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Advanced Data Structures for National Cyber Security

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(and many co-authors)

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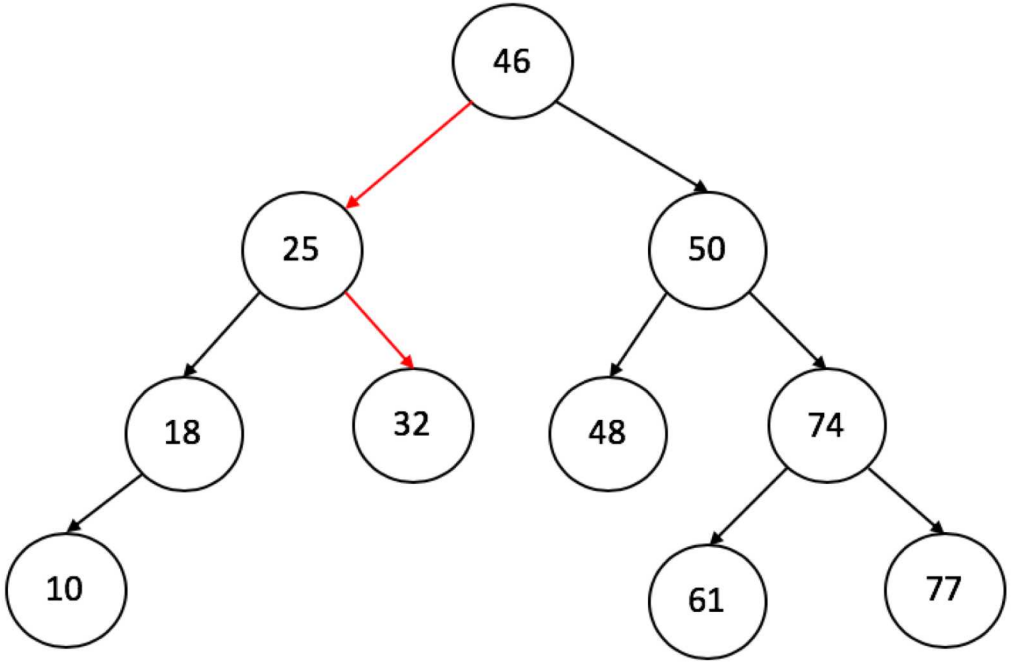
Dictionary Data Structures

Operations for a dictionary

- Insert, say (key, value)
- Delete
- Point query:
  - Is key k in the dictionary? (return pair)
- Range query:
  - Tell me all the keys in the dictionary between 100 and 1000.

In databases, these operations arrive one after the other (usually quickly) in a stream.

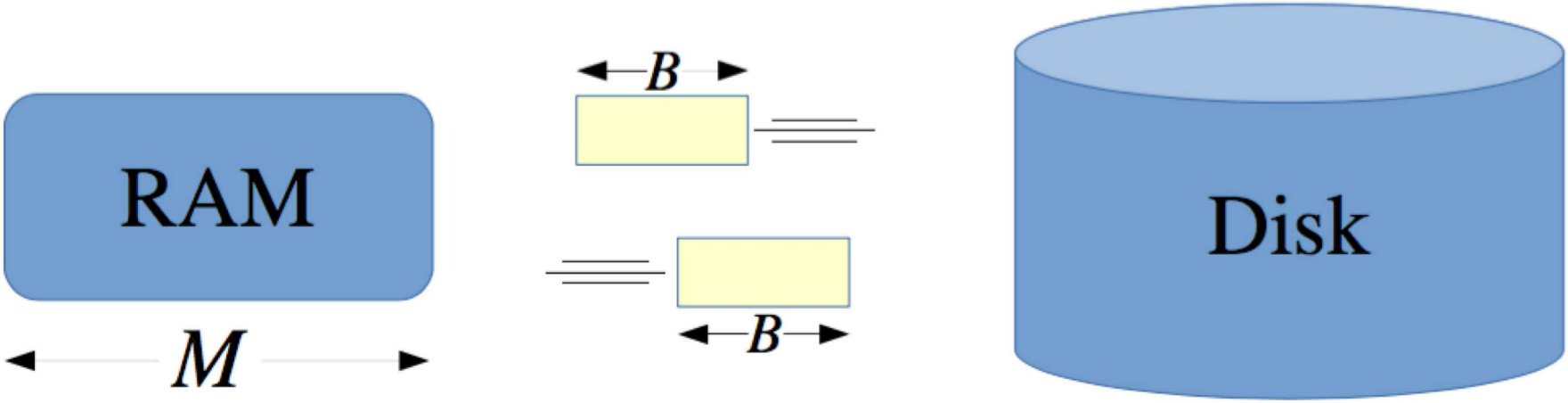
Binary Search Trees



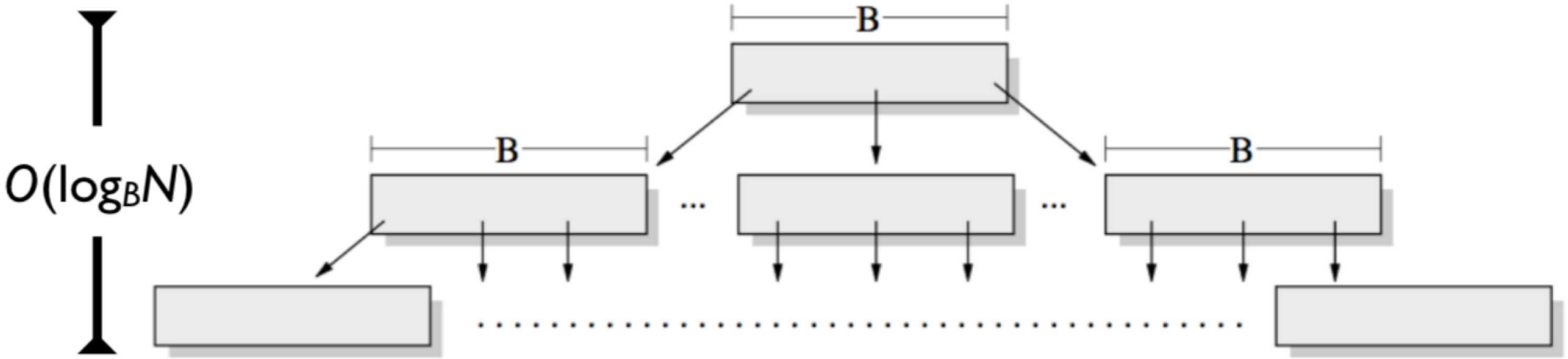
- A balanced binary tree with N elements has depth about $\log_2 N$
- Dictionary: insert, delete, search, range query

External Memory

- Disks, SSD (solid-state drives)
- Data transferred in blocks of size B
- Efficient algorithms ensure most of the block is used
- When possible, delay block transfers to fill blocks
- Theoretical analysis uses B, M, and data size N
  - Analysis counts only block transfers



B-trees

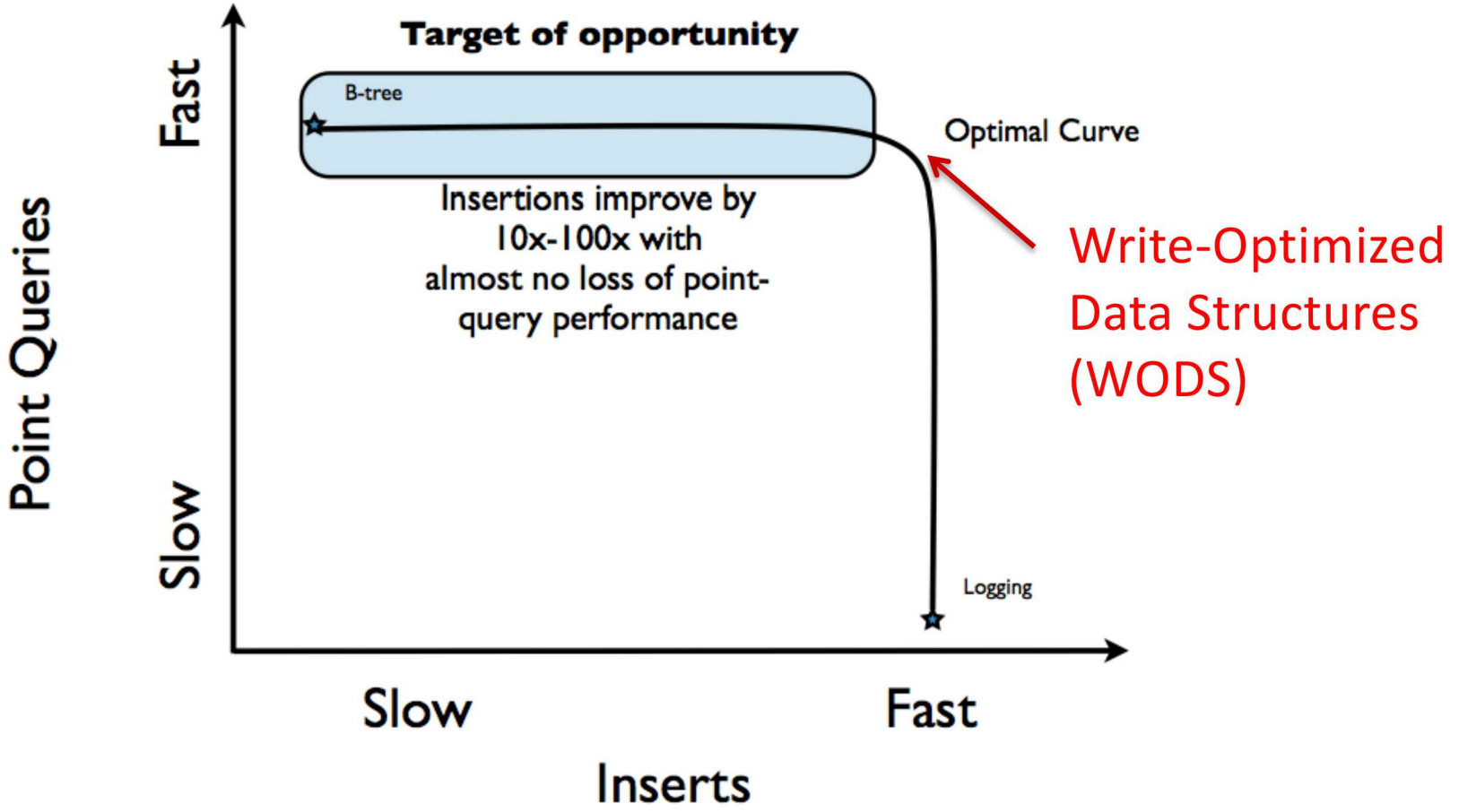


- Larger branching factor. B is block size

$$\log_B N = \frac{\log_2 N}{\log_2 B}$$

- If B is about 1024, this is $\log_2$ B = 9x fewer levels than binary trees
  - Fewer I/Os when lower levels are on disk/SSD

Write Optimization



Write-Optimized Data Structures (WODS)

- The basis for TokuDB

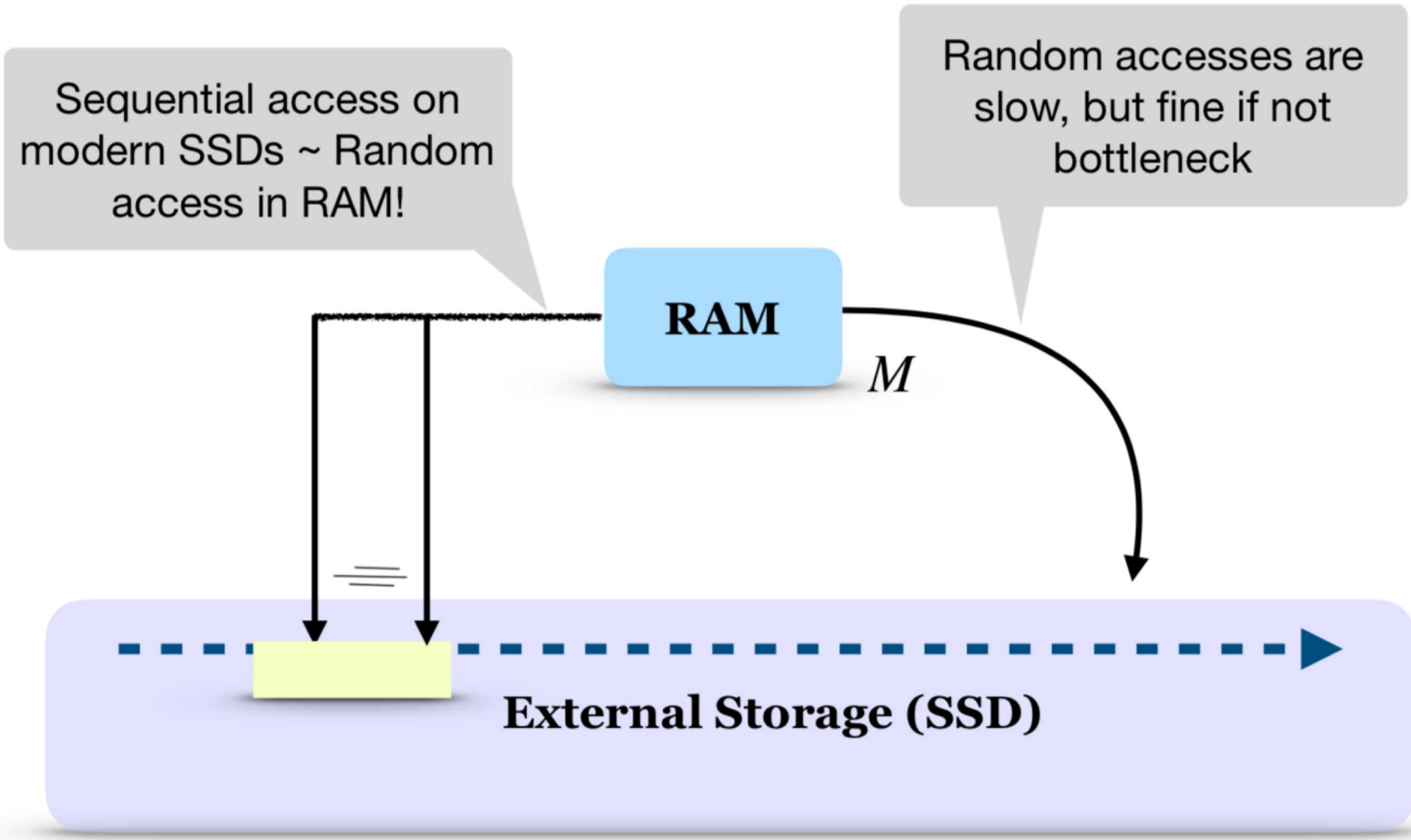
Write-Optimized Data Structures

Write optimized data structures like COLA, cascade filters, etc. (WODs) let you do fast inserts and B-tree like queries

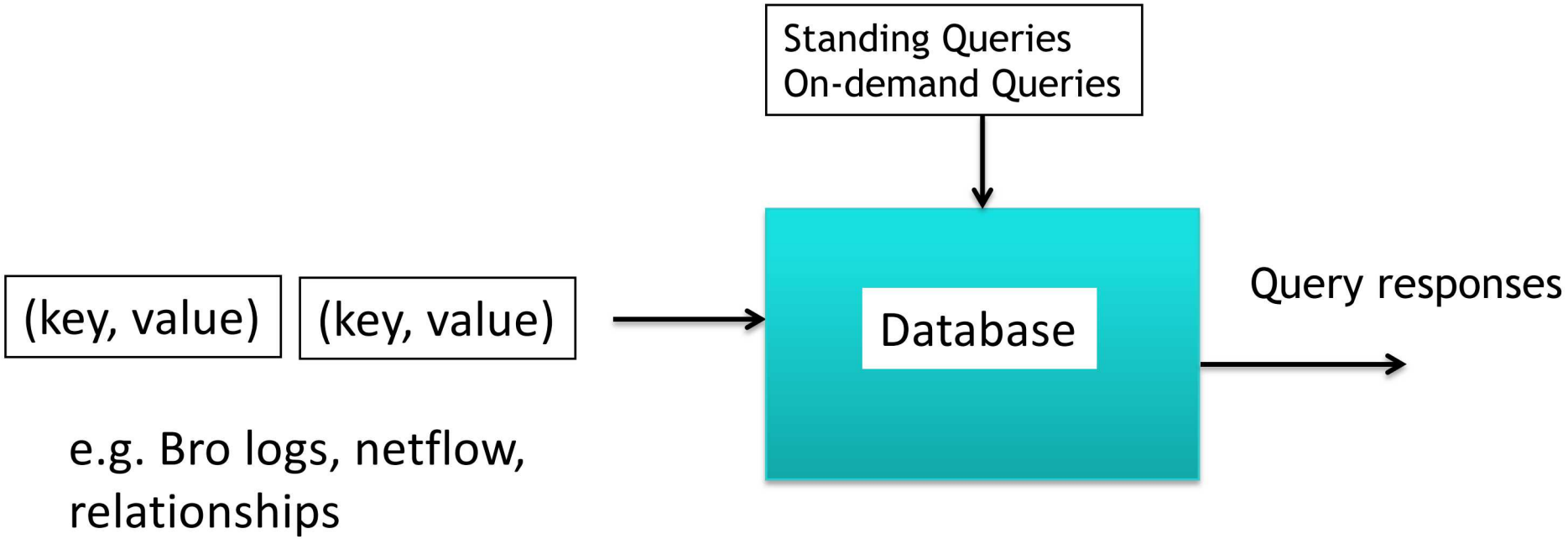
Amortized complexity: for a data structure with N elements

Optimal Insert	Optimal Query
$O\left(\frac{\log N/M}{B}\right)$	$\Omega(\log_B N)$

Modern External Memory: SSDs

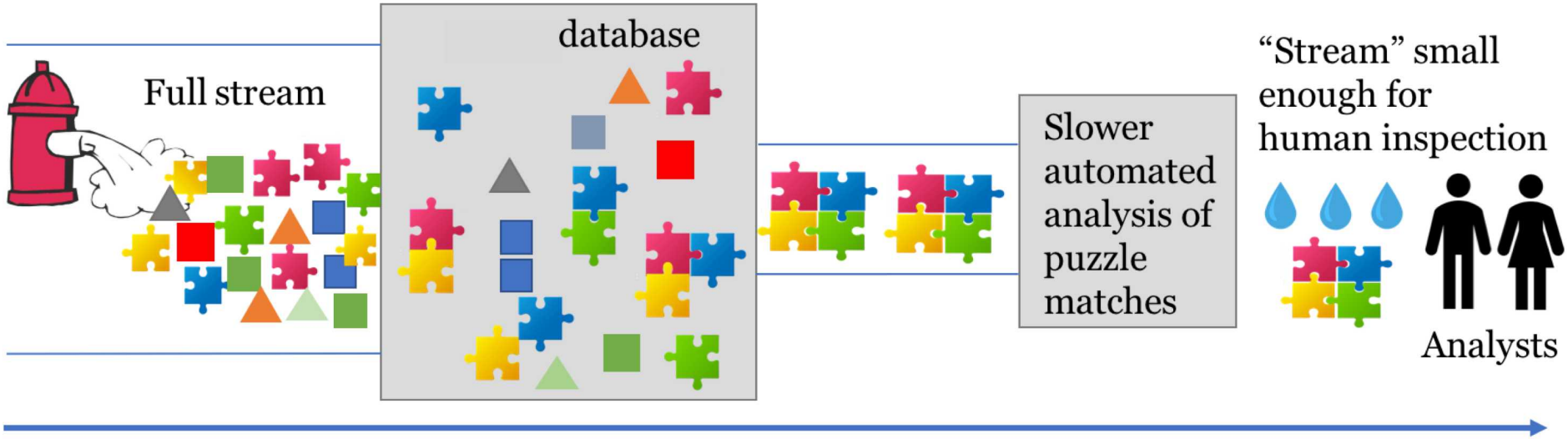


Cyber Streams and Analysis



- Stream is fast
- Interesting events can have multiple pieces that are spread in time and can hide among non-interesting pieces

Standing Queries



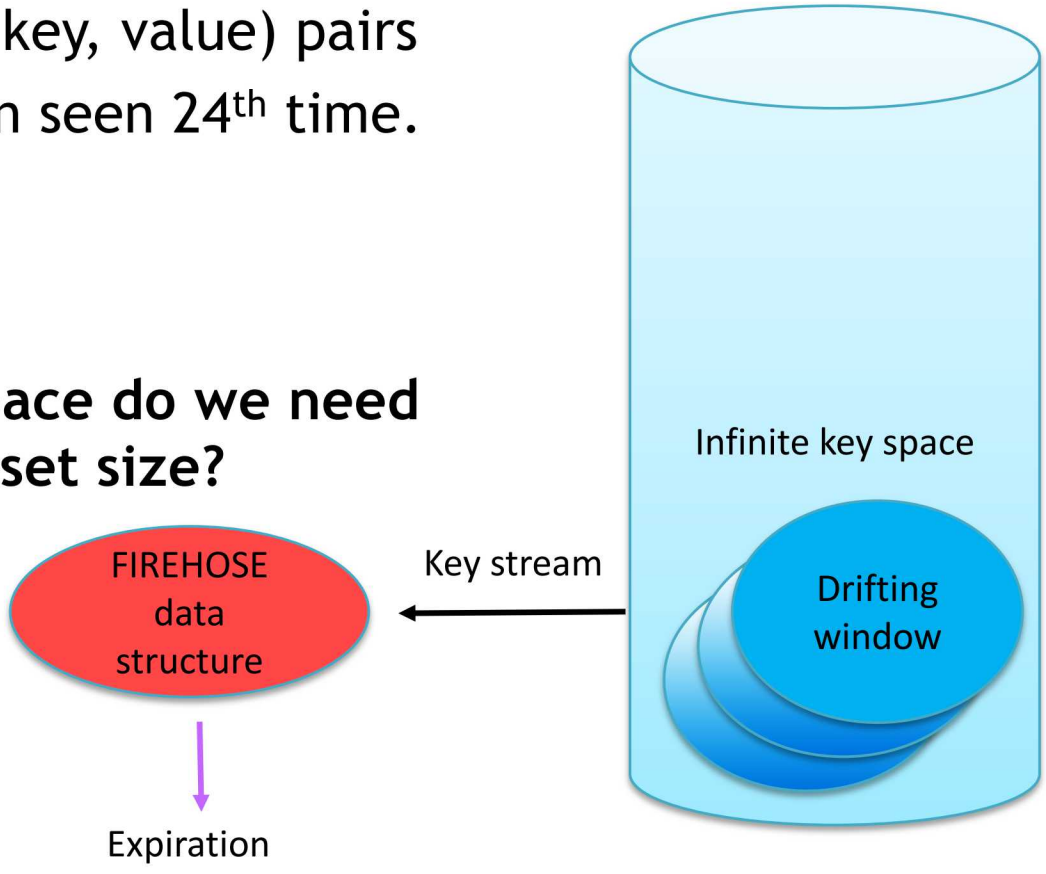
Database requirements:

- No false negatives
- Limited false positives
- Immediate response preferred
- Also relevant to other monitoring problems: power, water utilities

Firehose

- Benchmark that captures the essence of cyber standing queries
  - Sandia National Laboratories + DoD
- Input: stream of (key, value) pairs
- Report a key when seen 24th time.

How much working space do we need relative to the active set size?



http://firehose.sandia.gov/

Critical Data Structure Size

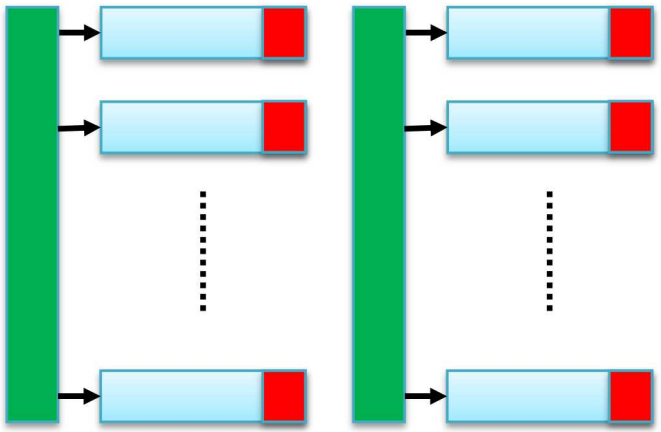
- Testing with benchmark reference implementation in Waterslide
  - 50M keys (varying counts)
  - Stable window
- Accuracy of cyber-analytics depends on keeping enough data
- Difficult to determine what to throw away
  - Most keys act the same at their start
- Keep as much data as we can!

Table Size	Generator Window Size	Reportable keys	Reported keys	**Packet drops**
2^20	2^20	94,368	62,317	0
2^20	2^21	63,673	15,168	0
2^20	2^22	17,063	9	0

https://github.com/waterslideLTS/waterslide

What is Happening?

- **Waterslide uses 'd-left hashing'**
  - Two rows of buckets
  - Constant-size
  - Fast
  - Waterslide adds LRU expiration *per bucket*



Broder, Andrei, and Michael Mitzenmacher. "Using multiple hash functions to improve IP lookups." *INFOCOM 2001*

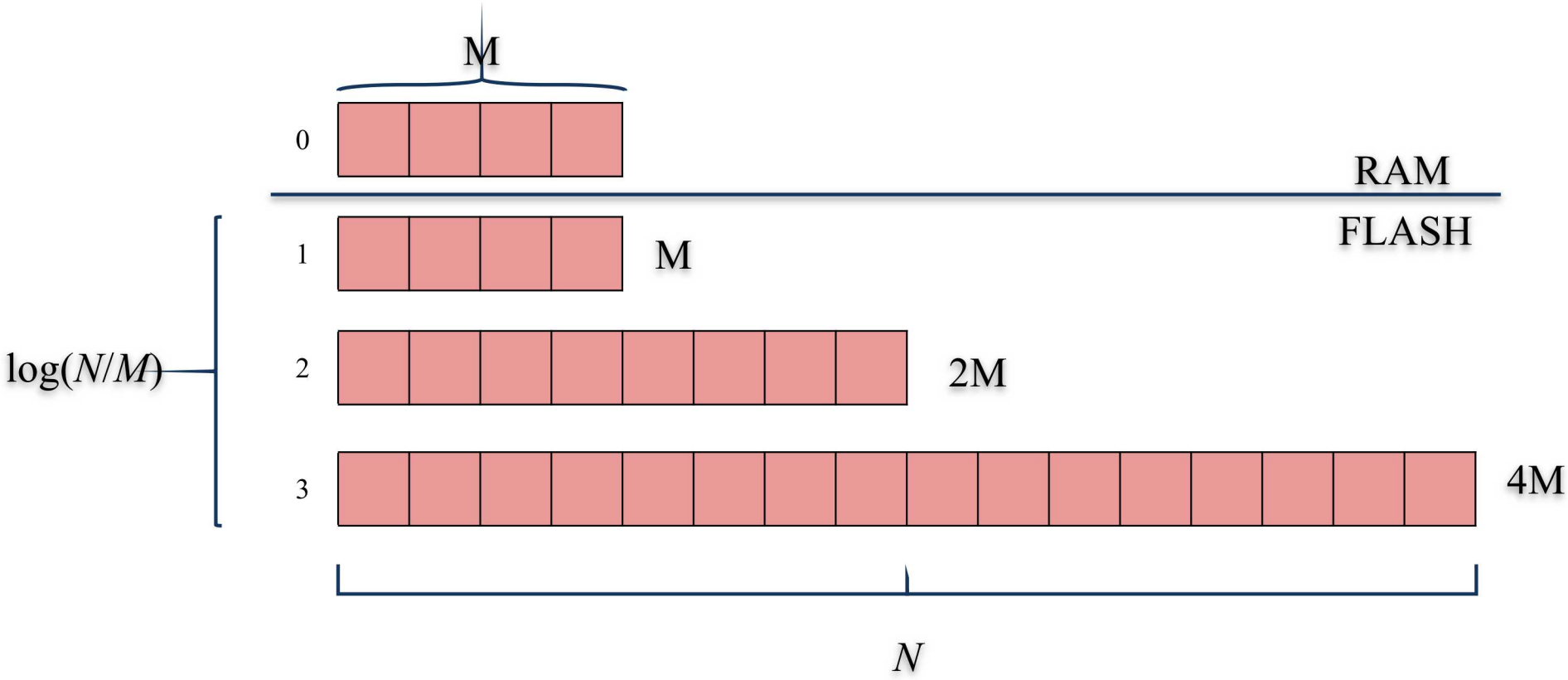
- **1/16 of all data is always subject to immediate expiration in steady state**

- **As active generator window grows, FIREHOSE accuracy quickly goes to zero**

Even when window size is only 4x data structure size, most reportable data are lost before It is reported.

Write optimization: Cascade filter

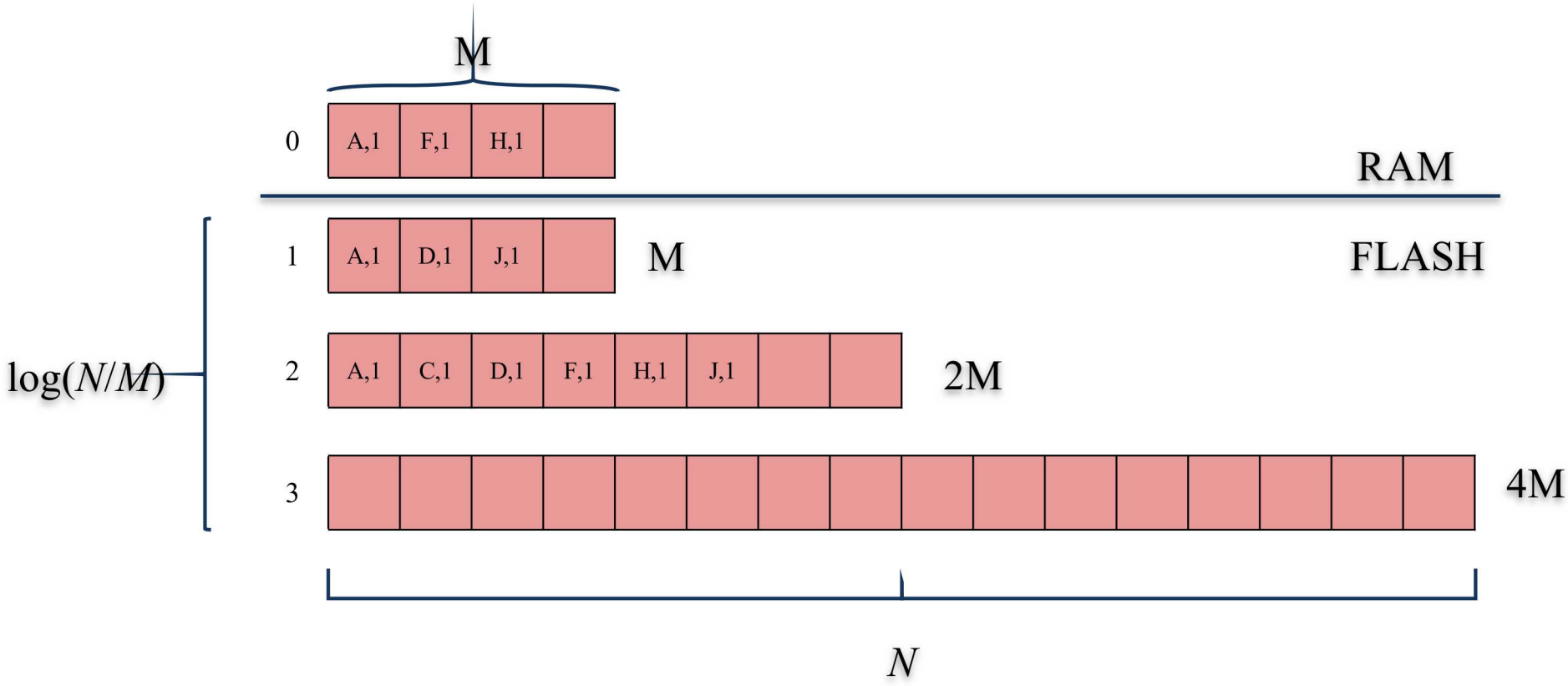
[Bender et al. 12, Pandey et al. 17]



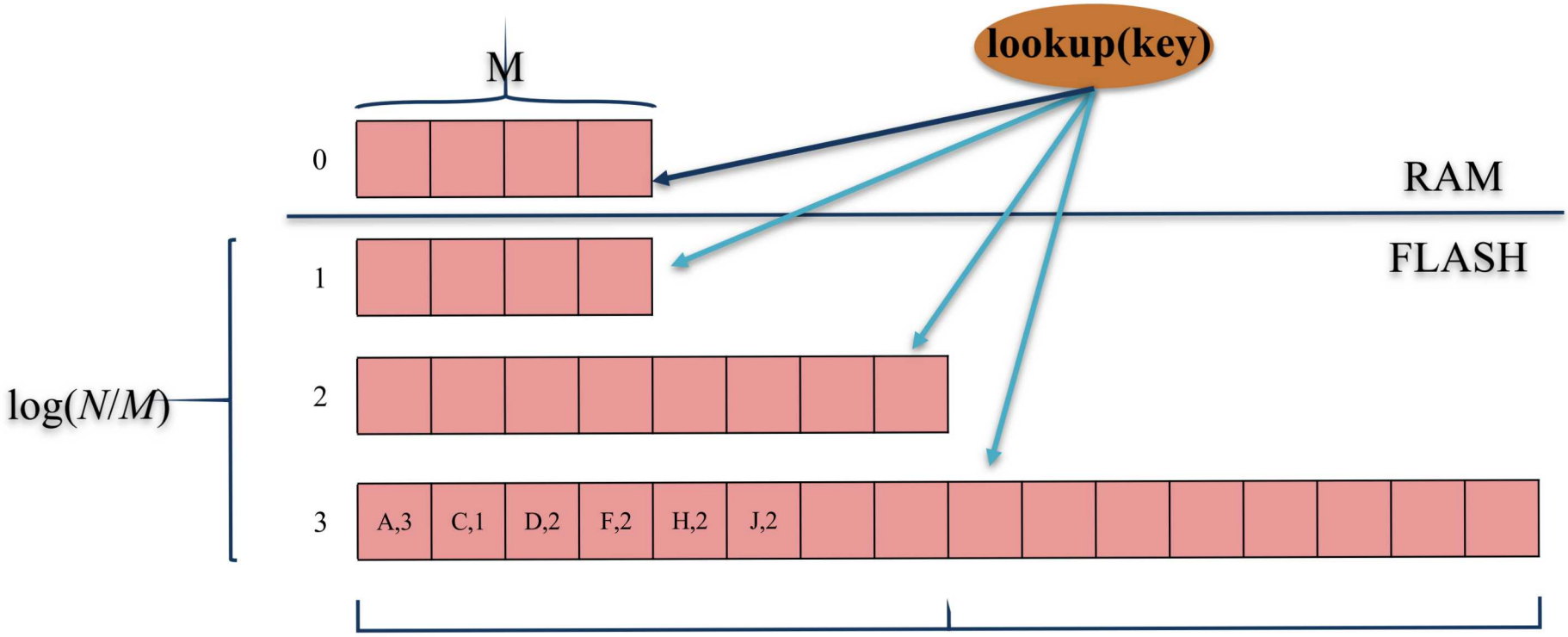
- Each level is an efficient hash table with counts
- It greatly accelerates insertions at some cost to queries.

e.g. N = 1T
M = 8B
8 levels

Ingestion “cascades”



Cascade filter Performance



Number of I/Os per item:

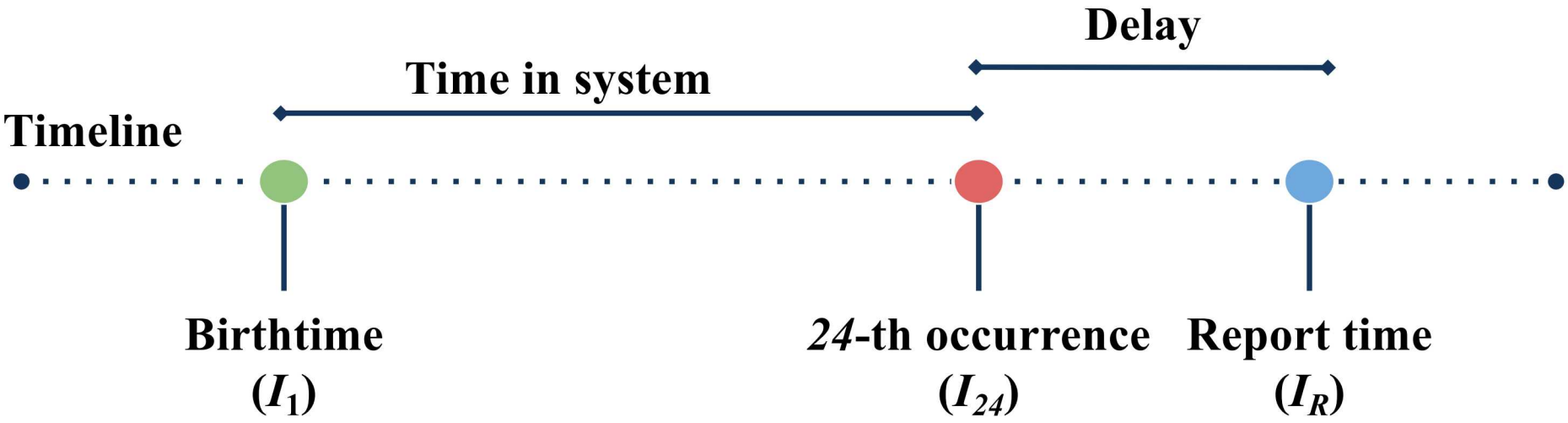
Look up: $O(\log(\frac{N}{M}))$

Insertion:

$O(\log(\frac{N}{M})/B)$

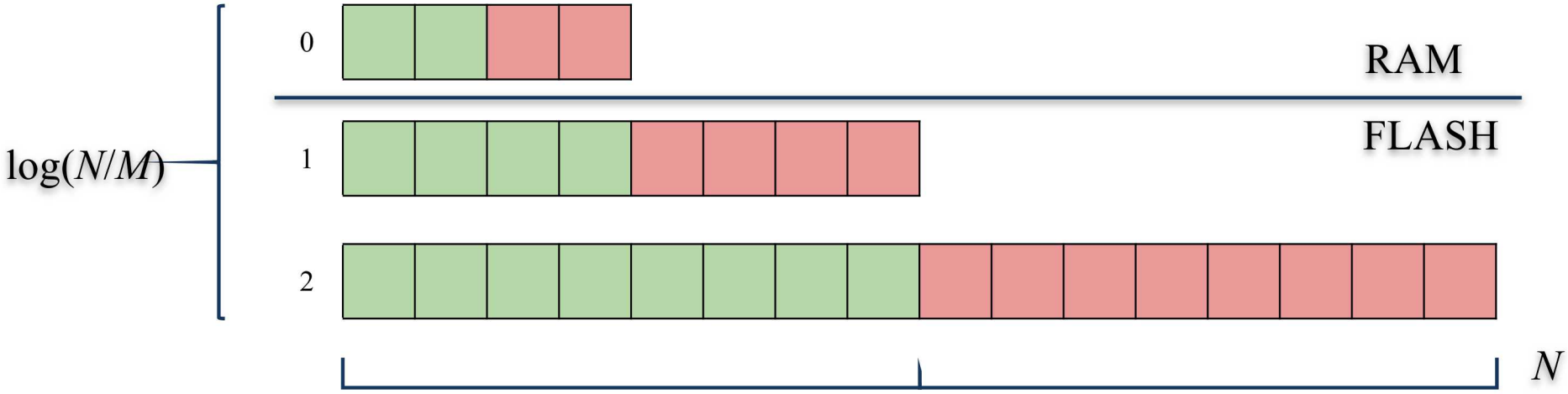
Time Stretch

- Can't afford multiple look ups per element
- Compromise: allow a little delay



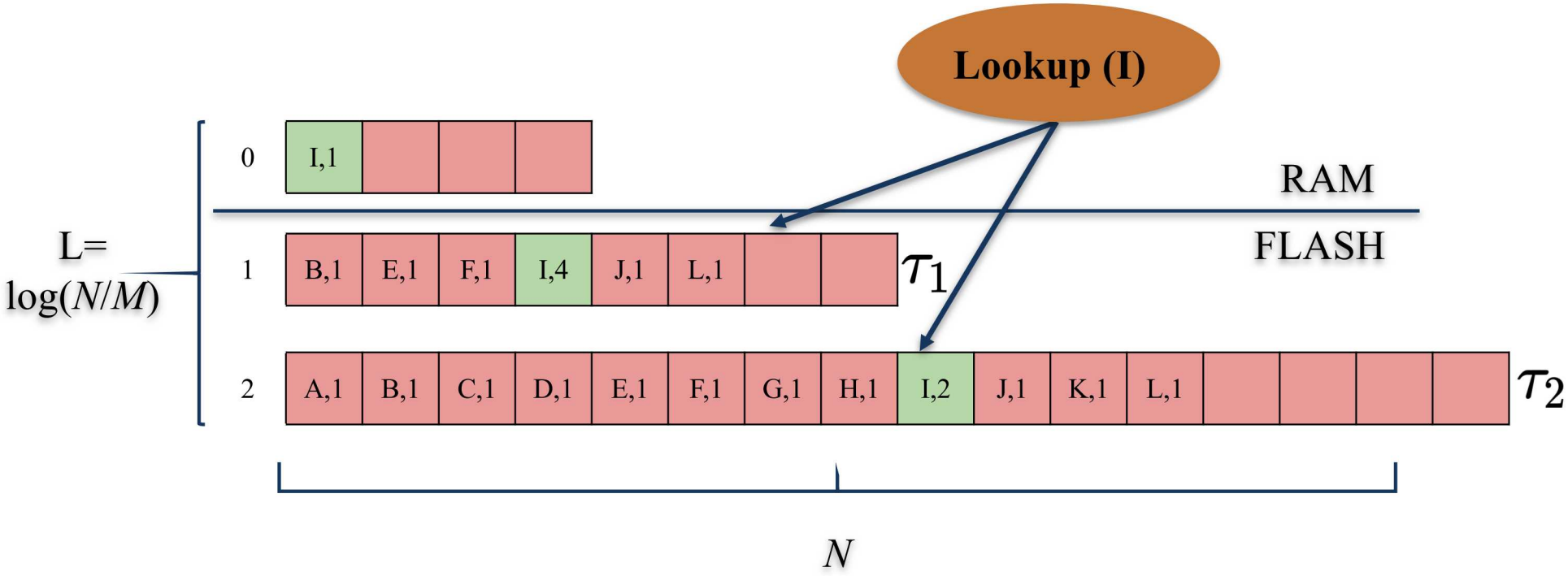
$$\text{delay} \leq \alpha * \text{time in system}$$

Time-stretch filter



- Arrays at each level split into $l = (\alpha+1)/\alpha$ equal-sized bins. Here $l = 2$ and $\alpha = 1$.
- Flushes at bin granularity on fixed round-robin schedule.
- Will always see the oldest element in time to report
- Bounded delay time, factor $(\alpha+1)/\alpha$ slower ingestion
- This example: 1 hour for 24 instances to arrive ➡ report up to 24 hours late and system runs 2x slower than when we gave no promises on delay

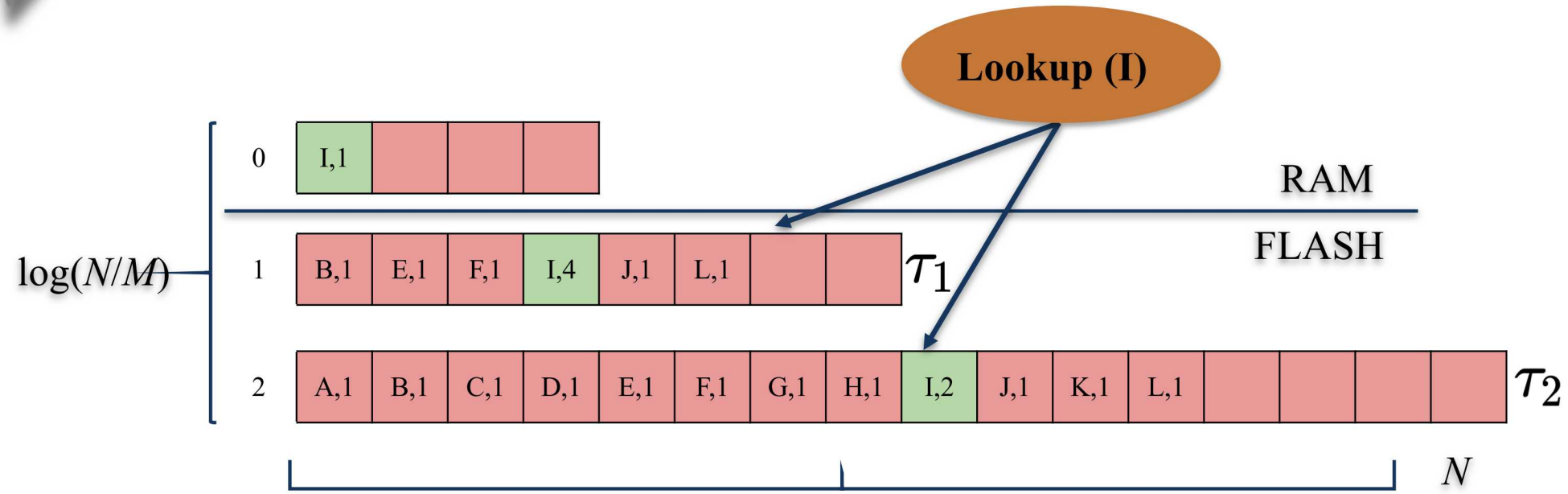
Popcorn filter: immediate reporting



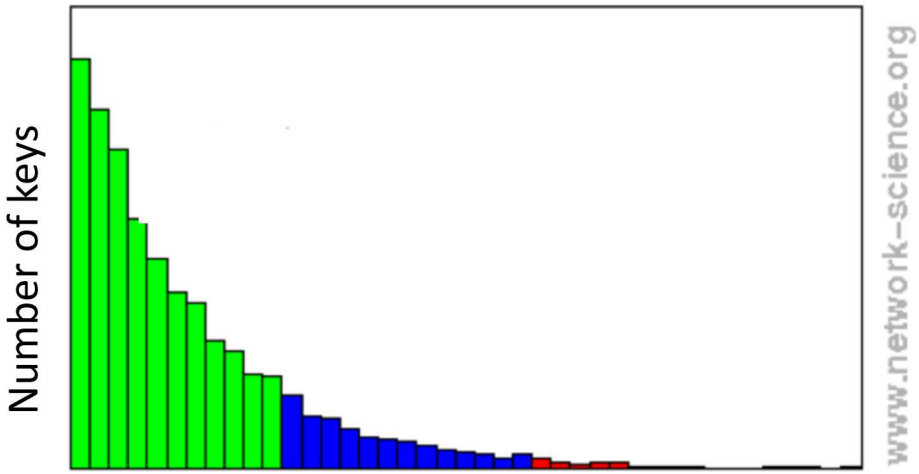
- Avoid unnecessary I/Os if we can **upper bound the total instances on disk**

$$\text{Lookup if } \text{RamCount} = 24 - \sum_{i=1}^{L} \tau_i$$

Popcorn filter



- Immediate reporting works if keys have power-law distribution
- Delay gives a count stretch: bounded extra counts



