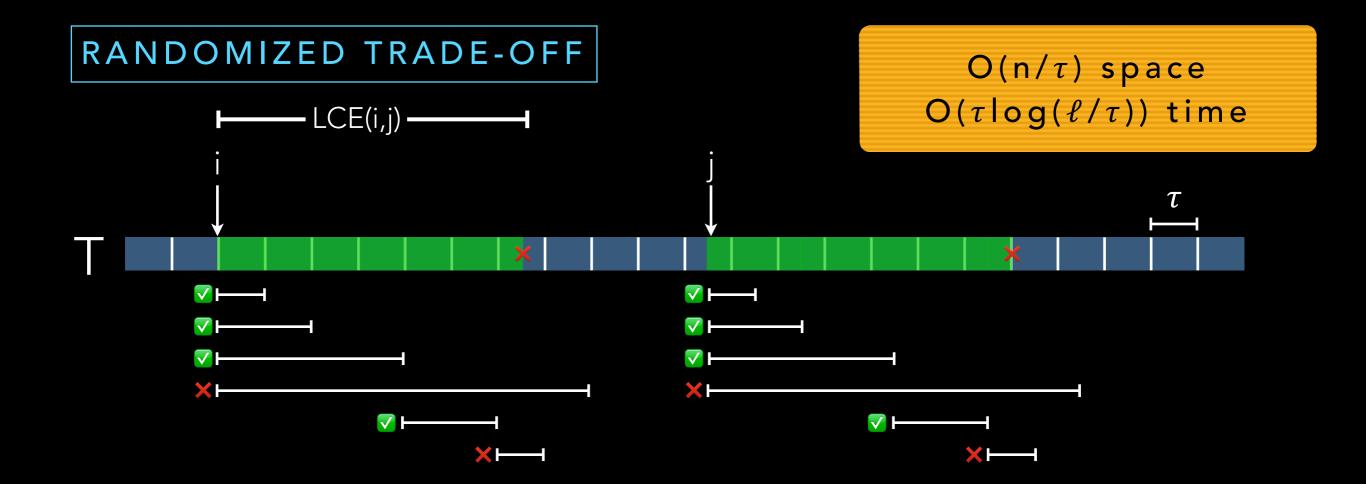




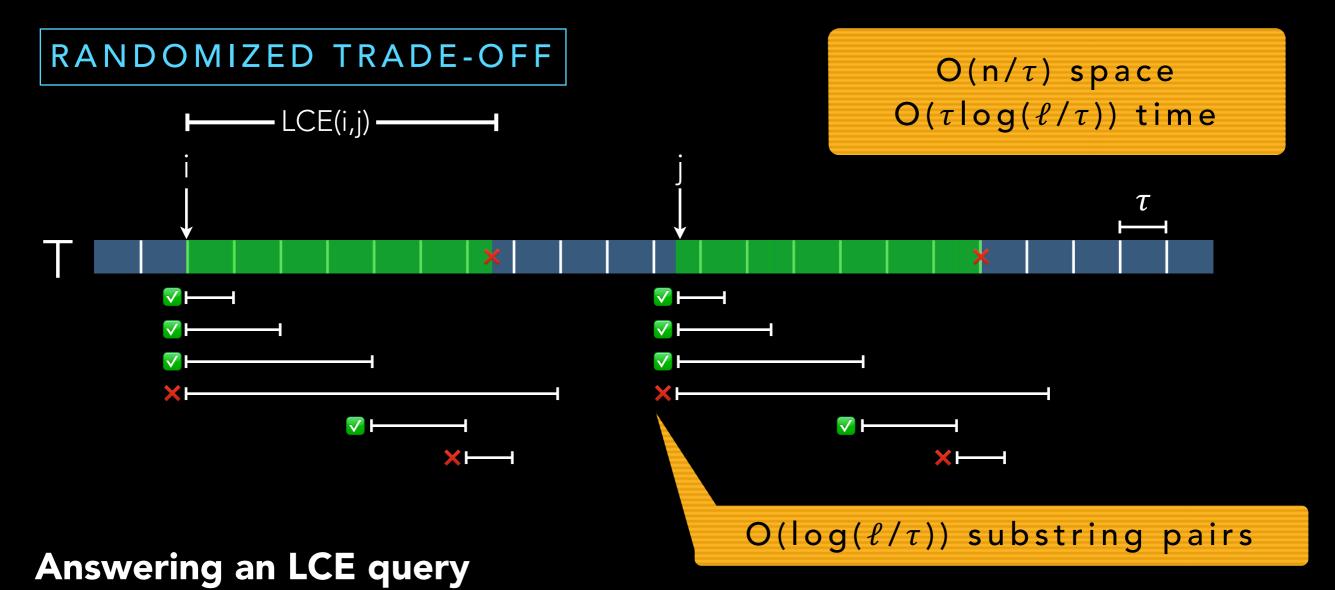
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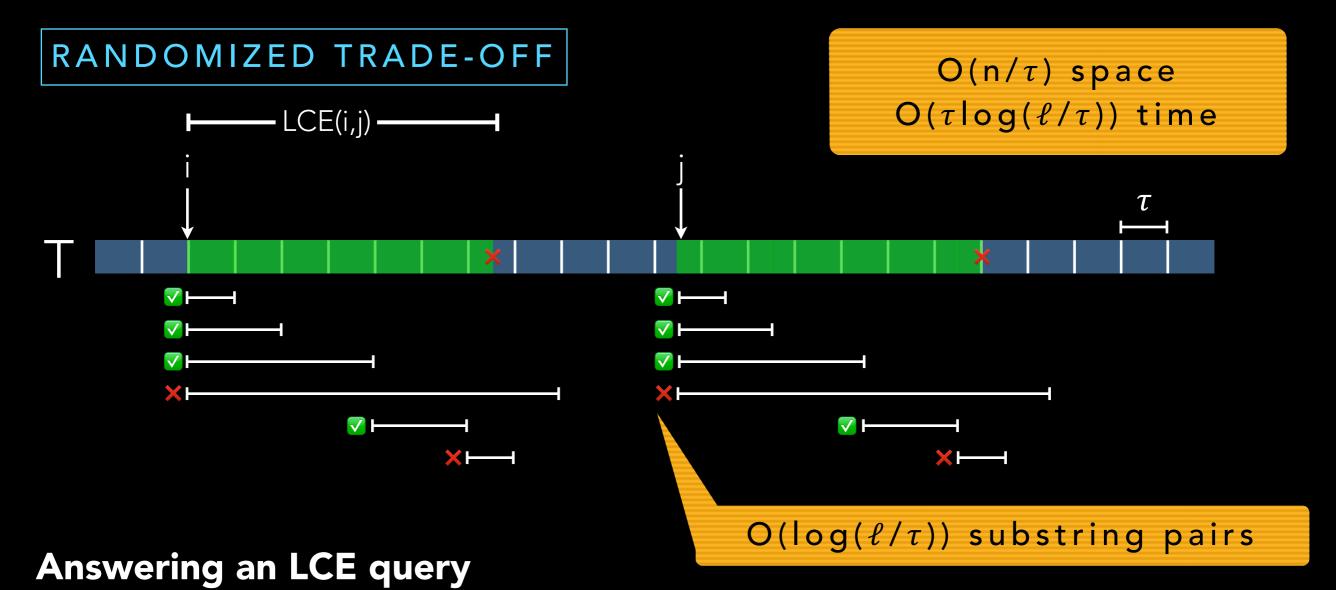
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Data structure

Stores fingerprint of every block aligned suffix

