# Continuously Tracking Core Items in Data Streams with Probabilistic Decays

Junzhou Zhao<sup>1</sup> Pinghui Wang<sup>1</sup> Jing Tao<sup>1</sup> Shuo Zhang<sup>1</sup> John C.S. Lui<sup>2</sup>

<sup>1</sup>Xi'an Jiaotong University <sup>2</sup>The Chinese University of Hong Kong

## **Background & Motivation**

- Data streams are ubiquitous:
- email stream, tweets stream, news stream, network traffic stream, etc
- geo-location stream generated by taxis, IoT devices, LBSNs, etc
- user consuming record stream from Amazon, Taobao, etc
- Applications:
  - real-time trending topic detection
  - network security monitoring
  - online collaborative filtering
- However, their high speed and large volume cause troubles.
- Core Items: informative or representative items in a data stream.
- Core Items Tracking (CIT): a streaming algorithm that can continuously track core items in a data stream in real-time.



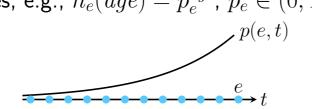
- The right to be forgotten:
  - (a) insertion-only stream

(b) sliding-window stream

- (c) probabilistic-decaying stream (this work)

#### **Problem Formulation**

- Utility Function: measuring the informativeness of a set of items:  $f: 2^V \mapsto \mathbb{R}_{>0}$
- Monotonicity:  $f(S) \leq f(T), \forall S \subseteq T \subseteq V$ .
- Submodularity:  $f(S \cup \{e\}) f(S) \ge f(T \cup \{e\}) f(T), \forall S \subseteq T \subseteq V, e \in V.$ 
  - aka the dimension return property [Nemhauser et al. 1978]
- Probabilistic-Decaying Stream (PDS) model:
   At time t, an item e arrived at time t<sub>e</sub> ≤ t participates in analysis with probability p(e,t) = h<sub>e</sub>(t t<sub>e</sub>)
  - $h_e : \mathbb{Z}_{\geq 0} \mapsto [0,1]$  is an item-specific decaying function.
  - $h_e(age)$  decreases as age increases, e.g.,  $h_e(age) = p_e^{age}$ ,  $p_e \in (0,1)$ .



- The Core Items Tracking (CIT) problem:
  - Given a monotone submodular utility function f, a PDS with item-specific decaying function  $h_e$ , and a budget k>0
  - Want to find a subset  $S_t^* \subseteq V$  at any query time t, s.t.

$$S_t^* = \underset{S \subseteq V \land |S| \le k}{\operatorname{arg \, max}} \, \mathbb{E}_{h_e}[f(S)|\mathcal{D}_t]$$

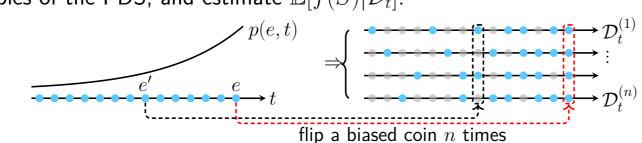
where  $\mathcal{D}_t \triangleq \{e \colon t_e \leq t\}$  denotes the items arrived before t.

# A Monte-Carlo Framework

- Expensive to calculate  $\mathbb{E}[f(S)|\mathcal{D}_t]$  exactly
- need to consider the participation possibility of each item in S, e.g.,

$$\mathbb{E}[f(\{a,b\})|\mathcal{D}_t] = \underbrace{p(a,t)p(b,t)f(\{a,b\})}_{\text{both $a$ and $b$ participate in the analysis}} + \underbrace{p(a,t)(1-p(b,t))f(\{a\})}_{\text{only $a$ participates in the analysis}} + \underbrace{(1-p(a,t))p(b,t)f(\{b\})}_{\text{only $b$ participates in the analysis}}$$

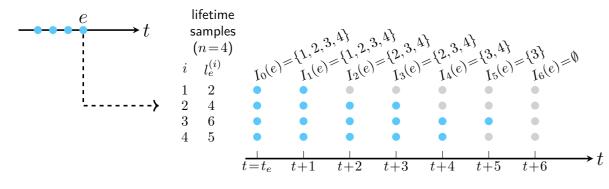
- exactly calculating  $\mathbb{E}[f(S)|\mathcal{D}_t]$  requires  $O(2^{|S|})$  oracle calls.
- Monte-Carlo Approximation:
- Generate n samples of the PDS, and estimate  $\mathbb{E}[f(S)|\mathcal{D}_t]$ .



