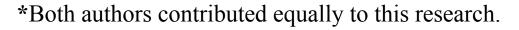
# Timely Reporting of Heavy Hitters using External Memory

**Prashant Pandey\***, Shikha Singh**\***, Michael A. Bender, Jonathan W. Berry, Martin Farach-Colton, Rob Johnson, Thomas M. Kroeger, Cynthia A. Phillips

iams





# Open problem in streaming

- A high-speed stream of key-value pairs arriving over time
- Goal: report every key as soon as it appears 24 times without missing any
- Firehose benchmark (Sandia National Lab) simulates the stream <u>https://firehose.sandia.gov/</u>



# Why should we care about this problem

Defense systems for cyber security monitor high-speed streams for malicious traffic

Malicious traffic forms a small portion of the stream

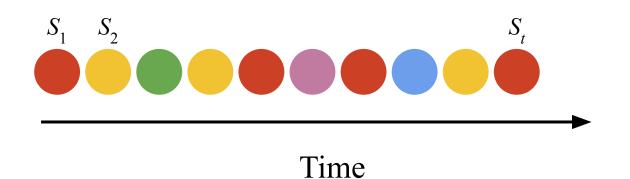
Catch all malicious events

Minimize false positives

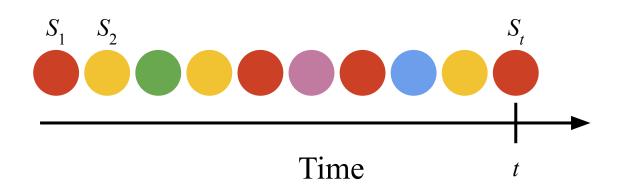
Automated systems take defensive actions for every reported event



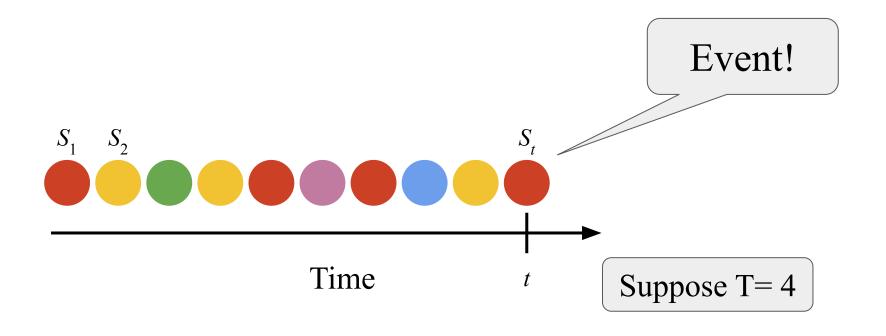
• Stream of elements arrive over time



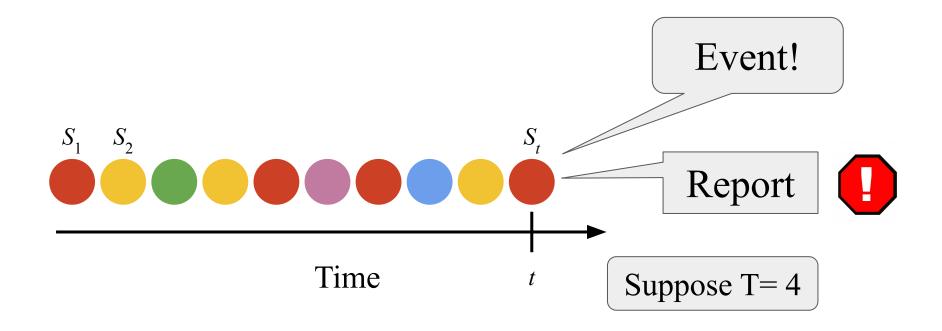
- Stream of elements arrive over time
- An event occurs at time t if  $S_t$  occurs exactly T times in  $(s_1, s_2, \dots, s_t)$



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- Stream of elements arrive over time
- An event occurs at time t if  $S_t$  occurs exactly T times in  $(s_1, s_2, \dots, s_t)$
- In **timely event-detection problem (TED)**, we want to report all events shortly after they occur.