 \Rightarrow the fingerprint of any substring can be retrieved in $O(\tau)$ time

NEXT STEP

 $O(n/\tau)$ space $O(\tau \log^2(n/\tau))$ time





 $O(n/\tau)$ space $O(\tau log(\ell/\tau))$ time





 $O(n/\tau)$ space $O(\tau + log(\ell/\tau))$ time



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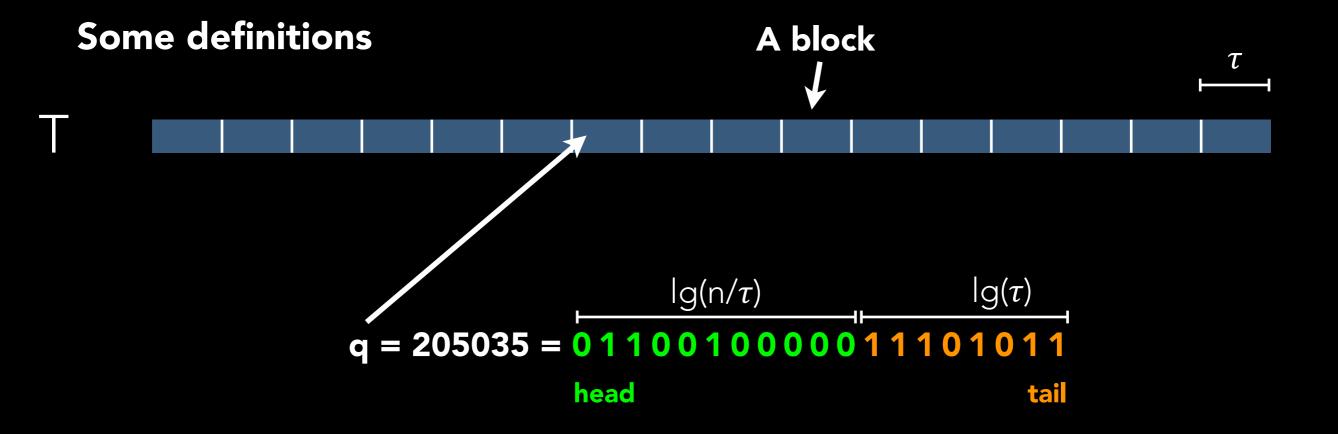
Some definitions