By Monte-Carlo approximation, we have

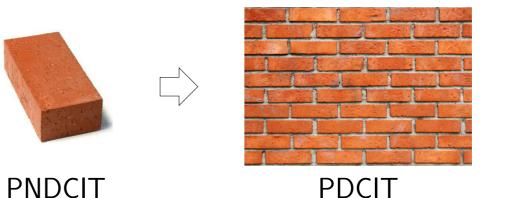
$$F(S) \triangleq \frac{1}{n} \sum_{i=1}^{n} f(S \cap \mathcal{D}_{t}^{(i)}) \xrightarrow{a.s.} \mathbb{E}[f(S)|\mathcal{D}_{t}], \quad n \to \infty.$$

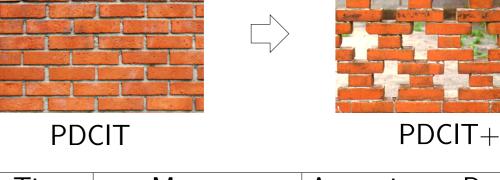
- The number of oracle calls reduces from  $O(2^{|S|})$  to O(n).
- F(S) is still monotone and submodular.
- Maintaining data stream samples:
  - naive sampling/incremental sampling/lifetime sampling



### **Algorithms**

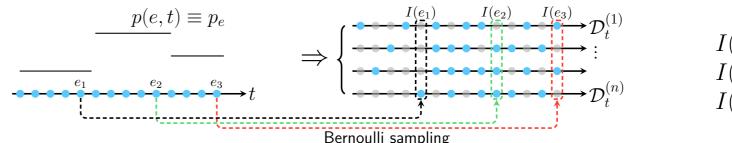
Overview





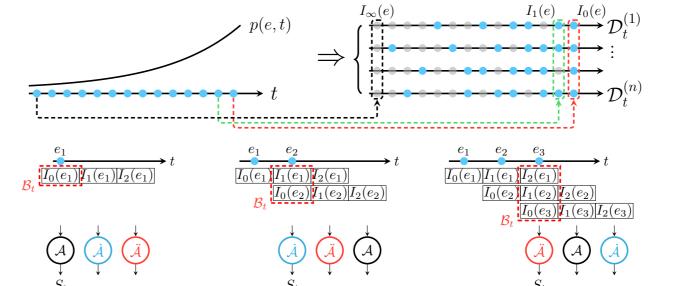
Algorithm	Update Time	Memory	Approximate Ratio
PNDCIT	$O(n\epsilon^{-1}\log k)$	$O(nk\epsilon^{-1}\log k)$	$1/2 - \epsilon$
PDCIT	$O(Ln\epsilon^{-1}\log k)$	$O(Lnk\epsilon^{-1}\log k)$	$1/2 - \epsilon$
PDCIT+	$O(n\epsilon^{-2}\log^2 k)$	$O(nk\epsilon^{-2}\log^2 k)$	$1/4 - \epsilon$

• PNDCIT: probabilistic non-decaying case, i.e.,  $p(e,t) \equiv p_e$ 



 $I(e_1) = [0, 0, 0, 1]^T$   $I(e_2) = [0, 1, 1, 1]^T$  $I(e_3) = [1, 0, 1, 0]^T$ 

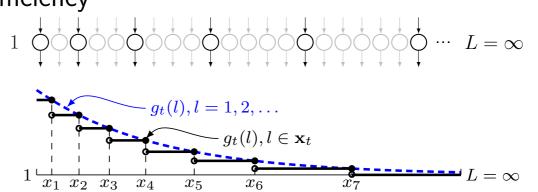
PDCIT: probabilistic decaying case



 $I_{1}(e) = [1, 1, 0, 1]^{T}$   $I_{\infty}(e) = [0, 0, 0, 0]^{T}$   $\downarrow e \qquad t \qquad \downarrow t$   $\downarrow I_{0}(e) \mid I_{1}(e) \mid \cdots \mid I_{L-1}(e) \mid t$ 

 $I_0(e) = [1, 1, 1, 1]^T$ 

• PDCIT+: improve efficiency

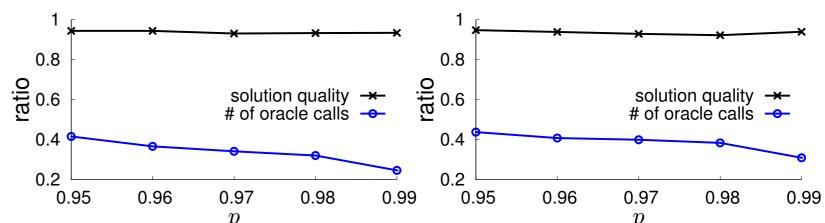


## **Experiments**

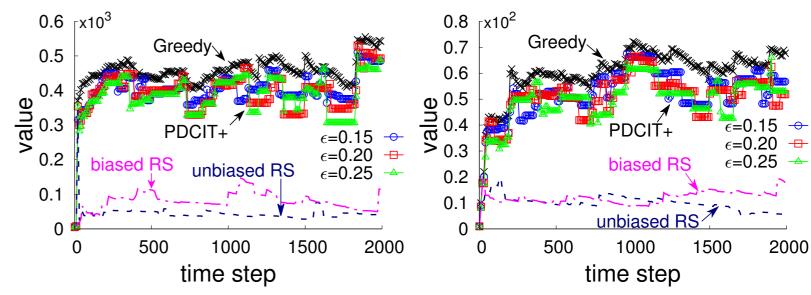
Data

data stream	item	length	time period
DBLP	author	371,690	1936 - 2018
${\sf MemeTracker}$	article	714,072	1/2009 (one month)
math. Stack Exchange	question	955, 284	7/2010 - 6/2018
${\sf StackOverflow}$	question	2,904,450	1/2015 - 3/2016

- Goal: maintain k most representative items that jointly have the maximum coverage, i.e.,  $f(S) = |\bigcup_{e \in S} e|$ .
- PDCIT vs PDCIT+:



Solution quality:



Scalability:

