

Differential Privacy on Fully Dynamic Streams

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Backgrounds – Fully Dynamic Streams

- A data stream is a sequence of pairs (s_t, x_t)
 - Insertion $(s_t = +)$ \Longrightarrow $D_t = D_{t-1} \cup \{x_t\}$
 - Deletion $(s_t = -)$ \Longrightarrow $D_t = D_{t-1} \{x_t\}$
 - No-op $(s_t = \bot)$ \Longrightarrow $D_t = D_{t-1}$
- Notation
 - N_t : number of *updates* up to time t
 - n_t : data size at time t

$$N_t^+ + N_t^- = N_t \gg n_t = N_t^+ - N_t^-$$

$$\downarrow \qquad \downarrow$$

Increases over time Fluctuates and even hits zero

Timestamp	Update	Dataset
0	-	Ø
1	+ , a	{ <i>a</i> }
2	+, <i>b</i>	$\{a,b\}$
3	+, <i>c</i>	$\{a,b,c\}$
4		$\{a,b,c\}$
5	-, b	$\{a,c\}$
6	+, <i>d</i>	$\{a,c,d\}$
7	-, c	$\{a,d\}$
8	-, a	$\{d\}$
9	-, d	Ø

Backgrounds – Differential Privacy

- DP: for any neighboring instances $D \sim D'$ and any subset of outputs Y, $\Pr[\mathcal{M}(D) \in Y] \leq e^{\varepsilon} \cdot \Pr[\mathcal{M}(D') \in Y] + \delta$.
- For streams, neighboring instances differ by one update.

Timestamp	Update	Dataset	_	Timestamp	Update	Dataset
0	-	Ø		0	-	Ø
1	+ , a	{ <i>a</i> }		1	+ , a	{ <i>a</i> }
2	+, <i>b</i>	$\{a,b\}$		2	+ , b	{ <i>a</i> , <i>b</i> }
3	+, <i>c</i>	$\{a,b,c\}$		3	+, <i>c</i>	$\{a,b,c\}$
4	上	$\{a,b,c\}$	← →	4	+, e	$\{a,b,c,e\}$
5	-, b	$\{a,c\}$		5	-, b	$\{a,c,e\}$
•••		•••			•••	

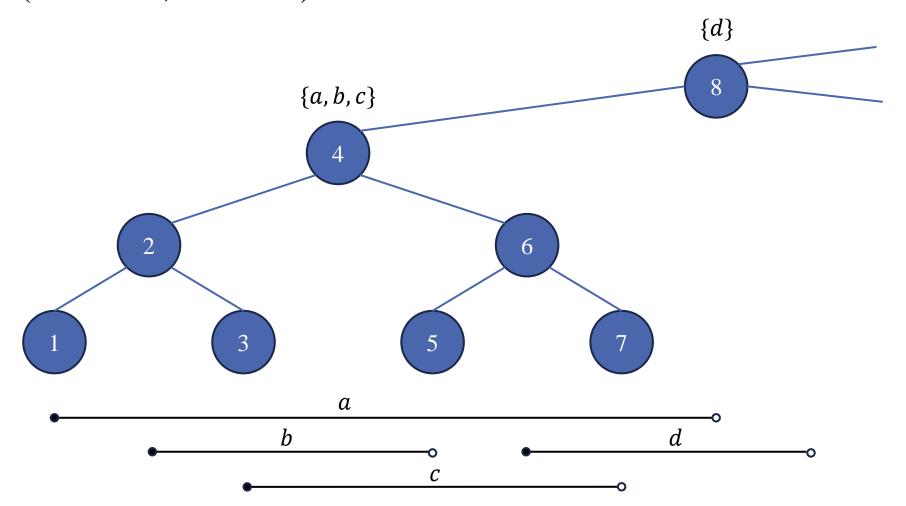
Backgrounds – DP Linear Queries

- Linear queries: $f(D) = \sum_{x \in D} f(x)$

 - Counting: $f(x) \equiv 1 \implies f(D) = |D|$ Mean: $f(x) = \frac{x}{n} \implies f(D) = \frac{\sum_{x \in D} x}{n} = \mathbb{E}[x]$ Variance: $f(x) = \frac{x^2}{n} \implies f(D) = \frac{\sum_{x \in D} x^2}{n} = \mathbb{E}[x^2]$
- For *static data*: PMW mechanism has error $\tilde{O}(\sqrt{n})$
- For *insertion-only streams*: Binary Tree mechanism has error $\tilde{O}(\sqrt{N_t})$
- Direct extension: Separate the stream into D_t^+ and D_t^-
 - Problem: The error becomes $\tilde{O}\left(\sqrt{N_t^+} + \sqrt{N_t^-}\right) = \tilde{O}\left(\sqrt{N_t}\right)$
 - Our target is $\tilde{O}(\sqrt{n_t})$

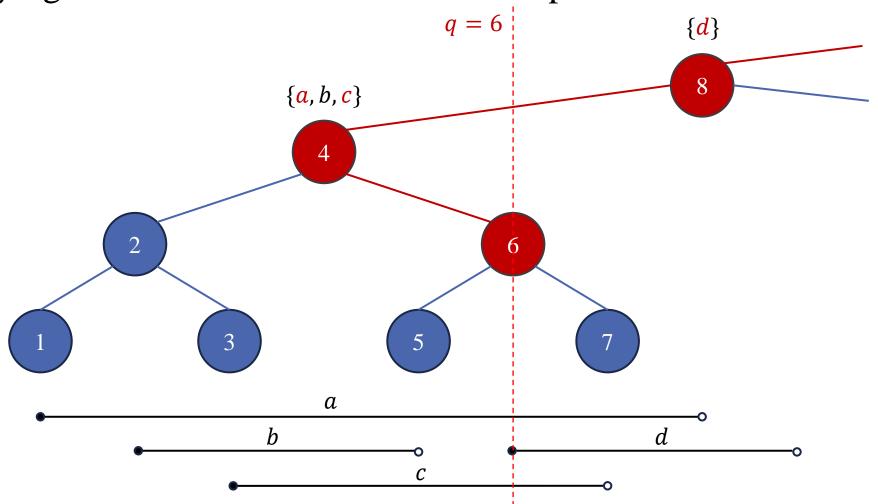
Interval Tree for Stabbing Queries

• Each (insertion, deletion) of an item can be considered an interval.