 $O(n/\tau)$ space $O(\tau + \log(\ell/\tau))$ time

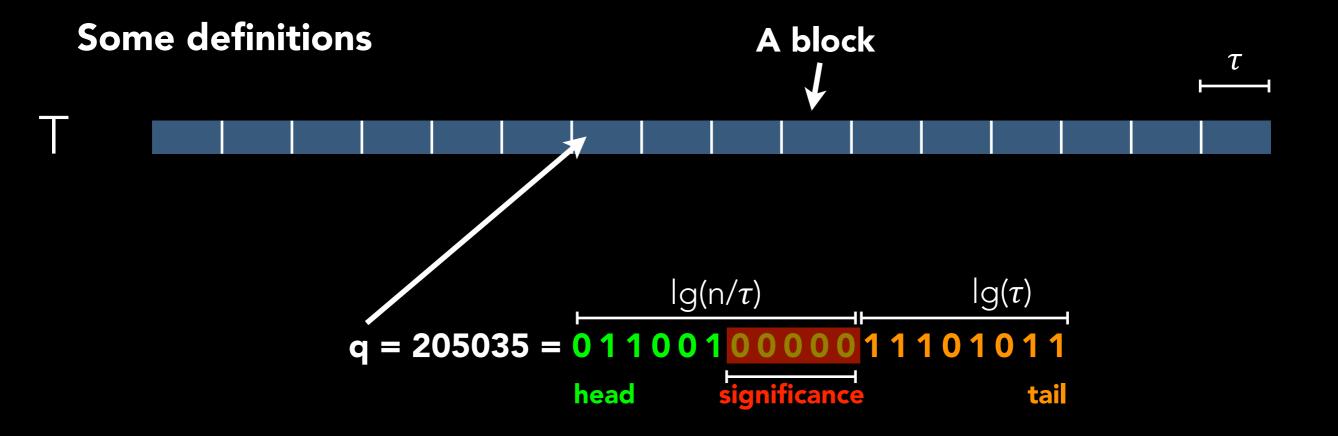
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A block

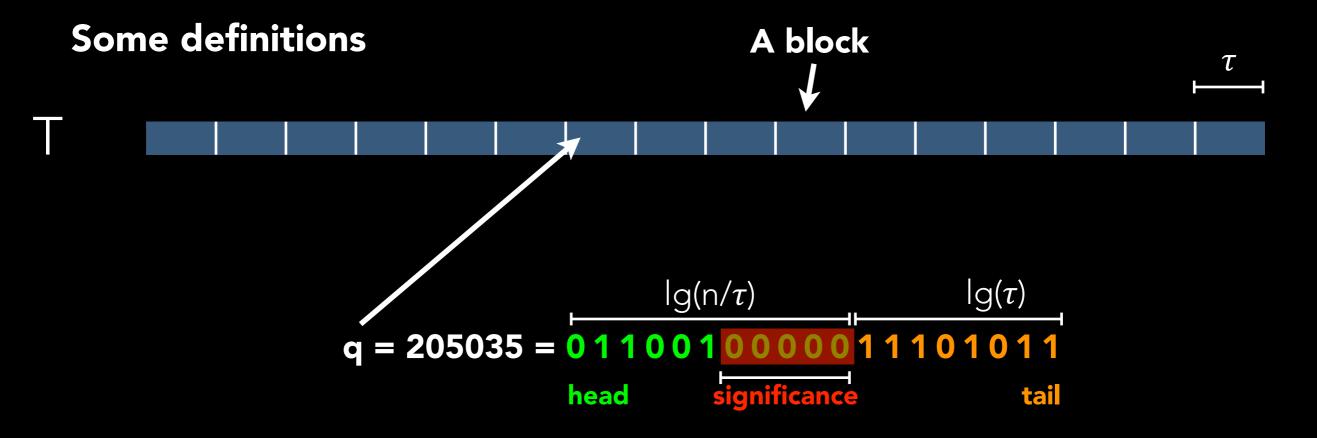
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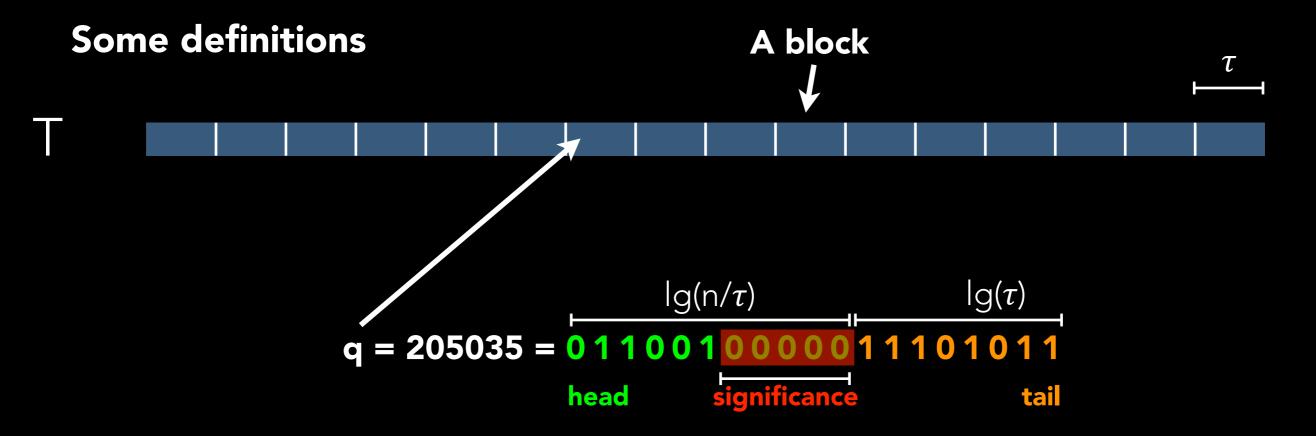


 $O(n/\tau)$ space $O(\tau + log(\ell/\tau))$ time



In a block k we sample b_k evenly spaced positions, where $b_k = \min(2^{\mu/2}, \tau)$

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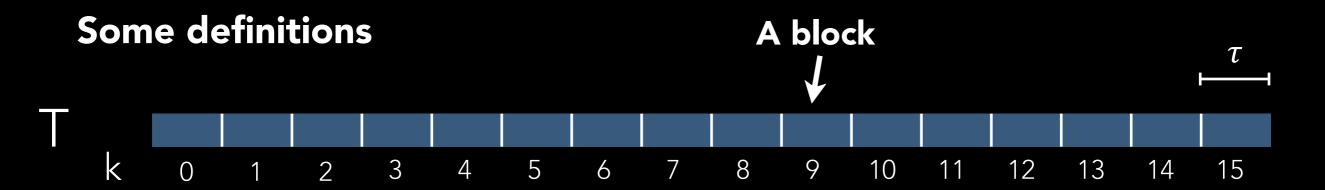
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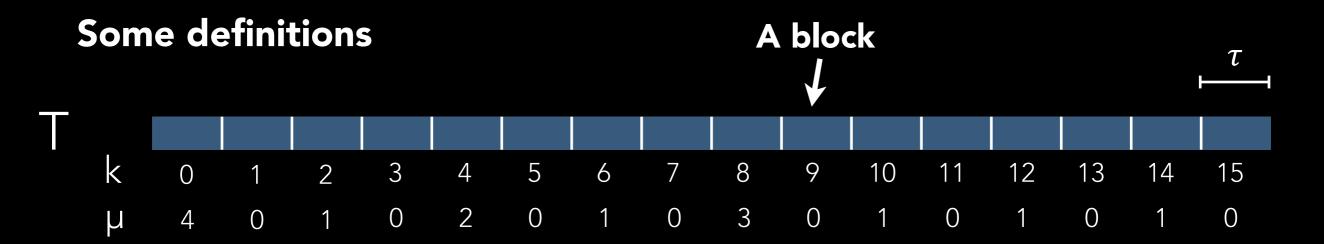
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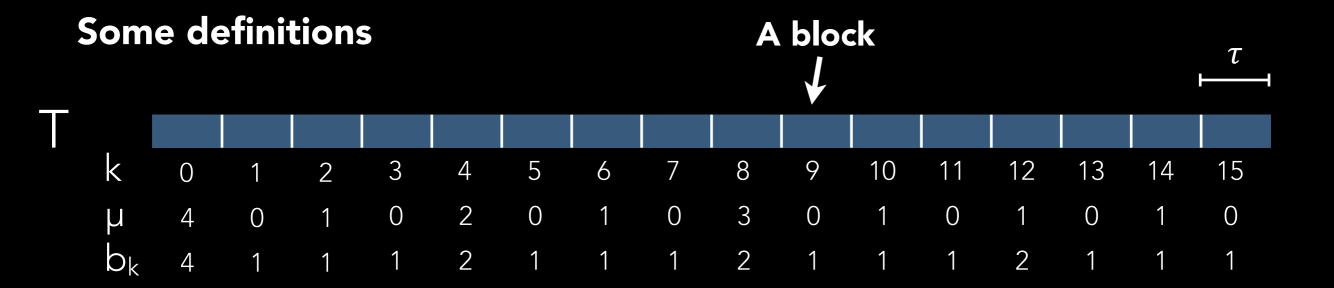
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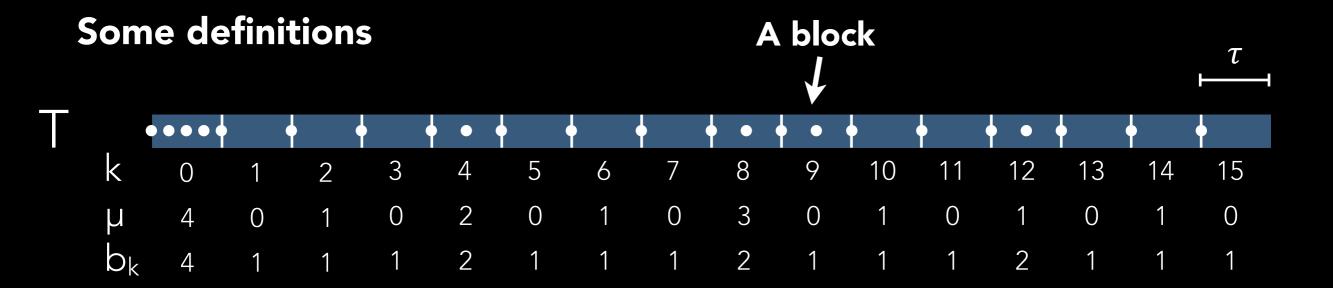
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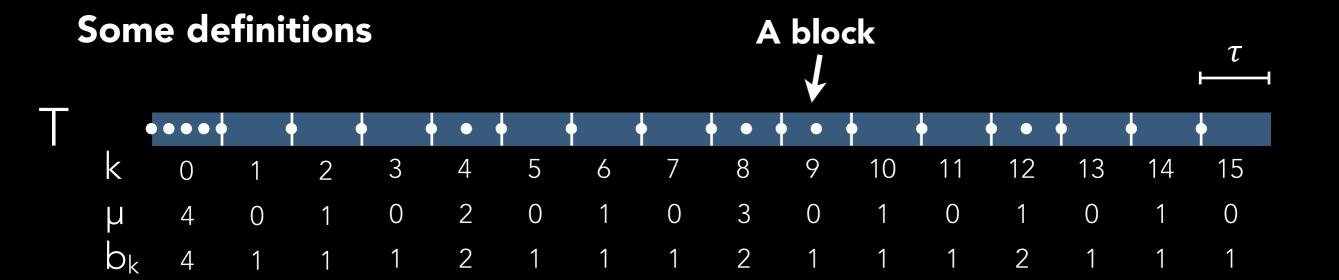
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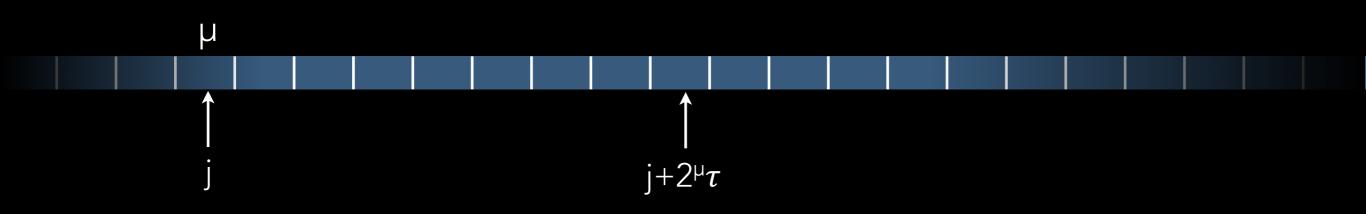
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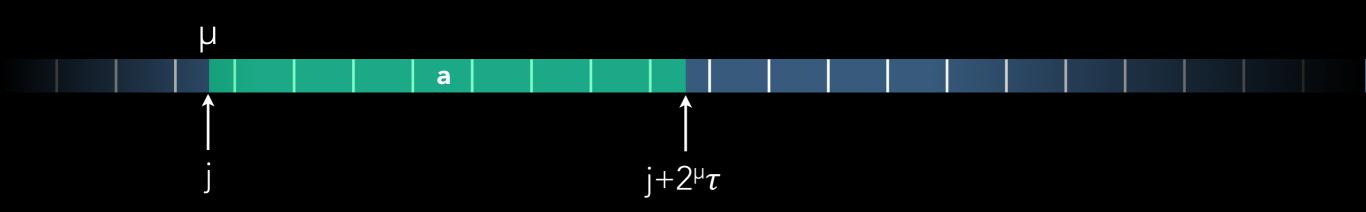
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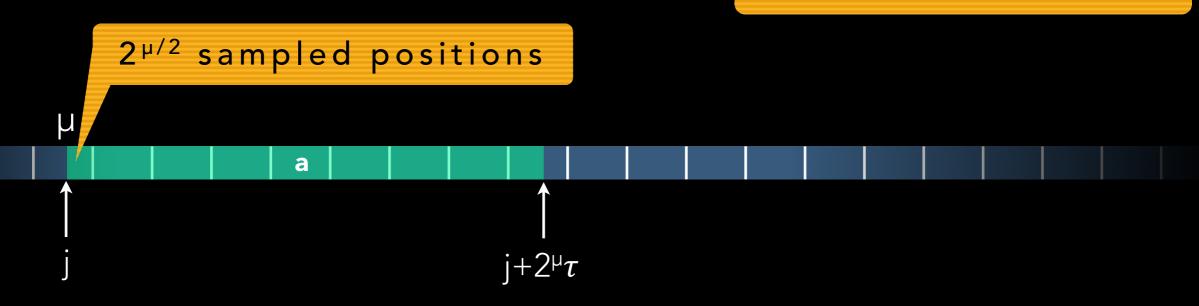
Bounding the number of sampled positions

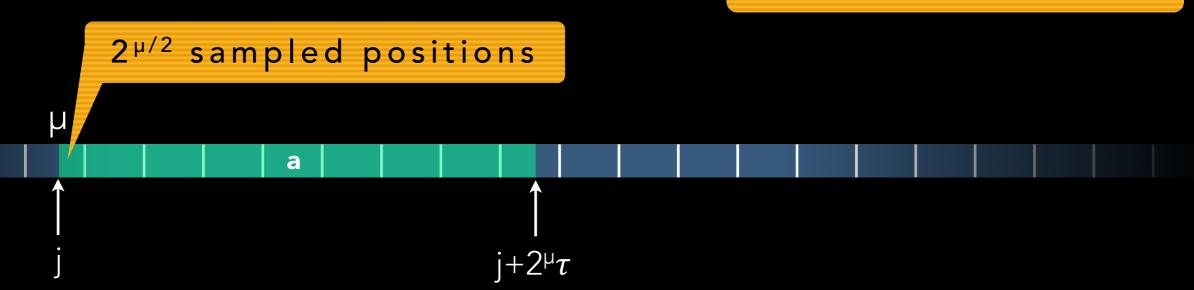
$$|\mathcal{S}| = \sum_{k=0}^{n/\tau - 1} b_k \le \sum_{\mu=0}^{\lg(n/\tau)} 2^{\lg(n/\tau) - \mu} 2^{\lfloor \mu/2 \rfloor} \le \frac{n}{\tau} \sum_{\mu=0}^{\infty} 2^{-\mu/2} = \left(2 + \sqrt{2}\right) \frac{n}{\tau} = O\left(\frac{n}{\tau}\right)$$

