Data Stream Algorithms I

Joaquim Madeira

Version 0.5 – November 2024

Overview

- The data stream model
- Finding frequent items
- The MAJORITY problem
- The FREQUENT problem

MOTIVATION

Data Streams

- Many data generation processes can be modeled as data streams
  - Huge numbers of simple pieces of data
  - Arriving at enormous rates
  - Taken together lead to a complex whole

- Hundreds of gigabytes per day or higher !

Data Streams

- Sequence of queries posed to an Internet search engine
- Collection of transactions across all branches of a supermarket chain
- Sequence of packets in network traffic monitoring
- …

Data Streams

- Such data may be archived and indexed within a data warehouse
- BUT it may also be important to process it “as it happens” (Data Stream Algorithms)
- Up to the minute analysis and statistics on current trends

Data Streams

- Quick response to each new piece of information

- Resources used very small when compared to the total quantity of data

THE DATA STREAM MODEL

The streaming model

- Data arrives in a streaming fashion
  - Scan the sequence in the given order
  - No random access to the data tokens !
- Must be processed on the fly !
- Accurate computations

The streaming model

σ lowercase sigma
Φ Fi

- Compute some function $\Phi(\sigma)$ of a massively long input stream σ
- Make just one pass over σ !
- Goal:
  - Use resources (space and time) sublinear on the size of the input !

The streaming model

- When to produce output ?

- At the end of the stream
- When queried on the stream prefix observed so far
- Whenever there is a stream update
- On a “sliding window” of the most recent updates

The basic streaming model

- The data stream:

$$\sigma = \langle a_1, a_2, \ldots, a_m \rangle$$

- Each data token a_i is drawn from a set of n elements

- Goal:
  - Process σ using a small amount of memory *s*
  - I.e., make *s* much smaller than *m* and *n* !

The quality of an algorithm's answer

- $\Phi(\sigma)$ is usually a real-valued function
- Allow for
  - Computing an estimate or approximation of $\Phi(\sigma)$
  - Possibly using randomized algorithms
    - That may err with a small, but controllable probability
- How to evaluate the quality of the result ?

The quality of an algorithm's answer

- $A(\sigma)$ is the output of a randomized algorithm
  - It is a random variable !
- (ε, δ)-approximation of $\Phi(\sigma)$

$$P\left(\left|\frac{A(\sigma)}{\Phi(\sigma)} - 1\right| > \varepsilon\right) \leq \delta$$

- (ε, δ)-additive-approximation of $\Phi(\sigma)$

$$P(|A(\sigma) - \Phi(\sigma)| > \varepsilon) \leq \delta$$

Probability of the adhitive error being bigger is smaller

FINDING FREQUENT ITEMS

Finding frequent items

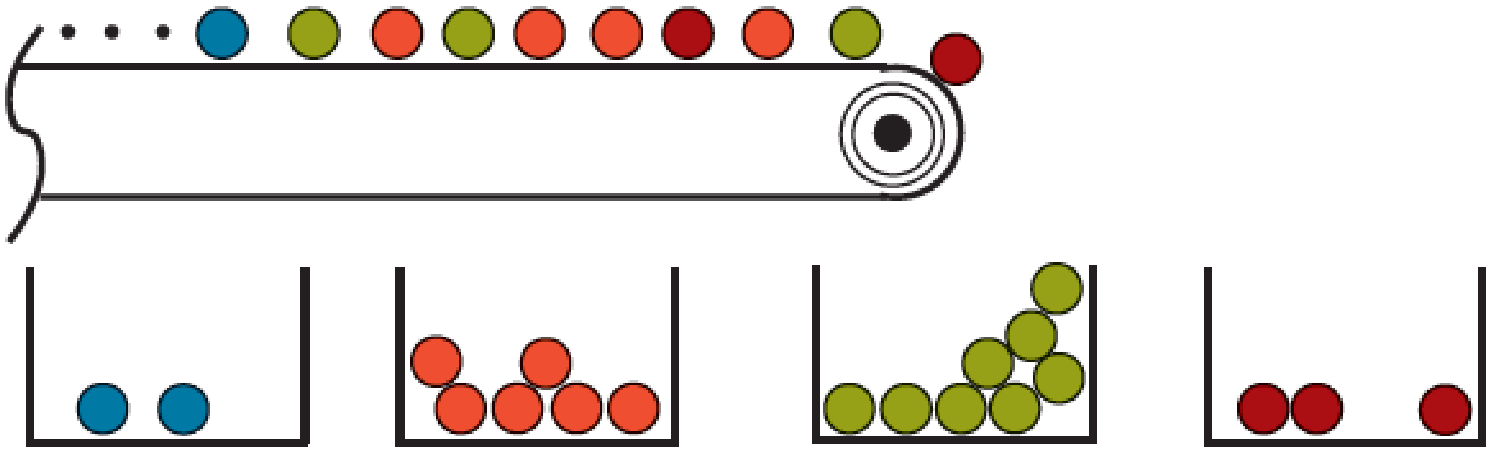
- The frequent items / “heavy-hitters” problem

- Given a sequence of items, identify those which occur most frequently

- More formally :
- Find all items whose frequency exceeds a specified fraction of the total number of items

Finding frequent items

Figure 1. A stream of items defines a frequency distribution over items. In this example, with a threshold of $\phi = 20\%$ over the 19 items grouped in bins, the problem is to find all items with frequency at least 3.8—in this case, the green and red items (middle two bins).