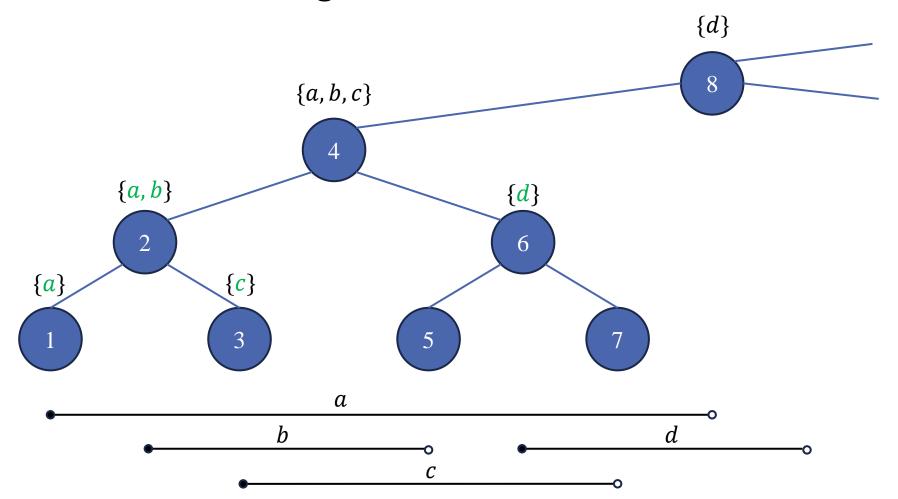
Interval Tree for Stabbing Queries

• Querying: visit nodes on the root-to-node path.



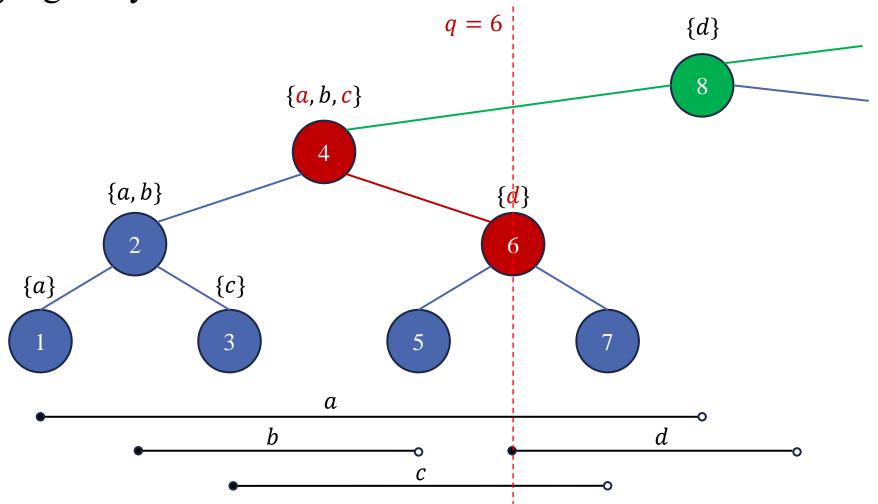
Contribution 1: Online Interval Tree

• Duplicate each node $O(\log t)$ times.



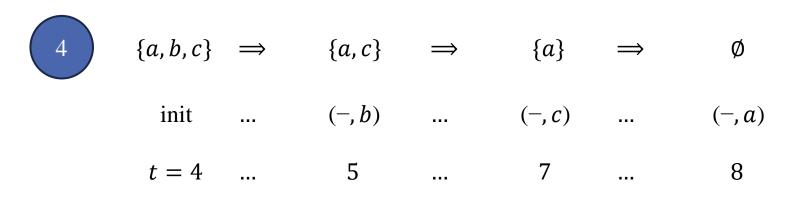
Contribution 1: Online Interval Tree

• Querying: only consider "left" nodes.



Contribution 2: Deletion-only Mechanism

- For each node, it is a deletion-only problem
 - Node i starts with n_i elements, but we can have $n_i \gg n_t$
- Our solution: Track the number of deletions
 - In each round, privately compute: |D|, $|D_t^-|$, F(D), $F(D_t^-)$
 - If there are few deletions, then $n_i = O(n_t)$, we simply use $F(D) F(D_t^-)$
 - If approximately more than $\frac{n_i}{2}$ items are deleted, we allocate new budgets
 - There can only be $O(\log N_t)$ restarts



Conclusion

- There is an (ε, δ) -DP mechanism for arbitrary linear queries on fully dynamic streams with error $\tilde{O}(\sqrt{n_t})$.
- \tilde{O} hides $\frac{1}{\varepsilon}$ and polylog factors in $\frac{1}{\delta}$, $\frac{1}{\beta}$, t, and N_t
- This improves over separating D_t^+ and D_t^- , whose error was $\tilde{O}(\sqrt{N_t})$