 $O(n/\tau)$ space $O(\tau + \log(\ell/\tau))$ time









$$j = \dots 10 \dots 0[tail]$$

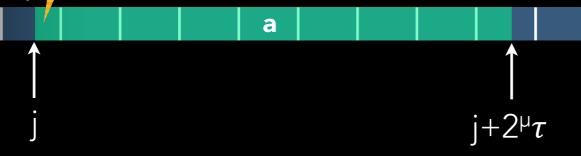




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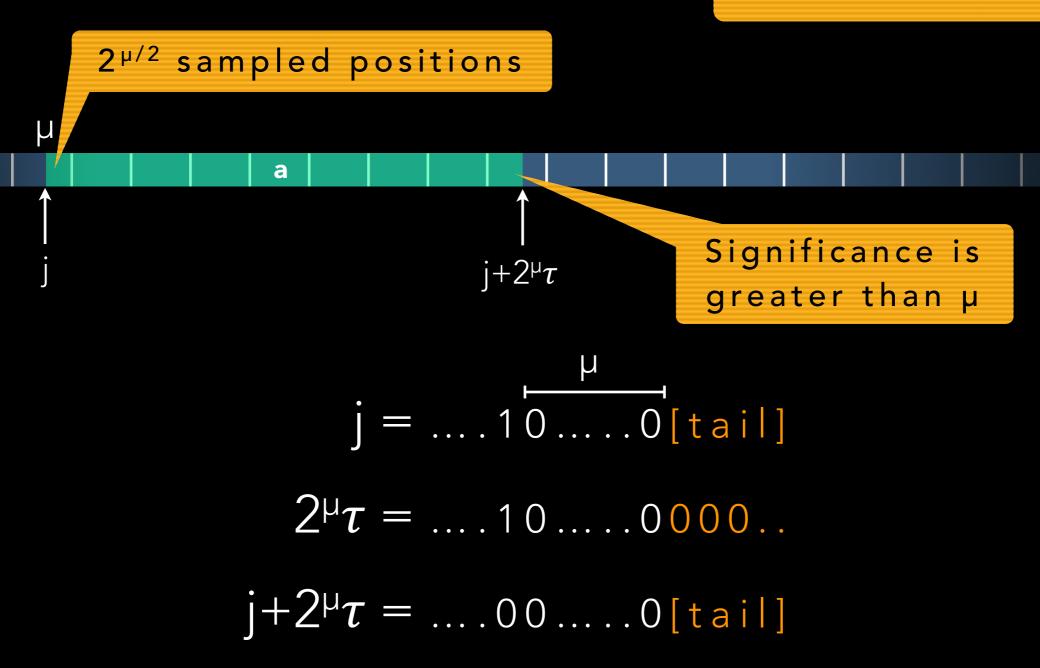
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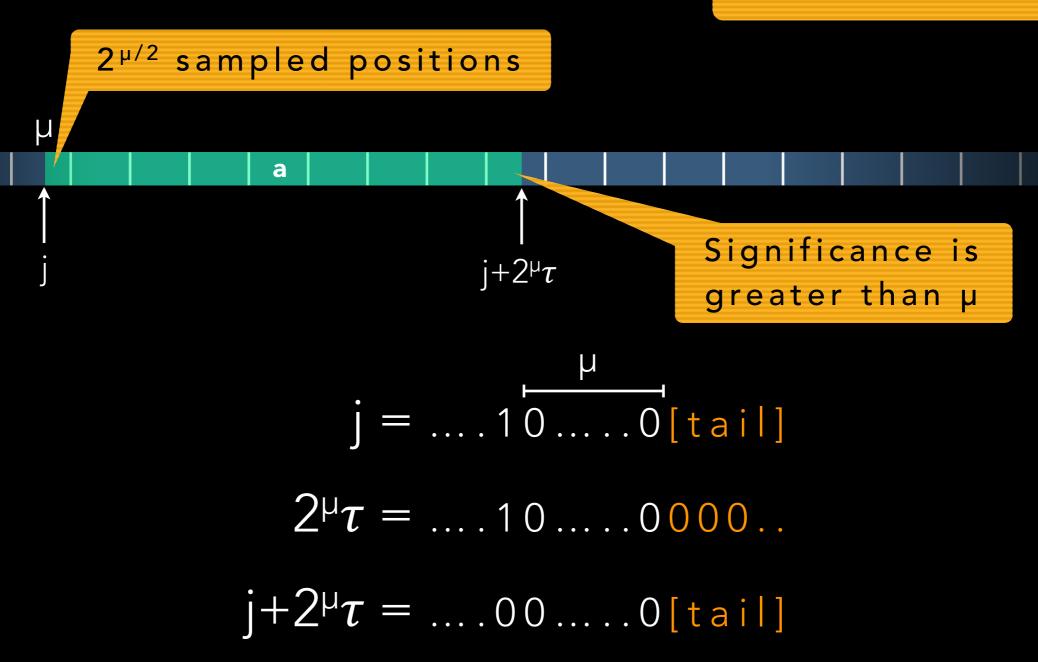