[Cormode and Hadjieleftheriou]

Finding frequent items

- Network packet monitoring
  - Frequent items represent the heaviest bandwidth users
- Queries made to a search engine
  - Frequent items are the currently popular terms
- …

Finding frequent items

- Counter-based algorithms
  - Track and maintain counts associated with a (varying) subset of stream items
- Sketch algorithms
  - Randomized approach
  - Do not explicitely store stream elements
- Other approaches

Finding frequent items

- Given a stream: $\sigma = \langle a_1, a_2, \dots, a_m \rangle$
- It induces a frequency vector:

$$\boldsymbol{f} = (f_1, f_2, \dots, f_n)$$

$$f_1 + f_2 + \cdots, + f_n = m$$

- The MAJORITY problem
  - If $\exists\, j : f_j > \frac{m}{2}$, then output *j*, otherwise output null
- The FREQUENT problem, with parameter k

fj > m/k

THE MAJORITY PROBLEM

The MAJORITY problem

- Applications ?
- Elections
- Fault-tolerant computing
  - Perform multiple redundant computations
  - Check if a majority of the results agree
- …

The MAJORITY problem

- Naïve algorithm for a non-sorted list of values

Imagine a list with just zeros and ones

- Sort the list
- If there is a majority value, it is now the middle value
  - Odd vs even number of list elements
- O(n log n)
- BUT, not useful for data streams !

The MAJORITY problem

- Naïve algorithm

- n frequency counters

- Three-step algorithm
  - Scan the sequence and increment the counters
  - Scan the counters and find the most frequent element
  - Check if it is the majority element : > (m / 2)

- Efficiency ?

MJRTY ALGORITHM – BOYER & MOORE (1980)

Republican and democrat shake hands

The MAJORITY problem

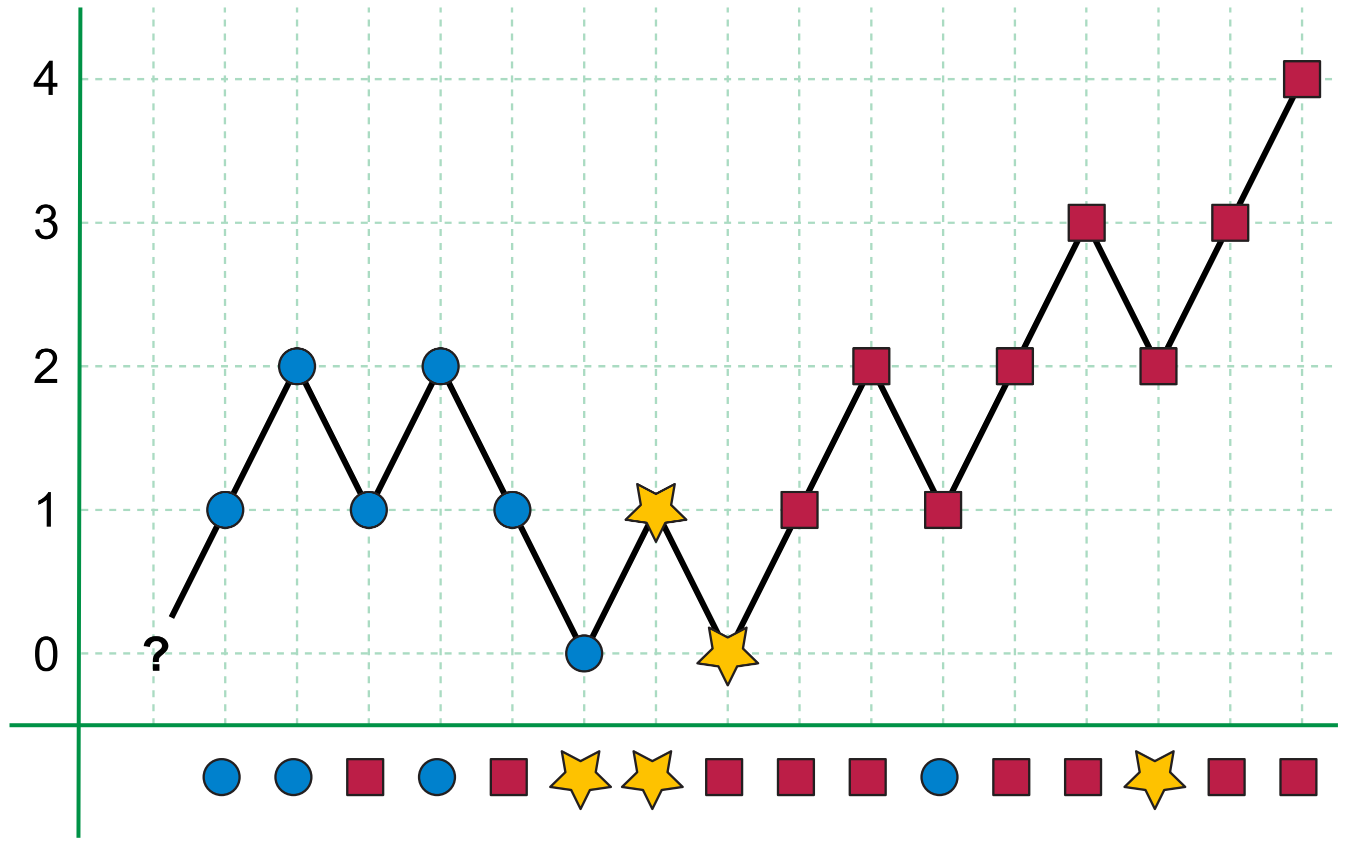
- Boyer & Moore : A fast majority vote alg.
  - 1980
  - http://www.cs.utexas.edu/~moore/best-ideas/mjrty/
- Provided there is such an element, it decides which sequence element is in the majority
- Two-pass algorithm
  - Scan the sequence to identify the majority candidate
  - Scan, again, the sequence, to verify if that candidate is indeed in the majority

MJRTY – A fast majority vote alg.

```
// Initialization
candidate = null; counter = 0;

// First-pass
while ( not end of sequence )
        x = current_token();
        if ( counter == 0 )
        then candidate = x; counter = 1;
        else    if ( candidate == x )
                then counter++;
                else counter--;
```

MJRTY – A fast majority vote alg.



[Wikipedia]

MJRTY – A fast majority vote alg.

```
// Second-pass
counter = 0;
while ( not end of sequence  and counter < (1 + m / 2) )
        x = current_token();
        if ( candidate == x )
        then counter++;
```

- Efficiency ?

MJRTY – A fast majority vote alg.

- Can we skip the second pass ?
  - Find a counter-example ! no caso de um huge array de dados- Imagine 2 with same number of elements

- O(1) extra space
- O(n) time

- BUT we cannot perform a second pass over a data stream…
  - However, we have a “partial guarantee”

Tasks – The MAJORITY problem

- Implement the naïve algorithm
- Implement the Boyer & Moore algorithm

- Compare their results and running times
  - For random strings over a given alphabet

- For the B & M algorithm, check how many times the majority candidate was indeed the majority

THE FREQUENT PROBLEM

The FREQUENT problem

- The FREQUENT problem, with parameter k
  - Output the set $\{ j : f_j > m/k \}$
- It solves the MAJORITY problem !
- Similar naïve algorithm !
- Can we do better ?

FREQUENCY ESTIMATION – MISRA & GRIES (1982)

Frequency estimation

- The FREQUENCY-ESTIMATION problem
  - Process the stream σ
  - Establish an estimate for the frequency of any stream token

- Misra & Gries : Finding repeated elements
  - 1982
  - http://www.sciencedirect.com/science/article/pii/0167642382900120

- One-pass algorithm

The Misra & Gries algorithm

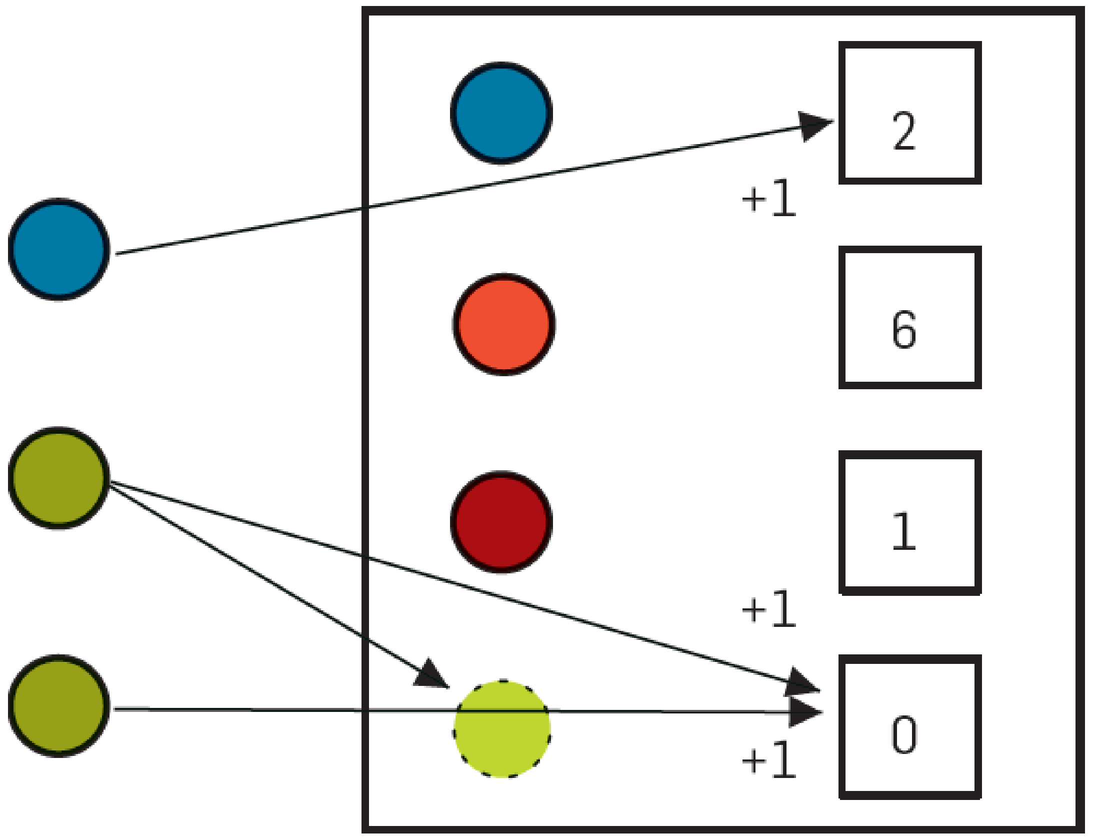
- Parameter k controls the quality of the results given

- It maintains an associative array (map, dictionary)
  - The keys are tokens seen in the stream
  - Array values are counters associated with the keys / tokens

- At most (k – 1) counters, at any time

The Misra & Gries algorithm

Figure 2. Counter-based data structure: the blue (top) item is already stored, so its count is incremented when it is seen. The green (middle) item takes up an unused counter, then a second occurrence increments it.



[Cormode and Hadjieleftheriou]

The Misra & Gries algorithm

```
Algorithm 1: FREQUENT(k)
n ← 0;
T ← ∅;
foreach i do
    n ← n + 1;
    if $i \in T$ then
        $c_i \leftarrow c_i + 1$;
    else if $|T| < k-1$ then
        $T \leftarrow T \cup \{i\}$;
        $c_i \leftarrow 1$;
    else forall $j \in T$ do
        $c_j \leftarrow c_j - 1$;
        if $c_j = 0$ then $T \leftarrow T \setminus \{j\}$;
```

Overcounts?	NO
Undercounts?	POSSIBLE

[Cormode and Hadjieleftheriou]

The Misra & Gries algorithm

```
// Initialization
A = empty associative array;
// Processing
while ( not end of sequence )
        j = current_token();
        if ( j in keys(A) ) then A[ j ] = A[ j ] + 1;
        else    if ( | keys(A) | < ( k – 1 ) ) then A[ j ] = 1;
                else    for each i in keys(A) do
                            A[ i ] = A[ i ] – 1;
                            if ( A[ i ] == 0 ) then remove i from A;
// Output
if( a in keys(A) ) then freq_estimate = A[ a ];
else freq_estimate = 0;
```

The Misra & Gries algorithm

- The algorithm, with parameter k, provides, for any token *j*, a freq. estimate f_j^* satisfying

$$f_j - \frac{m}{k} \leq f_j^* \leq f_j$$

  - If some token has $f_j > m / k$, its counter A[j] will be positive

- With an additional pass through the stream, to count the exact frequencies, we can now solve the FREQUENT problem !

Tasks – The Misra & Gries algorithm

- Implement the naïve algorithm
- Implement the Misra & Gries algorithm
  - Choose an appropriate data structure for the associative array
- Test them, using the same input sequences as for the B & M algorithm
  - For different k values !!

Misra & Gries – Recap

- Finds up to (k – 1) items that occur more than a 1/k fraction of the time in the input
- Keeps, at most, (k – 1) candidates at the same time
- No item with frequency m / k is missed
- Algorithm “rediscovered” twice in 2002 !

Implementation issues

- Basic steps
  - Lookup for an item
  - Update a counter
  - Decrement all counters
  - Delete an item with zero counts
- How to ?
  - Optimize speed and space

Implementation issues – Lookup

- Which dictionary data structure ?

- Misra & Gries used a balanced search tree
  - Worst and average case are O(log k)
- Hash table : hash to O(k) buckets
  - Collisions / deletions : how to handle ?
  - Use chaining ?
  - Optimizations ?
- Other ?

Implementation issues – Decrement

- Iterate through all counters : O(k)
- BUT it happens O(n/k) times
- Optimize ?

- Use a linked list of lists to keep elements grouped by their frequency counts
- Memory space overhead
  - Circular linked lists
  - Also, pointers to and from hash table

LOSSY-COUNTING – MANKU & MOTWANY (2002)

Additional algorithms

- There are other algorithms which can be regarded as variations of Misra & Gries' algorithm :

- Lossy-Counting
  - Manku and Motwani, 2002

- Space-Saving
  - Metwally et al., 2005

The Manku & Motwani algorithm

Algorithm 2: LossyCounting(k)

```
$n \leftarrow 0$; $\Delta \leftarrow 0$; $T \leftarrow \emptyset$;
foreach $i$ do
    $n \leftarrow n + 1$;
    if $i \in T$ then $c_i \leftarrow c_i + 1$;
    else
        $T \leftarrow T \cup \{i\}$;
        $c_i \leftarrow 1 + \Delta$;
if $\lfloor n/K \rfloor \neq \Delta$ then
    $\Delta \leftarrow \lfloor n/k \rfloor$;
    forall $j \in T$ do
        if $c_i < \Delta$ then $T \leftarrow T \setminus \{j\}$;
```

should be indented and lowercase k

j

- **k** — Inverse of the error parameter ϵ. The error parameter epsilon determines the maximum allowable error (in an overestimate) of the frequency count as $\epsilon \cdot n = n/k$, where n is the current number of processed elements. Therefore, a smaller value of ϵ (and consequently an higher value of k) leads to more accurate frequency counts, but requires more memory;
- **delta** — Δ corresponds to the maximum possible error in the frequency of the element and is the result of the application of the formula $\lfloor n/k \rfloor$, where n is the current number of processed elements. As the formula suggests, this value evolves as new elements of the stream are processed;
- **buckets** — The buckets or bins that store the words and their counts;
- **n** — The total number of processed items, which is increased every time an item from the stream (in this case a word) is processed. After parsing through all words in the list, return the word count map.

[Cormode and Hadjieleftheriou]

Manku & Motwani – Lossy-Counting

- Keep item names and counts
  - Counter value is a lower bound – initially zero
- And an "implicit" delta value

(maximum possible error)

- A new item – what to do ?

- If it has a counter, increment counter
- Otherwise, initiallize with a count of 1 + delta
- Whenever delta increases :
  - Delete tuples with a count smaller than delta

Manku & Motwani – Lossy-Counting

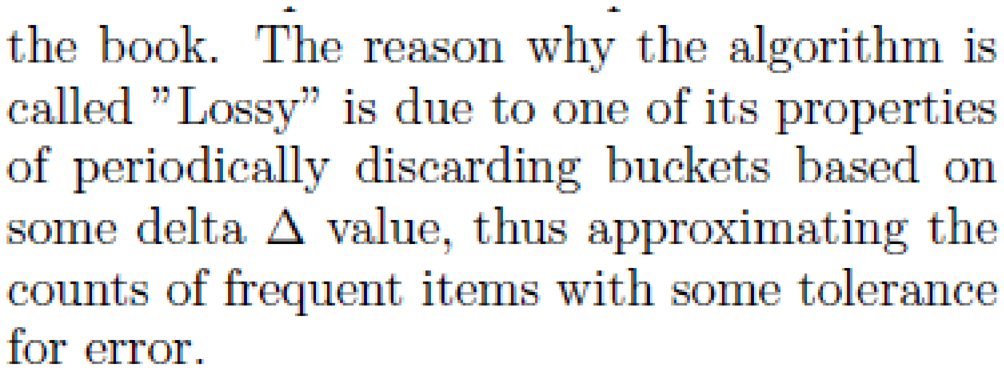
- Deleting tuples reduces the required space !

- Monitored items can have their frequencies overestimated by no more than n / k = ε × n

ε = 1 / k

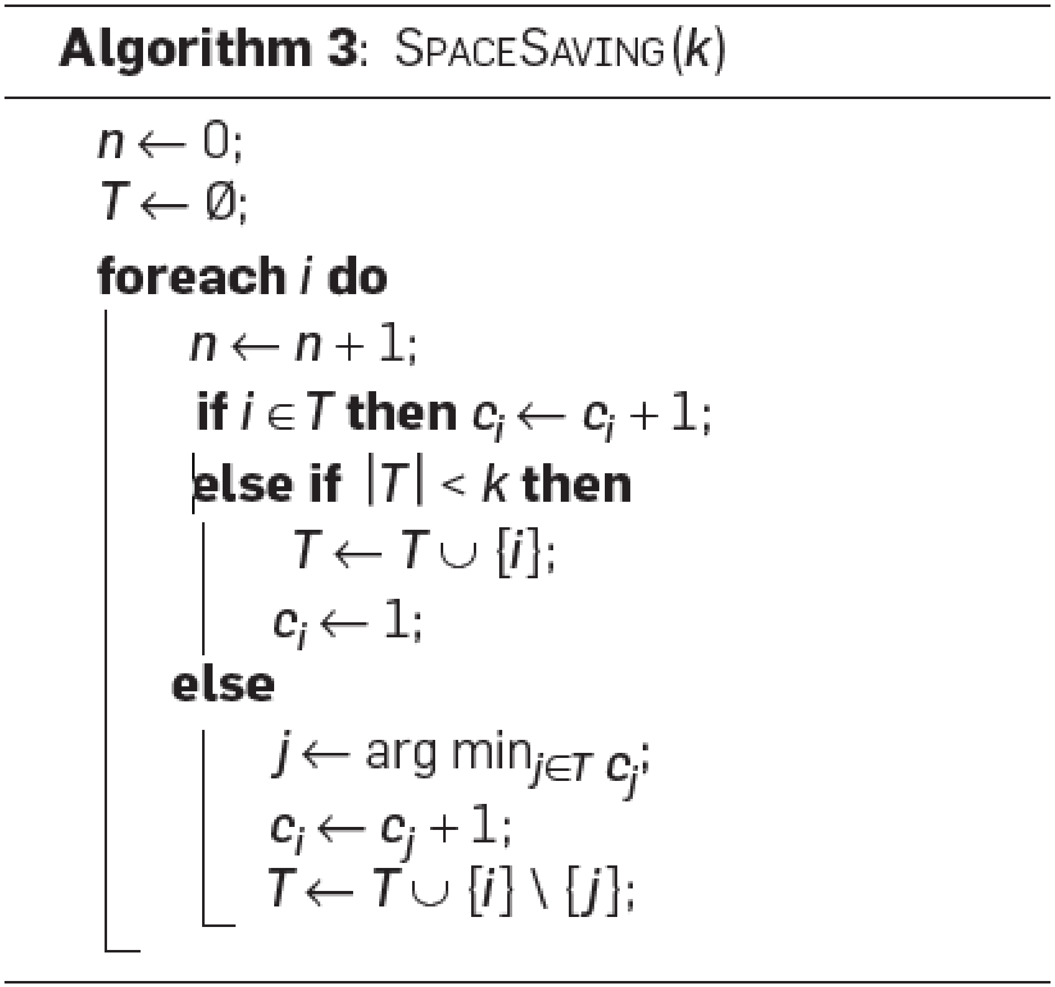
- BUT never underestimated !!

ONLY OVERCOUNTS


the book. The reason why the algorithm is called "Lossy" is due to one of its properties of periodically discarding buckets based on some delta Δ value, thus approximating the counts of frequent items with some tolerance for error.

SPACE-SAVING
– METWALLY ET AL (2002)

The Metwally et al. algorithm



Algorithm 3: SpaceSaving(k)

```
$n \leftarrow 0$;
$T \leftarrow \emptyset$;
foreach $i$ do
    $n \leftarrow n + 1$;
    if $i \in T$ then $c_i \leftarrow c_i + 1$;
    else if $|T| < k$ then
        $T \leftarrow T \cup \{i\}$;
        $c_i \leftarrow 1$;
    else
        $j \leftarrow \arg\min_{j \in T} c_j$;
        $c_i \leftarrow c_j + 1$;
        $T \leftarrow T \cup \{i\} \setminus \{j\}$;
```

[Cormode and Hadjieleftheriou]

Metwally et al. – Space-Saving

- Keep $k=1/\varepsilon$ item names and counts
  - Initially zero
- Count first k items exactly !
- A new item – what to do ?

- If it has a counter, increment counter
- Otherwise, replace item with least count
- And increment count

Metwally et al. – Space-Saving

- Counters sum to n !
- Average count value is n / k = ε × n
  - Smallest count min cannot be larger than ε × n
- True count of an uncounted item is between 0 and ε × n
- All items whose true count is > ε × n are stored !

Tasks

- Implement the Lossy-Counting and the Space-Saving algorithms
- Test them, using the same input sequences as for the M & G algorithm
- Compare the behavior of the three algorithms

Implementation issues

- Similar to Misra & Gries
- Finding the min item is a standard problem
  - Use a min-heap !
  - Binary, binomial, Fibonacci, … ?
  - O(log k)

Question

- What can you say about the estimated counts for items which are stored by the algorithms early in the stream and are not removed ?

Question

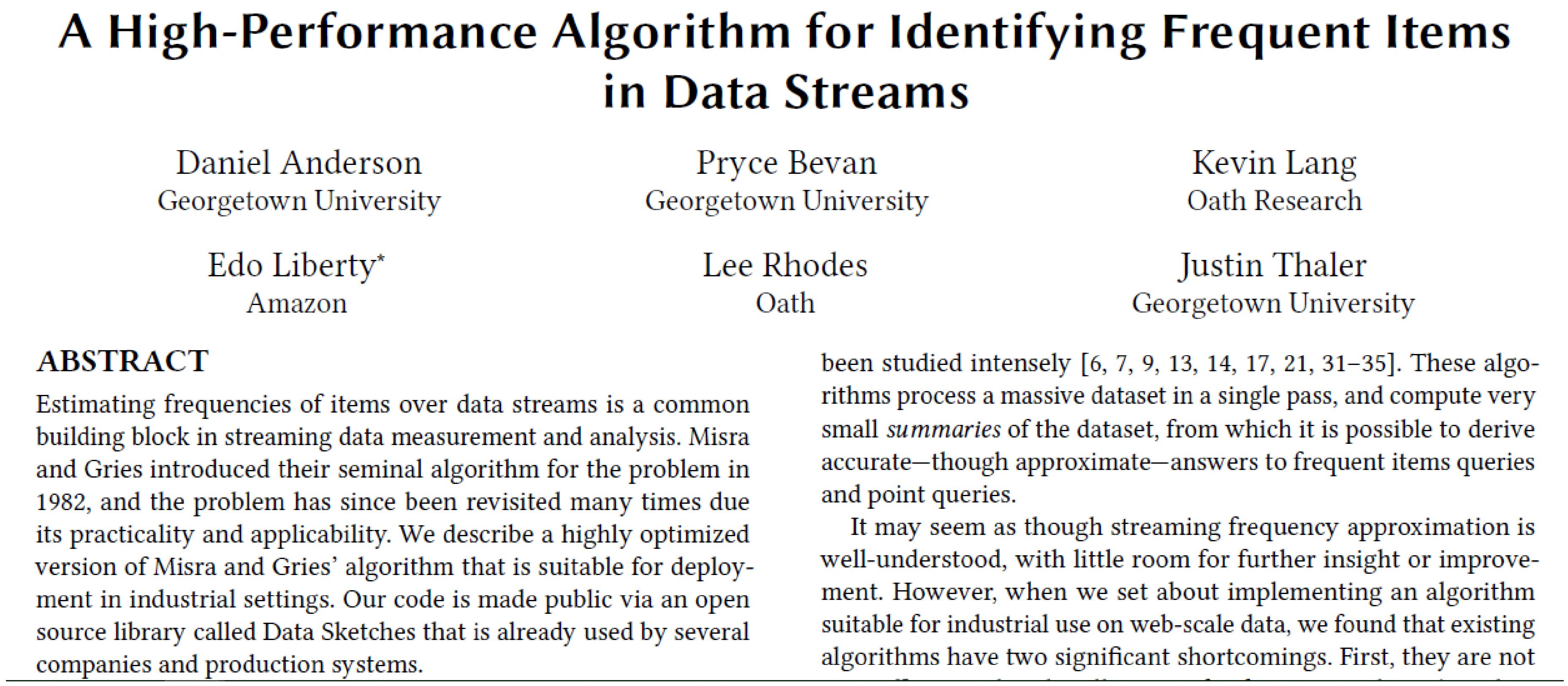
- Have we been discussing deterministic algorithms or randomized/probabilistic algorithms ?

Experimental comparison

- Cormode & Hadjieleftheriou
  - VLDB 2008 - https://dl.acm.org/citation.cfm?id=1454225
  - CACM 2009 - https://dl.acm.org/citation.cfm?id=1562789
- SPACESAVING has benefits over others !
- Very fast: 20M – 30M updates *per second*
- Implementation choices: speed vs space
  - E.g., a heap or lists of items grouped by frequencies

RECENT APPROACHES

2017 – Optimized Misra & Gries



A High-Performance Algorithm for Identifying Frequent Items in Data Streams

Daniel Anderson
Georgetown University

Pryce Bevan
Georgetown University

Kevin Lang
Oath Research

Edo Liberty*
Amazon

Lee Rhodes
Oath

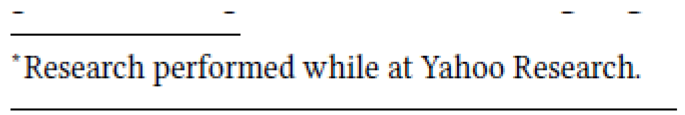
Justin Thaler
Georgetown University

ABSTRACT

Estimating frequencies of items over data streams is a common building block in streaming data measurement and analysis. Misra and Gries introduced their seminal algorithm for the problem in 1982, and the problem has since been revisited many times due its practicality and applicability. We describe a highly optimized version of Misra and Gries' algorithm that is suitable for deployment in industrial settings. Our code is made public via an open source library called Data Sketches that is already used by several companies and production systems.

been studied intensely [6, 7, 9, 13, 14, 17, 21, 31–35]. These algorithms process a massive dataset in a single pass, and compute very small *summaries* of the dataset, from which it is possible to derive accurate—though approximate—answers to frequent items queries and point queries.

It may seem as though streaming frequency approximation is well-understood, with little room for further insight or improvement. However, when we set about implementing an algorithm suitable for industrial use on web-scale data, we found that existing algorithms have two significant shortcomings. First, they are not

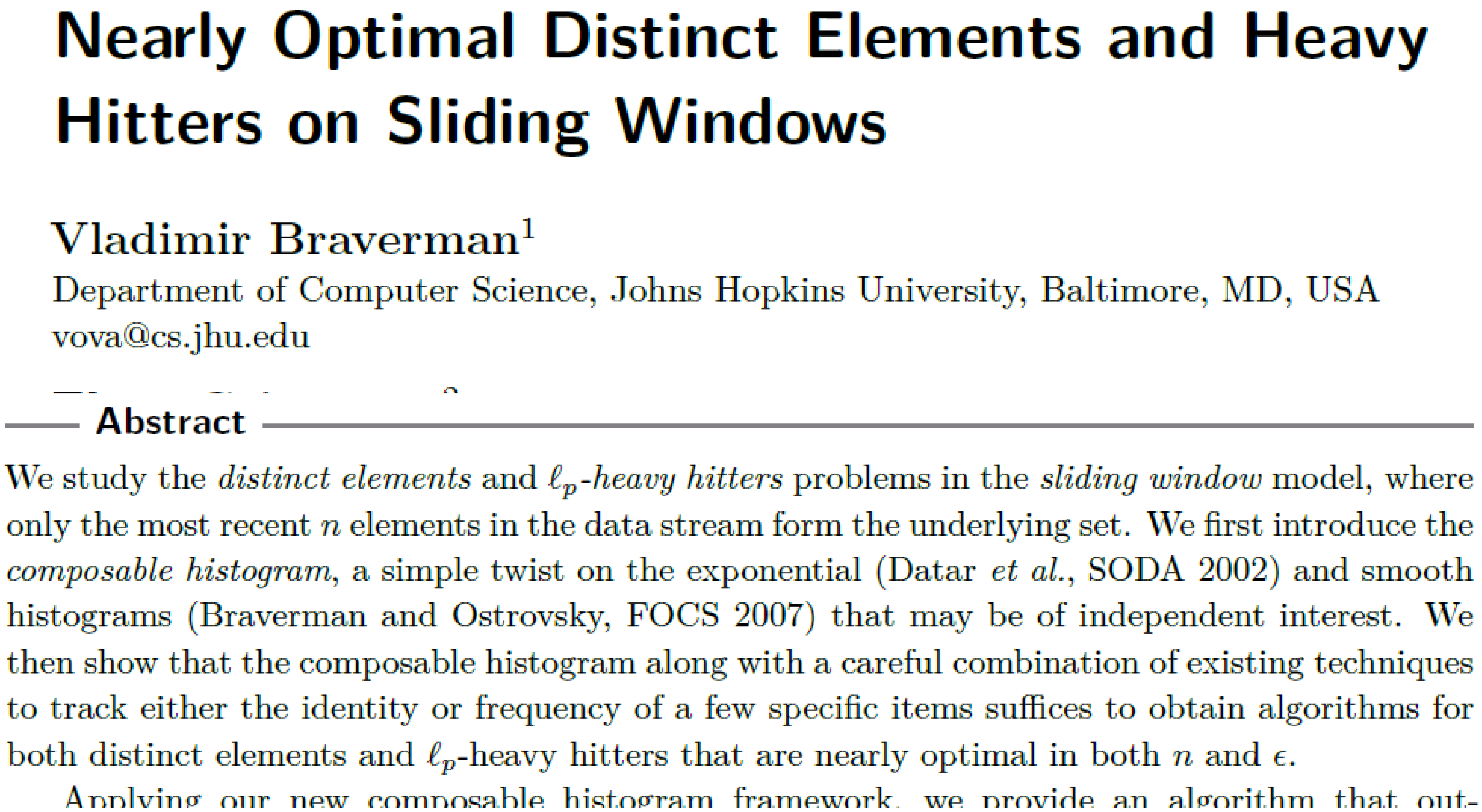


*Research performed while at Yahoo Research.

https://dl.acm.org/citation.cfm?doid=3131365.3131407

https://datasketches.github.io/

2018 – Braverman et al.



Nearly Optimal Distinct Elements and Heavy Hitters on Sliding Windows

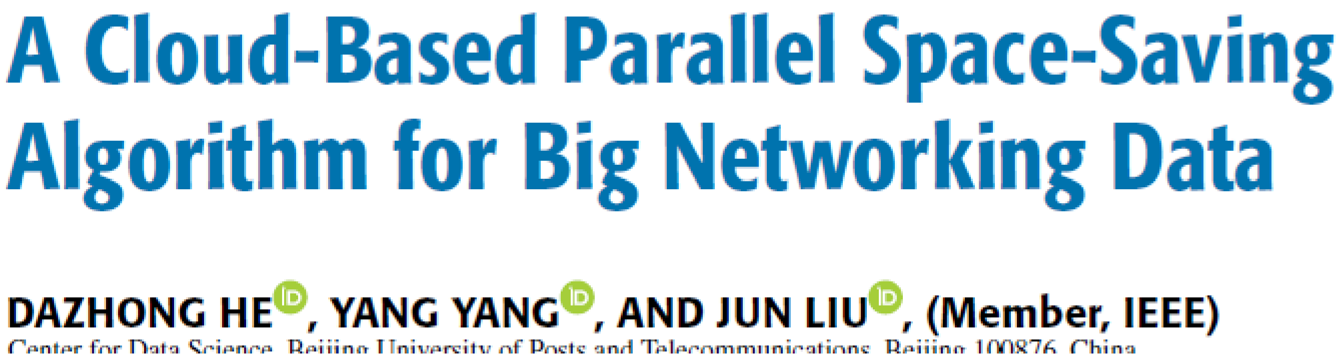
Vladimir Braverman[1]
Department of Computer Science, Johns Hopkins University, Baltimore, MD, USA
vova@cs.jhu.edu

Abstract

We study the *distinct elements* and ℓ_p*-heavy hitters* problems in the *sliding window* model, where only the most recent n elements in the data stream form the underlying set. We first introduce the *composable histogram*, a simple twist on the exponential (Datar *et al.*, SODA 2002) and smooth histograms (Braverman and Ostrovsky, FOCS 2007) that may be of independent interest. We then show that the composable histogram along with a careful combination of existing techniques to track either the identity or frequency of a few specific items suffices to obtain algorithms for both distinct elements and ℓ_p-heavy hitters that are nearly optimal in both n and ϵ.