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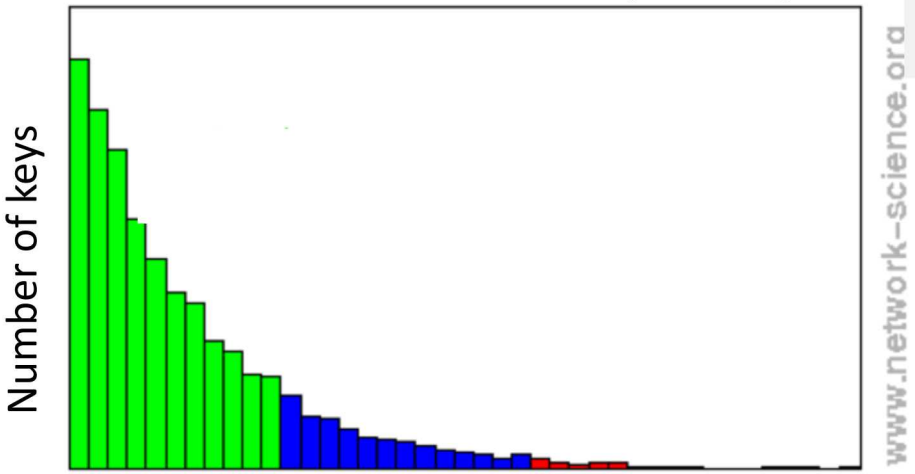
A little math

- Power-law distribution: Counts of keys follow a power-law distribution with exponent θ if the probability an item has count c is proportional to $c^{-(\theta-1)}$
- Theorem: If a stream has N elements with counts following a power-law distribution with $2 < \theta < 2.96$, T is the reporting threshold, and

$$T\omega > 2.5\left(\frac{N}{M}\right)^{\frac{1}{1-\theta}}$$

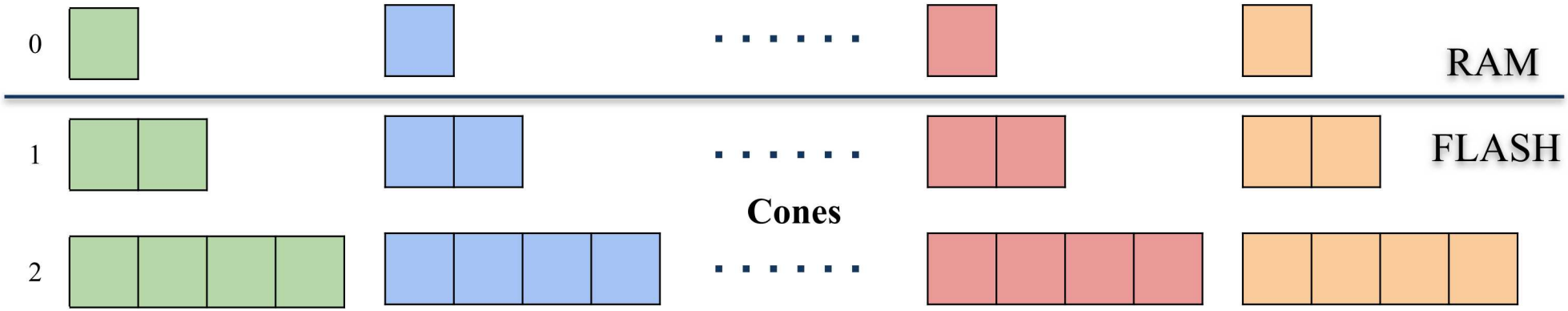
Then our algorithm gives a count stretch of $(1 + \omega)$ with amortized I/O complexity of $O\left(\frac{1}{B}\log\frac{N}{M}\right)$ per item w.h.p



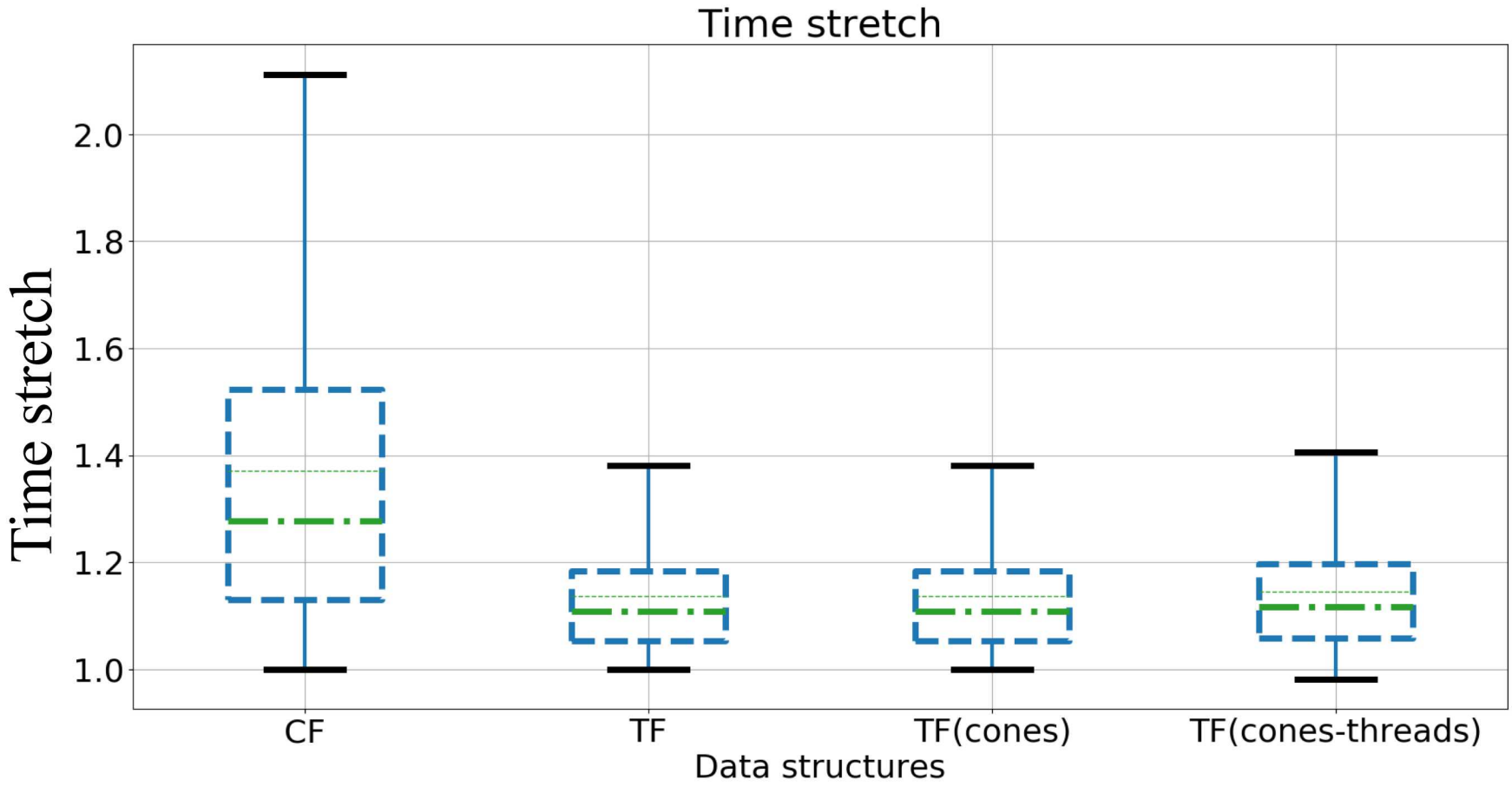
Key frequency

Multithreading and Deamortization

- Data structures run well on average, but some operations take a long time
- Do a little work for each arriving element

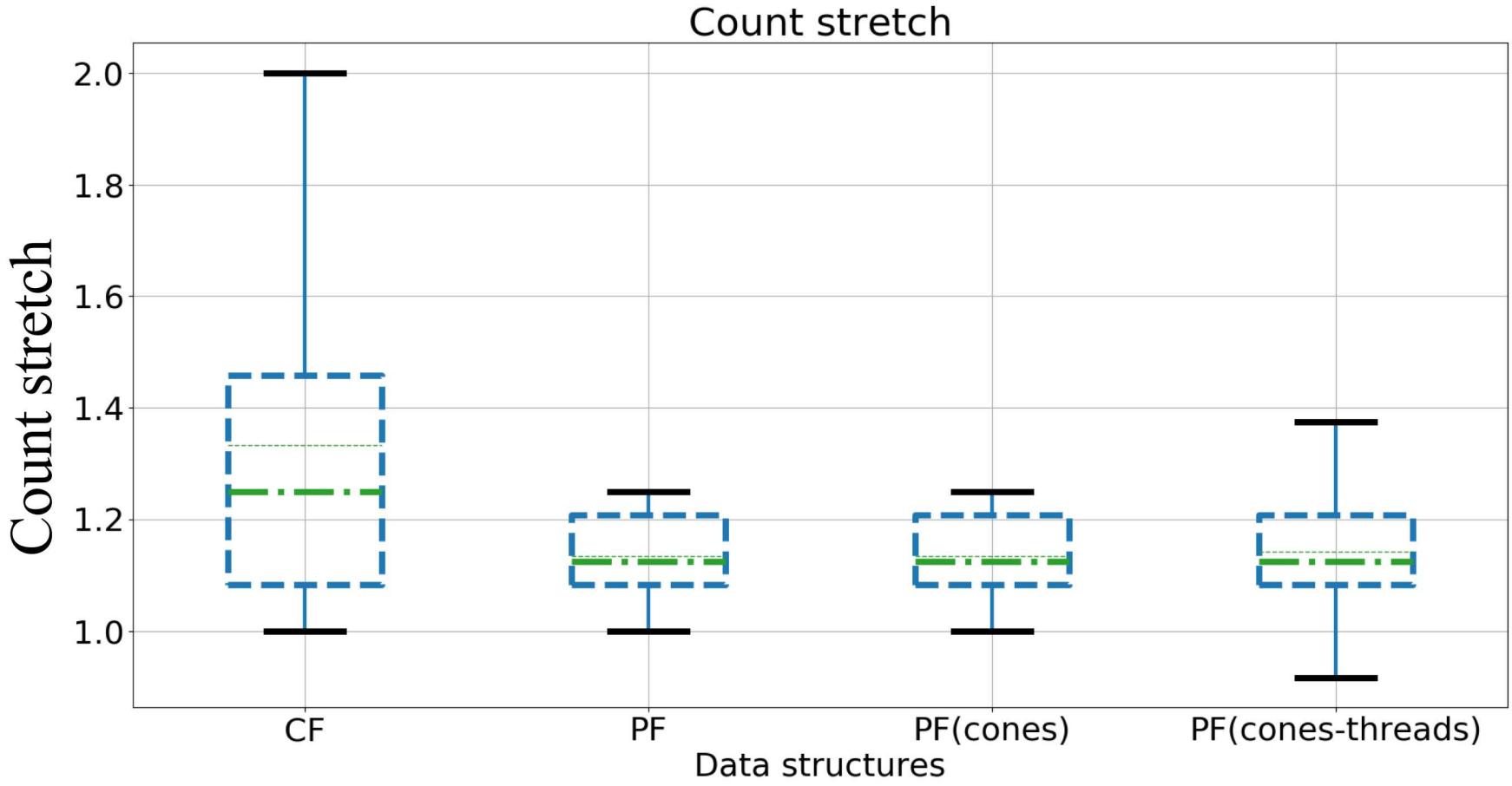


Time stretch



- Time-stretch filter has the smallest empirical time stretch.
- Deamortization and multithreading had negligible effect on empirical time stretch.

Count stretch



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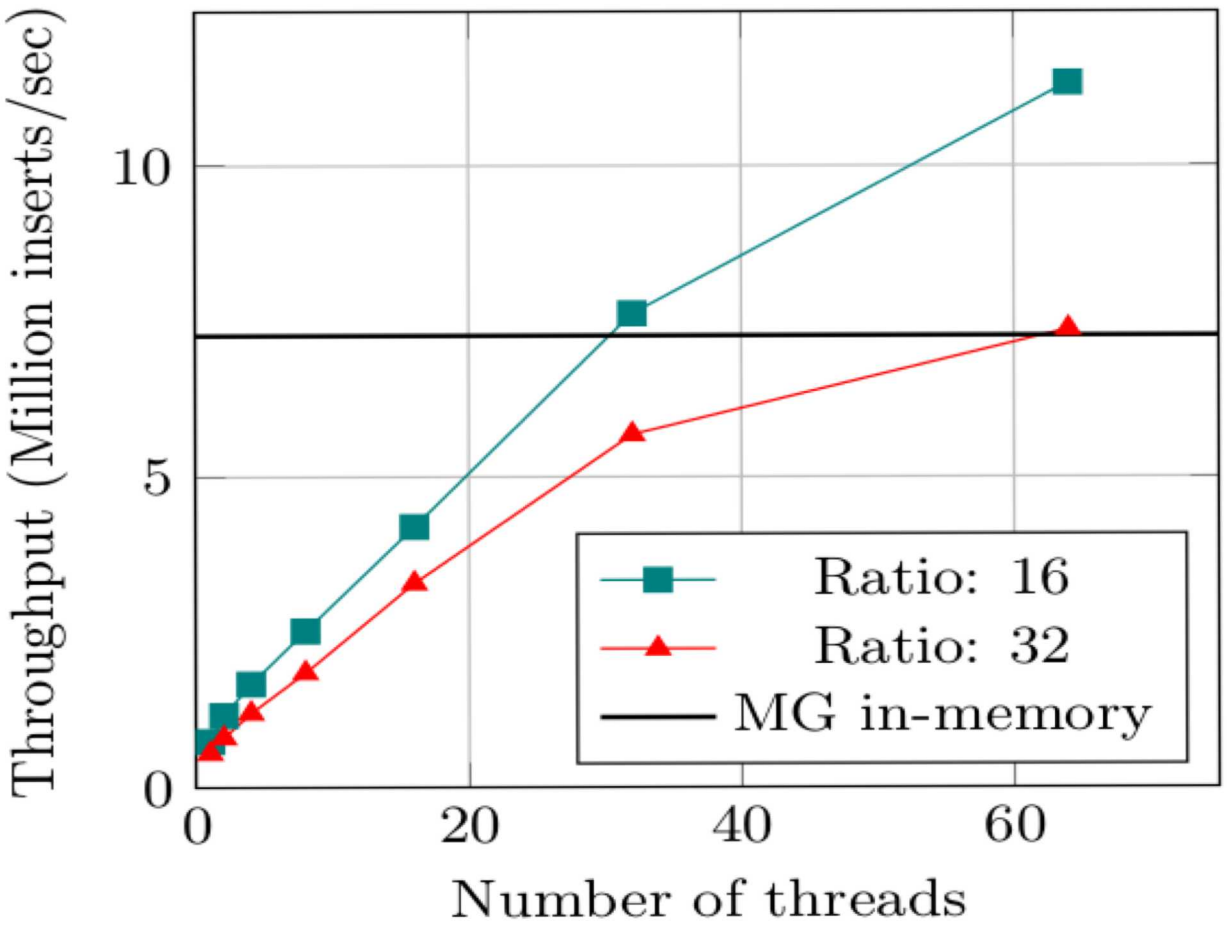
Scalability – count stretch

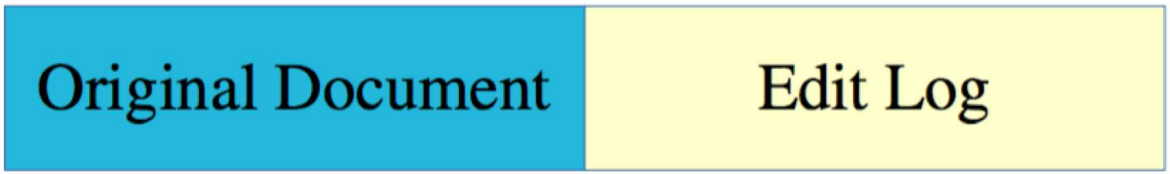


16 threads

- This runs faster than Waterslide (10M insertions/sec) and reports all reportable keys

Additional Challenge

- Systems sacrifice security for I/O efficiency
  - Example: Microsoft Word "fast save" appends edit log
  - Adversaries can recover old versions of documents



- Hide the history of a data structure on disk
  - Order of arrival
  - No idea if there has ever been a deletion

History-Independent Data Structures

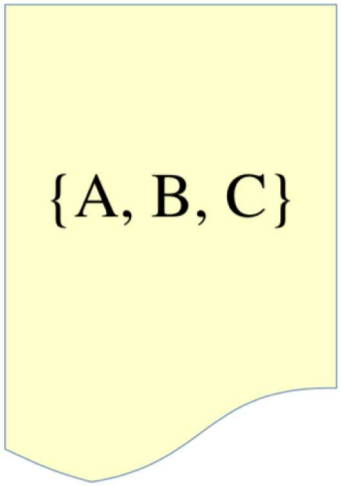
- An added level of protection for data on disk
- An adversary who acquires the disk and examines memory cannot determine anything more than API would give
- If the adversary can examine the disk cannot determine:
  - Order elements arrived
  - If any data has been deleted
- Order information can reveal sources, policy, etc.
- One potential motivation: drones

From: Wikipedia

History-Independent Data Structures [Naor & Teague '01]

[Blelloch & Golovin '07] [Buchbinder & Petrank '03] [Bajaj, Chakrabati, Sion '15] [Bajaj & Sion '13] [Molnar, Kohno, Sastry, Wagner '06] [Moran, Naor, Segev '07] [Naor, Segev, Wieder '08] [Roche, Aviv, Choi '15] [Tzouramanis '12] [Golovin '08, '09, '10]

- Bit representation reveals no additional info about past states of the data structure
- Example:



Observer cannot infer sequence of operations leading to current state

1.Insert A	1.Insert C
2.Insert B	2.Insert B
3.Insert C	3.Insert A
4.Insert D	
5.Delete D	

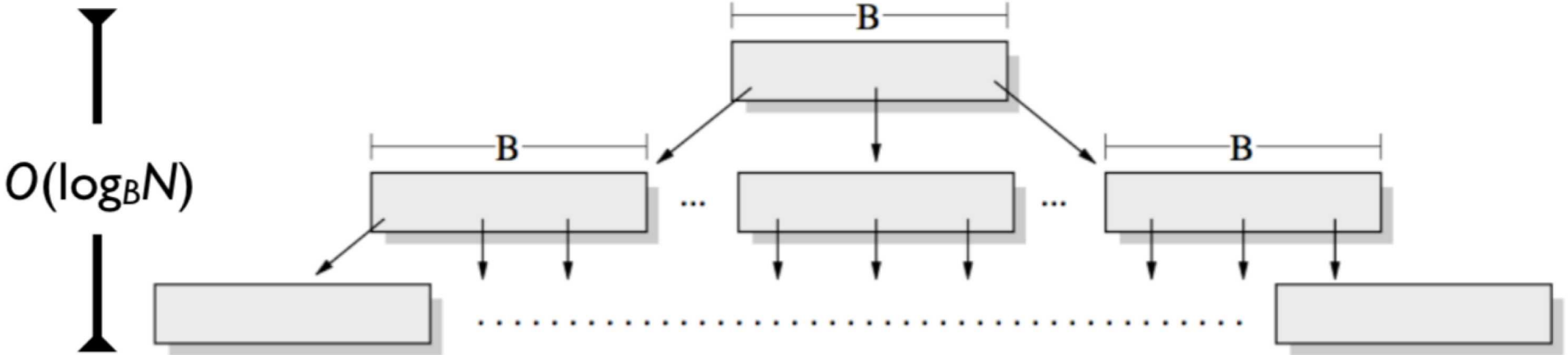
History Independence (HI)

- Strong history independence gives guarantees if the adversary sees the data representation multiple times
  - Requires a canonical representation
  - Expensive
    - Provably cannot achieve amortized o(N) operation cost whp
- Weak history independence protects against a one-time theft
  - Representation is drawn uniformly at random from a given large structured set
  - Can be much more efficient
  - The right model if a disk can only be stolen once

History-Independent Dictionaries

- Skip lists. External memory block size B, n items
  - Insert, delete, search: $O(\log_B n)$
  - Range search with k items in range: $O(\log_B n + k/B)$ block
  - Amortized, with high probability: $1 - O\left(\frac{1}{n^c}\right)$
  - Optimal
- Previous work for HI skip lists: insert $\Theta(\log n)$
- Cache-oblivious B-trees
  - Same bounds except inserts are (optimal) $O(\frac{log^2 n}{B} + \log_B n)$
  - O(n) space
  - Experiments show small slowdown
- Oblivious adversary for analysis: sets order of operations, but does not know the random tosses of the data structure

B-trees



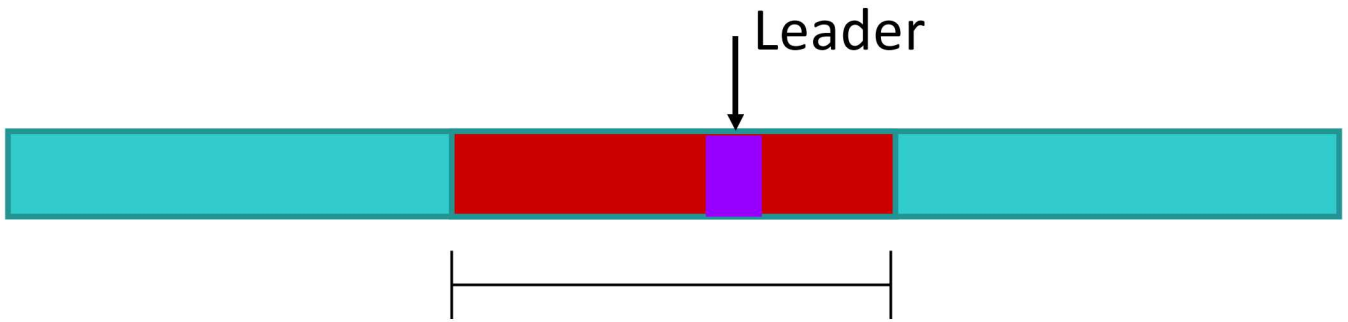
- All the elements are in the leaves (on disk)
- Randomization involves how many elements in each leaf

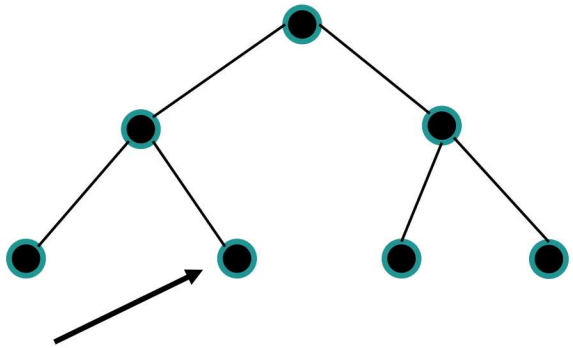
To start, though size/storage allocation

- For N elements, allocate array size |A| from N to 2N-1 uniformly
- For any insert/delete reallocate with probability $\Theta\left(\frac{1}{|A|}\right)$

Key ideas

Recursive stick breaking





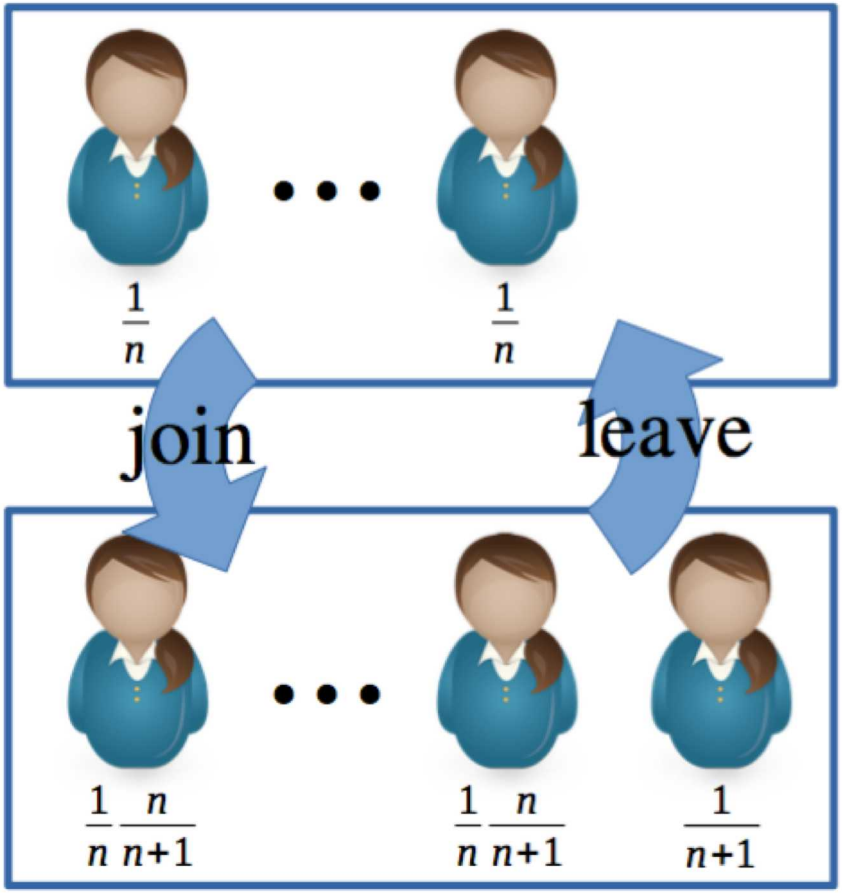
Leaves have log N elements
Always packed left

Reservoir Sampling with Joins and Leaves [Vitter '85]

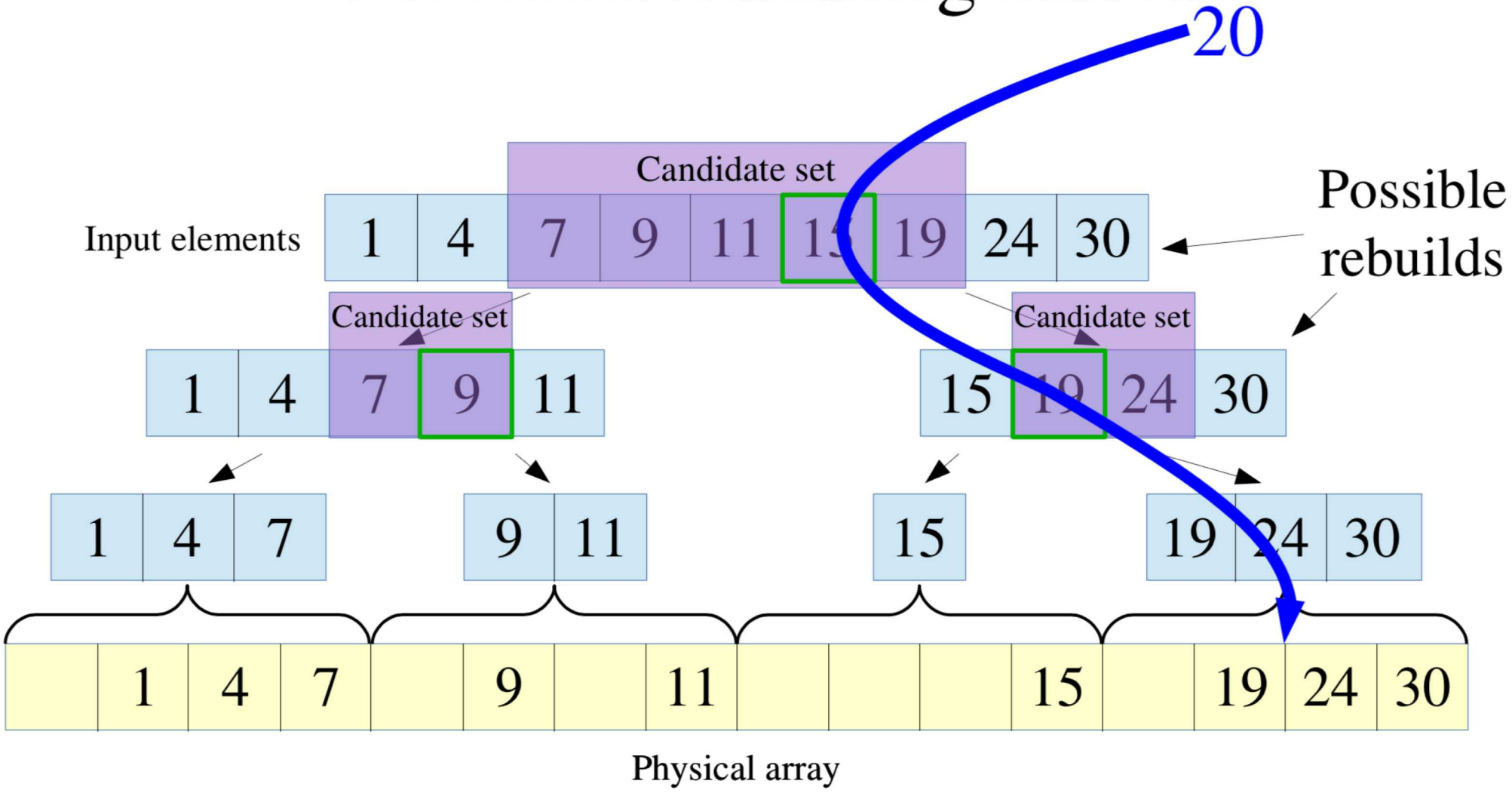
- Two goals:
  - Maintain a club leader uniformly randomly from all current club members
  - Make leader changes rare as members join and leave

1. Elect new member w/ prob $1/(n+1)$
2. Elect new leader when leader leaves

Prob[leader changes] $\approx 1/n$



HI PMA: Handling Inserts



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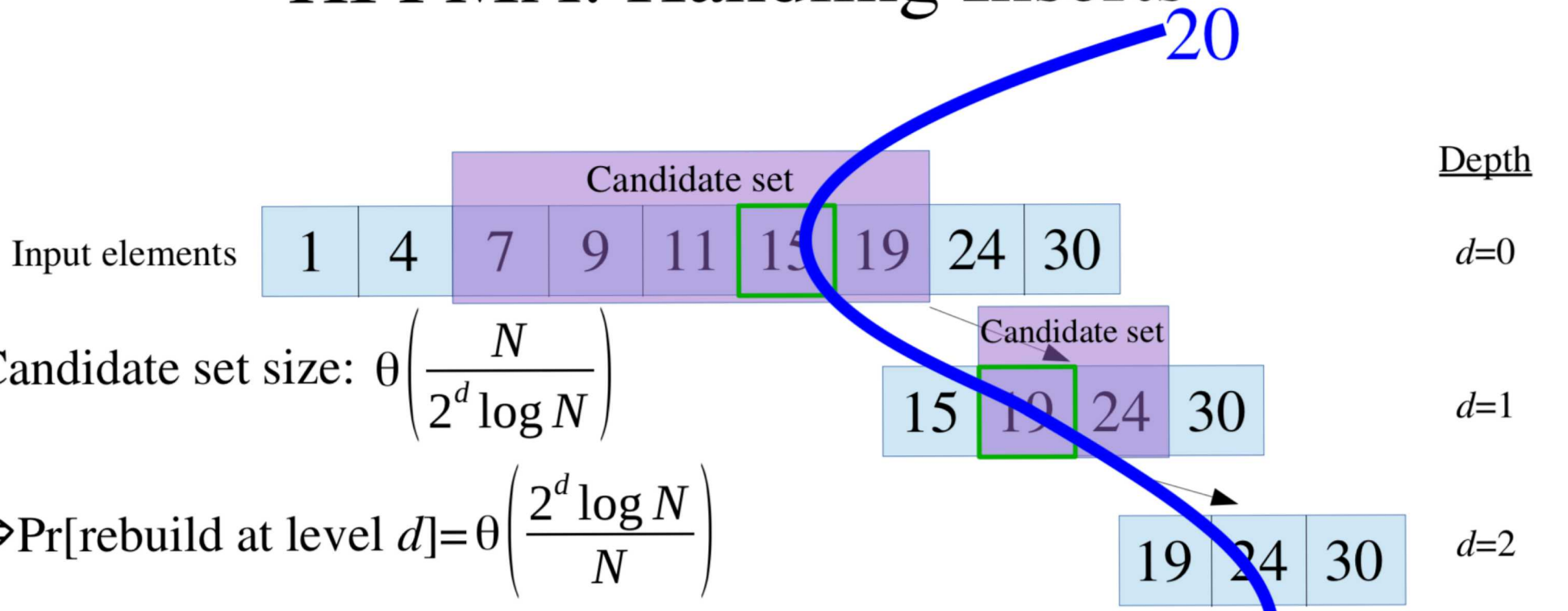


Candidate set size: $\theta\left(\frac{N}{2^d \log N}\right)$

$\Rightarrow$Pr[rebuild at level d]$=\theta\left(\frac{2^d \log N}{N}\right)$

$\Rightarrow$PMA size at level d: $\theta\left(N/2^d\right)$

$\Rightarrow$E[work for rebuild at level d]$=\theta\left(\log N\right)$

E[insert cost]$=\theta\left(\log^2 N\right)$

Validation

- HI data structures cost something (but only a constant factor in theory and about 7x on initial experiments
- If there is any error in the implementation, could lose HI property
  - History independence is delicate
- How to validate an implementation

Validation

1) Pick an arbitrary element $y \in S$,
2) Build an HIPMA from scratch on $S - \{y\}$,
3) Insert y into the PMA.

Let Y be the distribution of the PMA layout after this procedure. Finally consider the following procedure: 1) Pick an arbitrary element $z \notin S$, 2) build an HI PMA from scratch on $S \cup \{z\}$, and 3) delete z from the HI PMA. Let Z be the distribution of the HI PMA layout after this procedure. If insertion and deletion are implemented correctly, then all three distributions X , Y , and Z should be identical.

Kullback-Leibler Divergence (like testing for a fair die)

- Smallest size non-trivial data structure
- Trials in parallel

Final Thoughts

Online event detection:

- Algorithms and data structures allow rapid stream monitoring using "normal" architecture such as SSDs
- Compromise between fast ingestion and queries, but can approximately have both
- Store as much as you can to get the best information

Open research questions (firehose):

- Intentional data expiration in dictionaries for infinite streams
  - Theory and practice (larger tests)

History-independence:

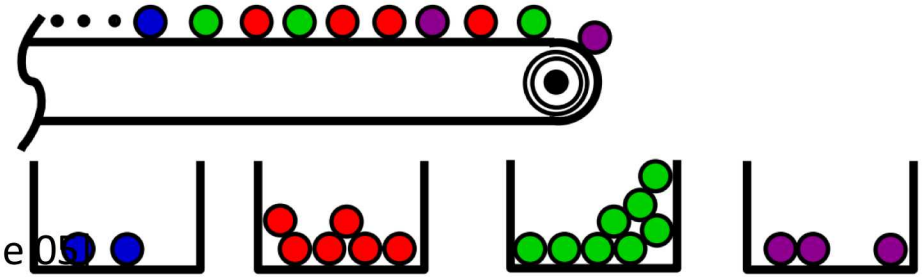
- Can have weak HI at no asymptotic cost
- Applications?