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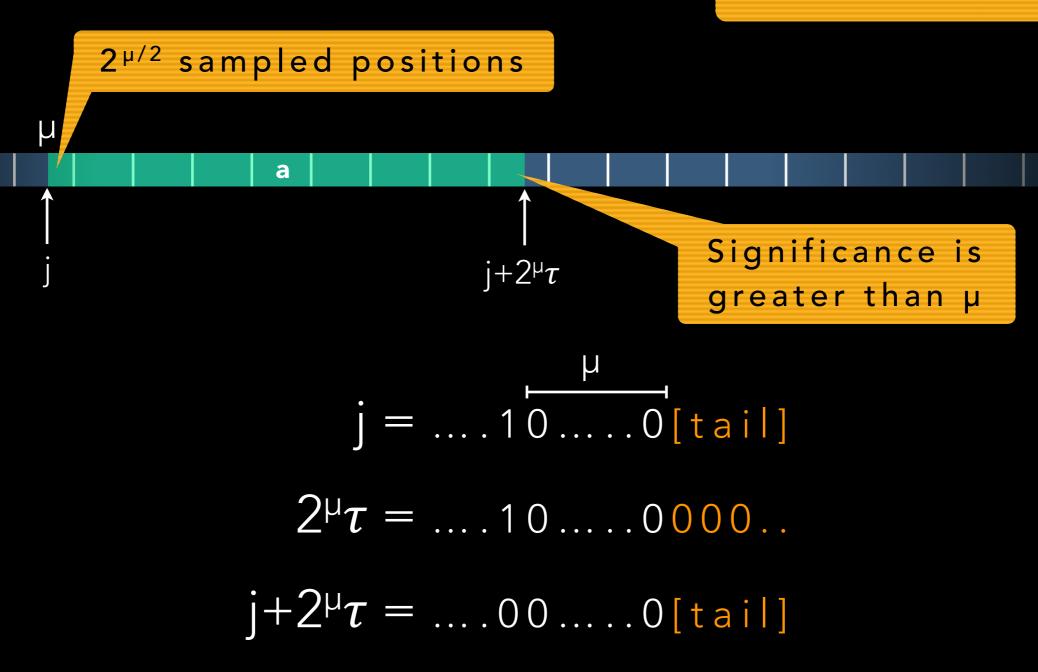


 $O(n/\tau)$ space $O(\tau + log(\ell/\tau))$ time



Distance to a sampled position is at most $\tau/2^{\mu/2}$

 $O(n/\tau)$ space $O(\tau + log(\ell/\tau))$ time



Distance to a sampled position is at most $\tau/2^{\mu/2}$ \Longrightarrow Time to compute φ (a) is O(1+ $\tau/2^{\mu/2}$)

Query time

Cost of computing a fingerprint is O(1+ τ /2 $^{\mu/2}$), and μ iterates from 0 to log(ℓ/τ) and back to 0, thus the query time becomes

$$O\left(\sum_{\mu=0}^{\lg(\ell/\tau)} 1 + \tau/2^{\lfloor \mu/2 \rfloor}\right) = O(\tau + \log(\ell/\tau))$$

Space

Cost is the total number of sampled positions/fingerprints

$$|\mathcal{S}| = \sum_{k=0}^{n/\tau - 1} b_k \le \sum_{\mu = 0}^{\lg(n/\tau)} 2^{\lg(n/\tau) - \mu} 2^{\lfloor \mu/2 \rfloor} \le \frac{n}{\tau} \sum_{\mu = 0}^{\infty} 2^{-\mu/2} = \left(2 + \sqrt{2}\right) \frac{n}{\tau} = O\left(\frac{n}{\tau}\right)$$

NEXT STEP

 $O(n/\tau)$ space $O(\tau log^2(n/\tau))$ time





 $O(n/\tau)$ space $O(\tau log(\ell/\tau))$ time





 $O(n/\tau)$ space $O(\tau + log(\ell/\tau))$ time





 $O(n/\tau)$ space $O(\tau)$ time

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Theorem

There is an $O(n/\tau)$ space data structure that in O(1) time either

- A. computes the answer to an LCE(i,j) query, or
- **B.** returns a certificate that $\ell < \tau^2$

Observation

In case B the query time of our previous algorithm becomes $O(\tau + \log(\ell/\tau)) = O(\tau)$

Technique

Difference covers

SUMMARY & OPEN PROBLEMS

MAIN THEOREM

The LCE problem can be solved in $O(n/\tau)$ space and $O(\tau)$ time for all $1 \le \tau \le n$

Lower bound from RMQ implies a time-space product of $\Omega(n/\log n)$ Can we close this gap?

Can we obtain optimal preprocessing times?