## Features we need in the solution

• Stream is large (e.g., terabytes) and high-speed (millions/sec)

High throughput ingestion



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Very small reporting threshold T << N (stream size)</li>

Very small reporting thresholds

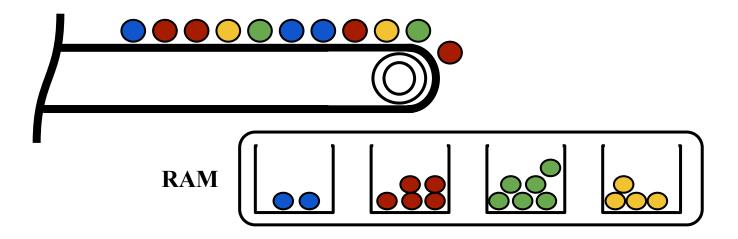






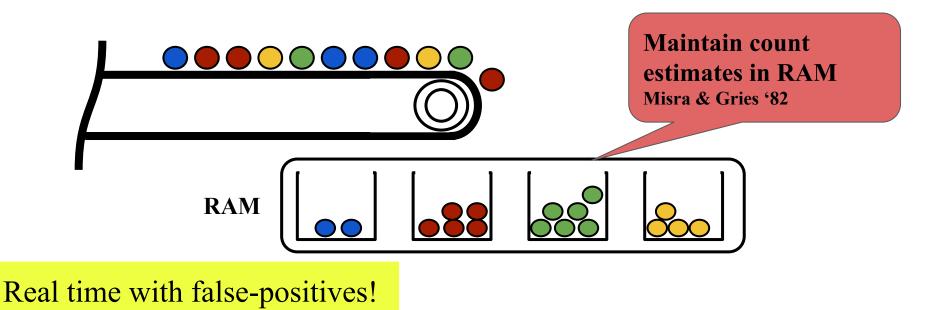
#### One-pass streaming has errors

- Heavy hitter problem: report items whose frequency  $\geq \varphi N$
- Exact one-pass solution solution requires  $\Omega(N)$  space



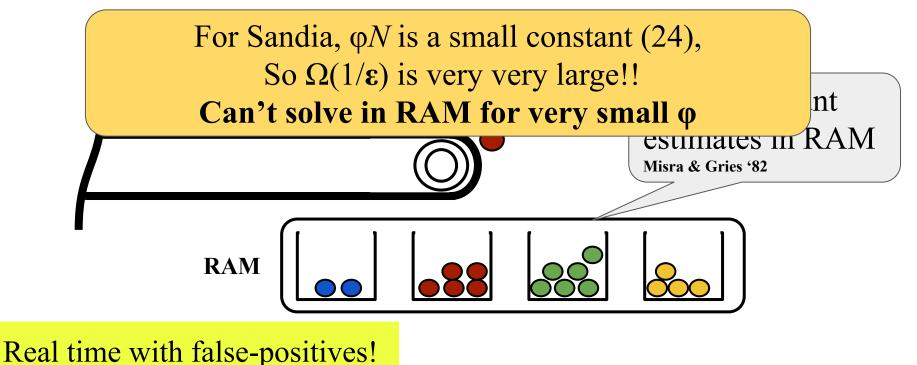
#### One-pass streaming has errors

- Approximate solution: report all items with count  $\geq \varphi N$ , none with  $\langle (\varphi - \varepsilon)N$  [Alon et al. 96, Berinde et al. 10, Bhattacharyya et al. 16, Bose et al. 03, Braverman et al. 16, Charikar et al. 02, Cormode et al. 05, Demaine et al. 02, Dimitropoulos et al. 08, Larsen et al. 16, Manku et al. 02.]
  - Approximate solutions requires:  $\Omega(1/\varepsilon)$



#### One-pass streaming has errors

- Approximate solution: report all items with count ≥ φN, none
   with < (φ−ε)N [Alon et al. 96, Berinde et al. 10, Bhattacharyya et al. 16, Bose et al. 03, Braverman et al.</li>
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# One-pass solution has:

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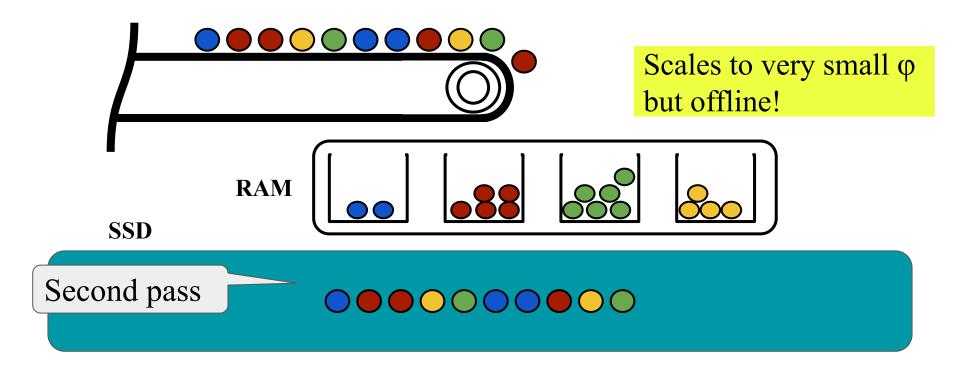
• Very small reporting threshold *T* << *N* (stream size)

Very small reporting thresholds



#### Two-pass streaming isn't real-time

- A second pass over the stream can get rid of errors
- Store the stream on SSD and access it later



# Two-pass solution has:

• Stream is large (e.g., terabytes) and high-speed (millions/sec)

High throughput ingestion

• Events are high-consequence real-life events

No false-negatives; few false-positives

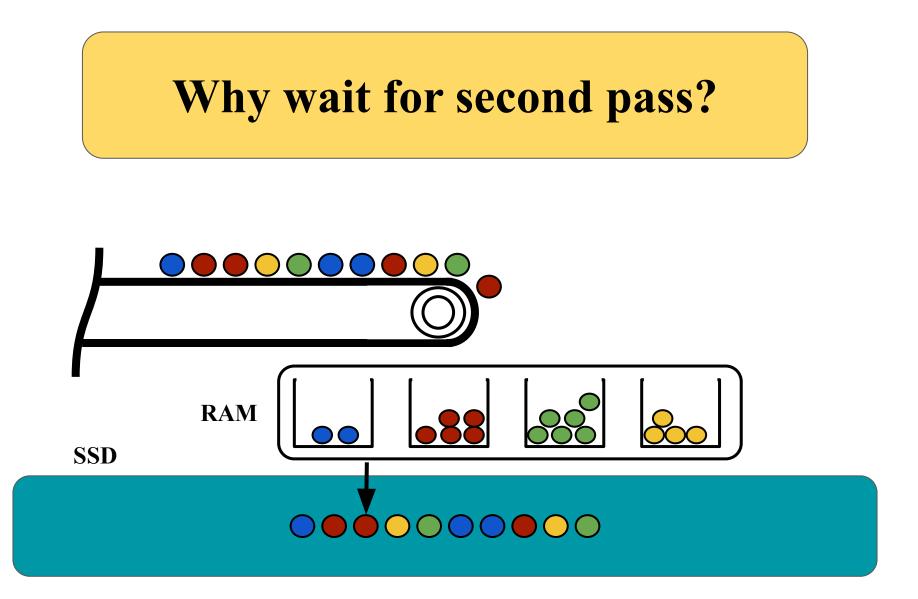
Timely reporting (real-time)

• Very small reporting threshold *T* << *N* (stream size)

Very small reporting thresholds



#### If data is stored: why not access it?



### Our contribution

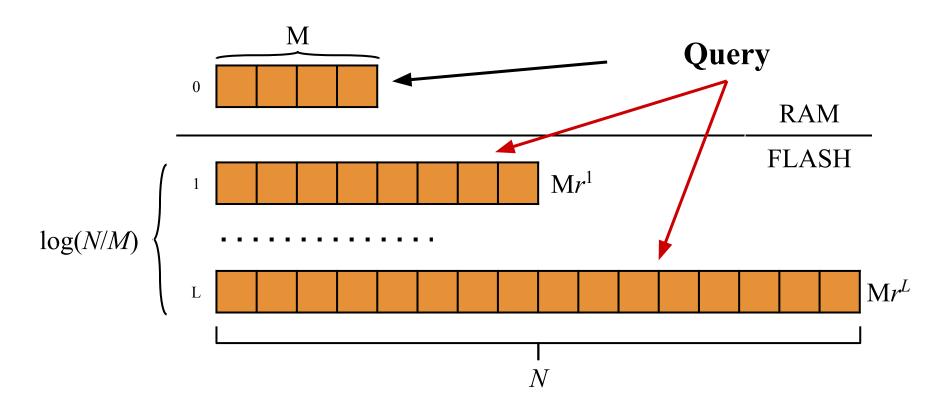


## **Combine streaming and EM algorithms to solve real-time event detection problem**



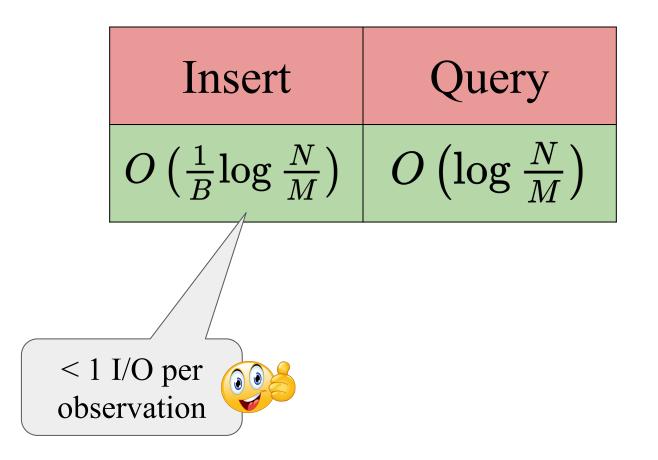
# Use an efficient external-memory counting data structure to scale Misra Gries algorithm to SSDs

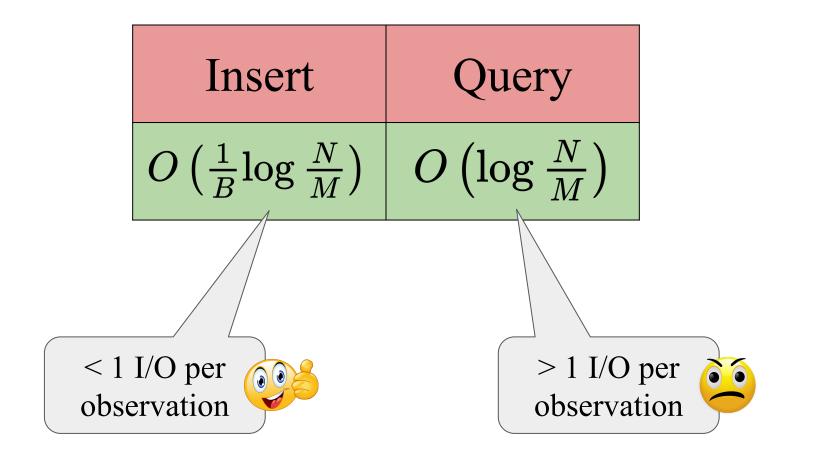
#### Cascade filter: write-optimized quotient filter Bender et al. '12, Pandey et al. '17



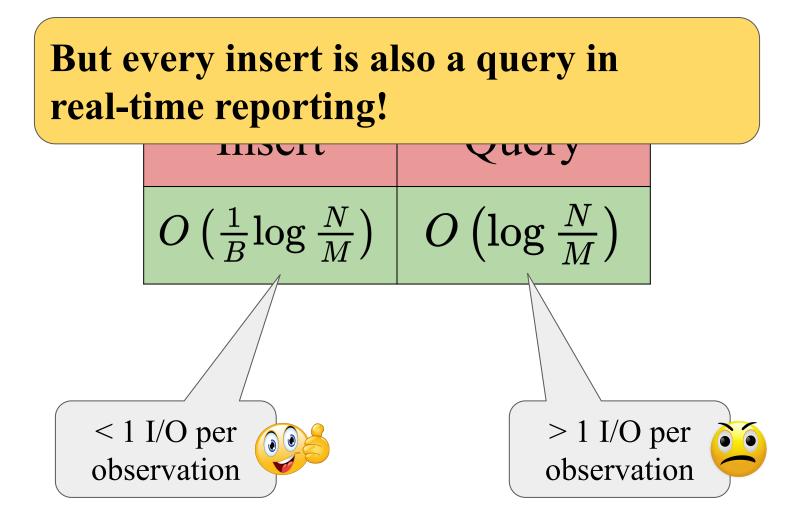
- The Cascade filter efficiently scales out-of-RAM
- It accelerates insertions at some cost to queries

InsertQuery
$$O\left(\frac{1}{B}\log\frac{N}{M}\right)$$
 $O\left(\log\frac{N}{M}\right)$ 



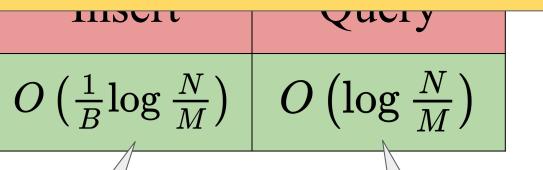


# Cascade filter doesn't have real-time reporting



# Cascade filter doesn't have real-time reporting





observation

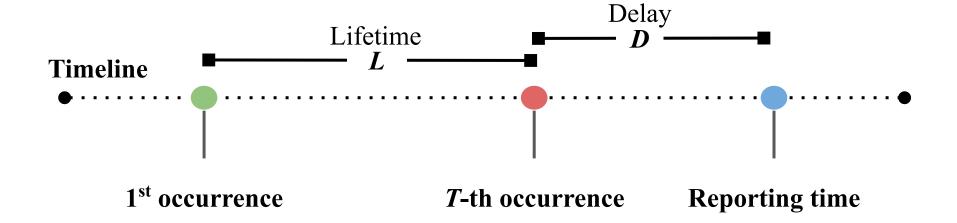
Traditional cascade filter doesn't solve the problem!