Bonus Time

- Suppose we want to find any element in a stream of size N that has a constant fraction (say 1/5) of the elements
- There can be at most 5 such elements
- If we find a count from 5 different elements, we can throw them away
  - Can do that fewer than N/5 times if don't throw all out
  - So any element with count at least N/5 still has a representative

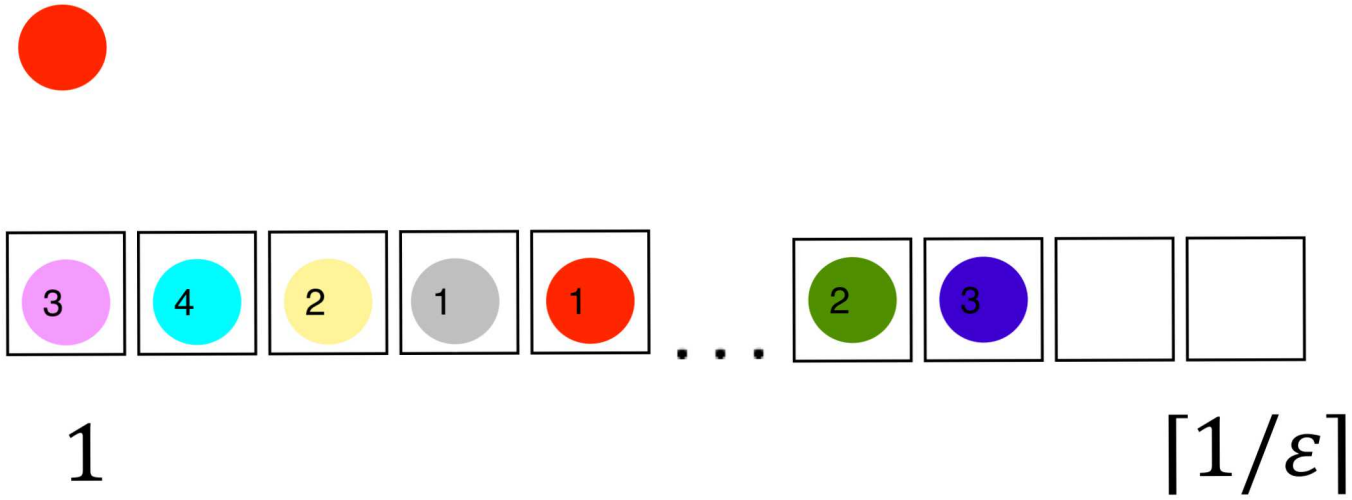
Misra Gries (MG) Algorithm

- Maintain $1/\varepsilon$ counters in memory
- When an item arrives
- if there is a counter for it, increment the counter
- if there is no counter for it
  - and there is space, add a counter and set to 1
  - otherwise, decrement all counters



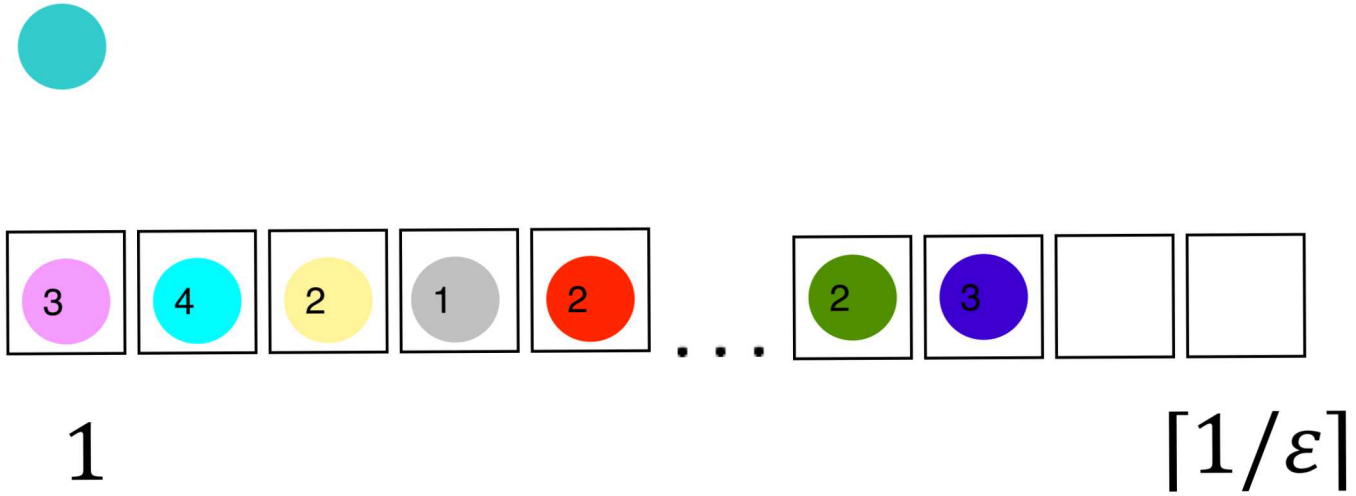
[Cormode 05]

Misra Gries (MG) Algorithm

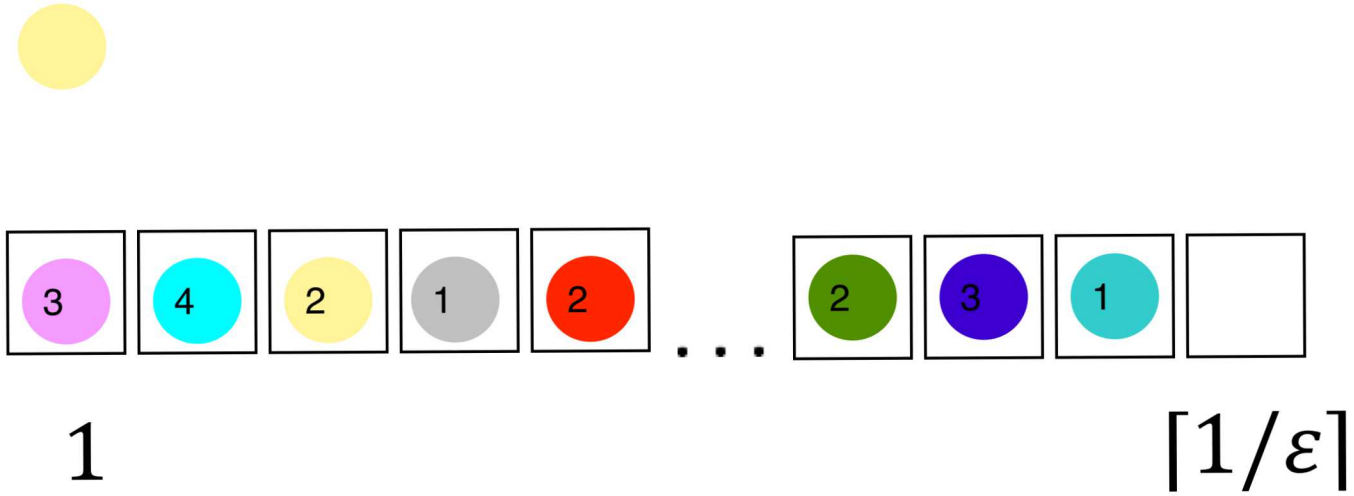


Items distinguished by color. Counts as shown

Misra Gries (MG) Algorithm



Misra Gries (MG) Algorithm



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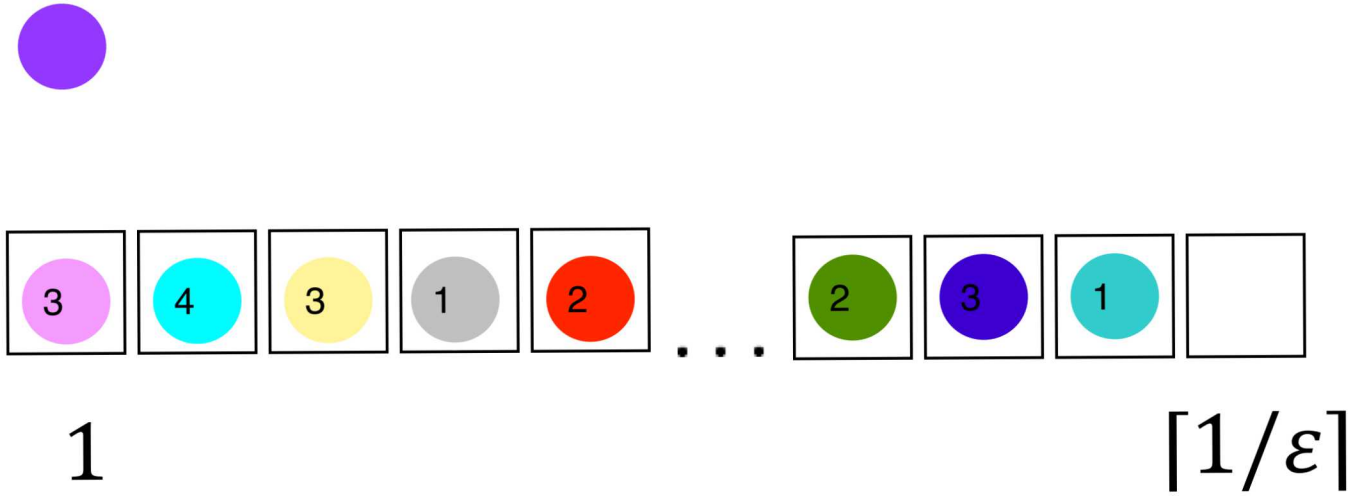
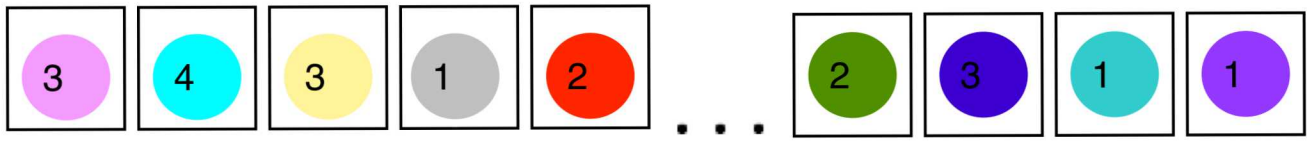


Misra Gries (MG) Algorithm

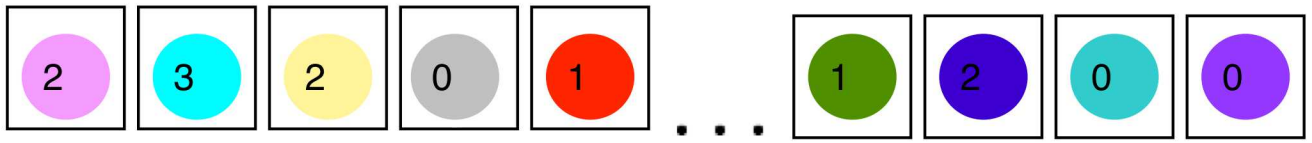
Item not in the list and there's no space



1 $\lceil 1/\varepsilon \rceil$

Misra Gries (MG) Algorithm

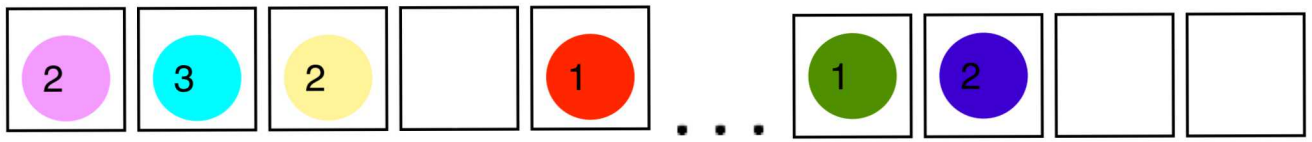
Decrement all counters



1 $\lceil 1/\varepsilon \rceil$

Misra Gries (MG) Algorithm

Remove if zero



1 $\lceil 1/\varepsilon \rceil$

External-Memory Misra Gries

Structure

- A sequence of geometrically increasing Misra-Gries tables
- The smallest table is in memory and is of size M, the last table is of size $\lceil 1/\varepsilon \rceil$
- Total levels = $O(\log 1/\varepsilon M)$

Algorithm

- The top level receives its input from the stream
- Decrements from one level are inputs to the level below
- Decrements from the last level leave the structure

Final Thoughts

Online event detection:

- Algorithms and data structures allow rapid stream monitoring using "normal" architecture such as SSDs
- Compromise between fast ingestion and queries, but can approximately have both
- Store as much as you can to get the best information

Open research questions (firehose):

- Intentional data expiration in dictionaries for infinite streams
  - Theory and practice (larger tests)

History-independence:

- Can have weak HI at no asymptotic cost
- Applications?