We define the time stretch of a report to be

Time stretch = 
$$1 + \alpha = 1 + \frac{\text{Delay}}{\text{Lifetime}}$$



# This paper: Leveled External-Memory Reporting Table (LERT)

• Given a stream of size N and  $\varphi N > \Omega(N/M)$  the amortized cost of solving real-time event detection is

$$O\left(\left(rac{1}{B}+rac{1}{(\phi-1/M)N}
ight)\lograc{N}{M}
ight)$$

• For a **constant**  $\alpha$ , can support arbitrarily small thresholds  $\varphi$  with amortized cost

$$O\left(\frac{1}{B}\log\frac{N}{M}\right)$$

**Takeaway**: Online reporting comes at the cost of throughput but almost online reporting is essentially free!

# This paper: Leveled External-Memory Reporting Table (LERT)

• Given a stream of size *N* and  $\varphi N > \Omega(N/M)$  the amortized cost of solving real-time event detection is

 $\Lambda \tau$ 

Can achieve timely reporting at effectively the optimal insert cost; no query cost

with amortized cost

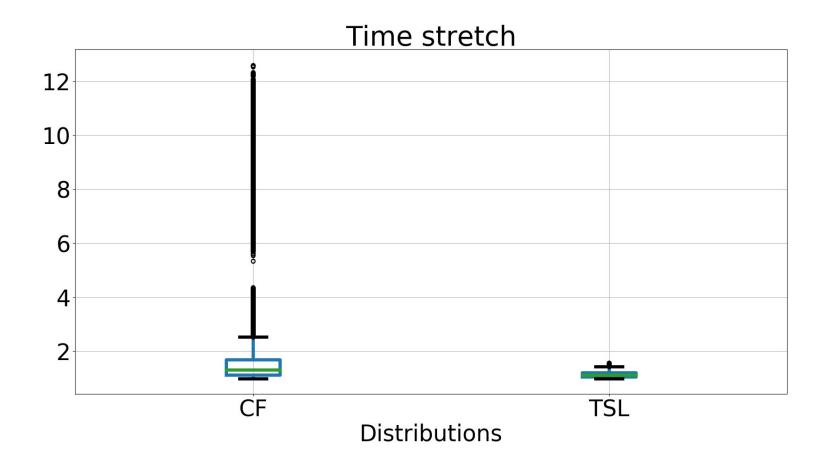
$$O\left(\frac{1}{B}\log\frac{N}{M}\right)$$

**Takeaway**: Online reporting comes at the cost of throughput but almost online reporting is essentially free!

## Evaluation

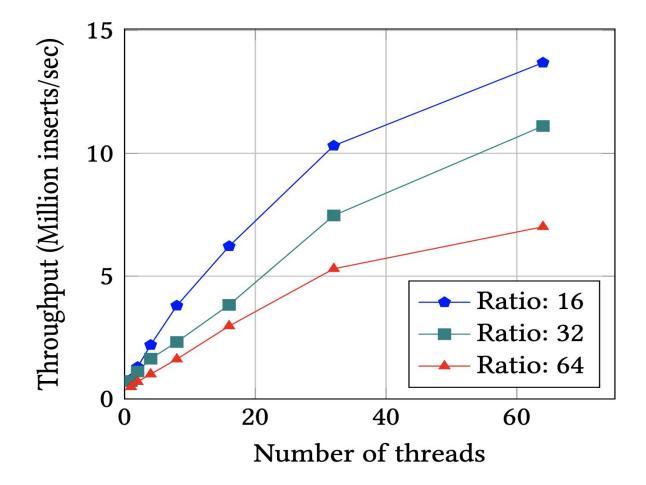
- Empirical timeliness
- High-throughput ingestion

### Evaluation: empirical time stretch



Average time stretch is 43% smaller than theoretical upper bound.

#### Evaluation: scalability



The insertion throughput increases as we add more threads. We can achieve > 13M insertions/sec.

# LERT: supports scalable and real-time reporting

• Stream is large (e.g., terabytes) and high-speed (millions/sec)

High throughput ingestion

• Events are high-consequence real-life events

No false-negatives; few false-positives

Timely reporting (real-time)



• Very small reporting threshold *T* << *N* (stream size)

Very small reporting thresholds



# Conclusion



- We can solve timely event detection problem at a level of precision that is not possible in the streaming model.
- This work suggests new research opportunities:
  - What other streaming problems can be solved in external memory at comparable speed?
  - What is the right model for streaming in modern external memory?