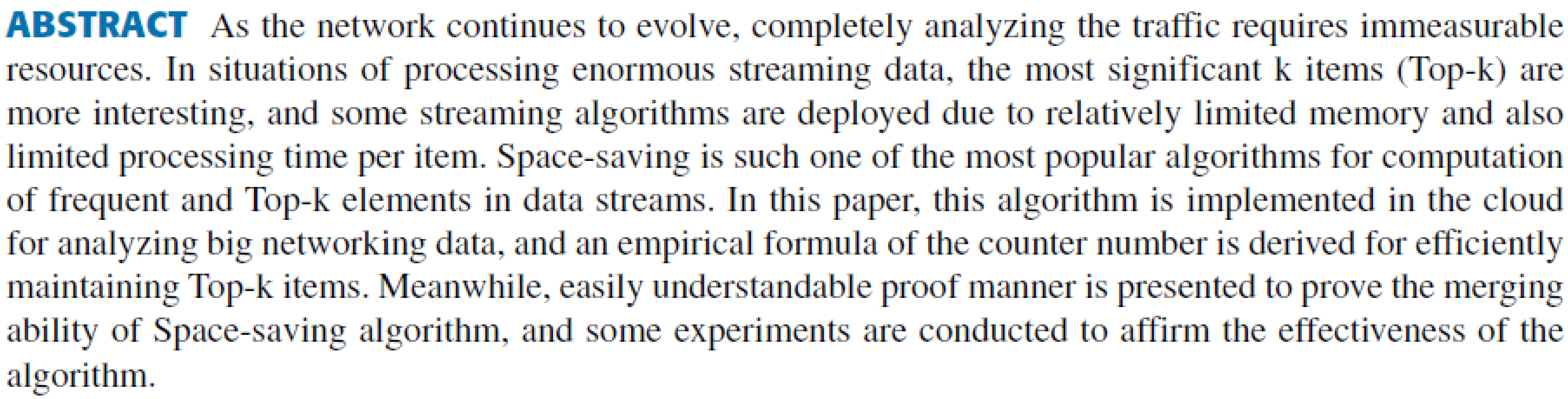
Applying our new composable histogram framework, we provide an algorithm that out-

2018 – Parallel Space-Saving Alg.



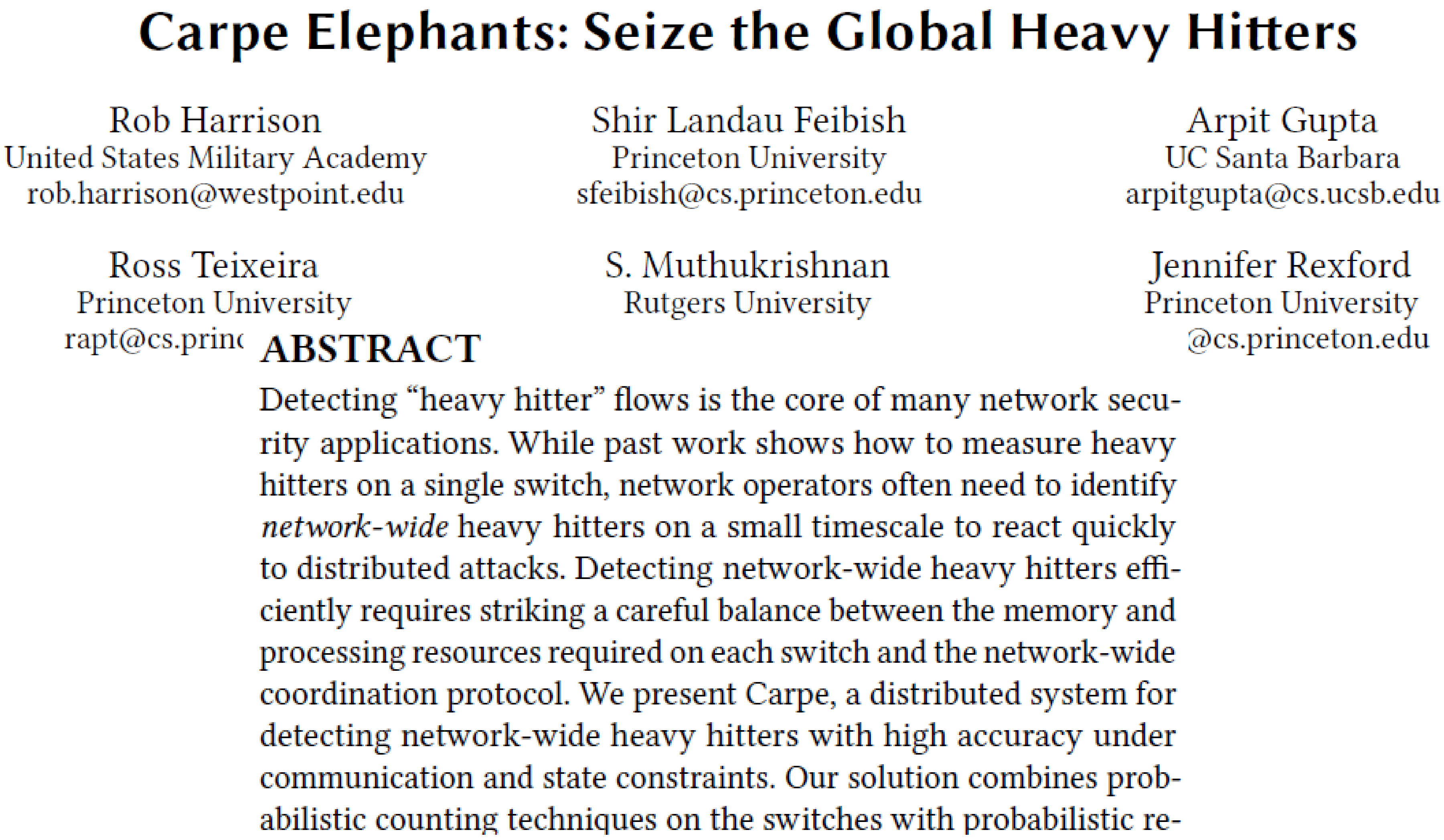
A Cloud-Based Parallel Space-Saving Algorithm for Big Networking Data

DAZHONG HE, YANG YANG, AND JUN LIU, (Member, IEEE)
Center for Data Science, Beijing University of Posts and Telecommunications, Beijing 100876, China



ABSTRACT As the network continues to evolve, completely analyzing the traffic requires immeasurable resources. In situations of processing enormous streaming data, the most significant k items (Top-k) are more interesting, and some streaming algorithms are deployed due to relatively limited memory and also limited processing time per item. Space-saving is such one of the most popular algorithms for computation of frequent and Top-k elements in data streams. In this paper, this algorithm is implemented in the cloud for analyzing big networking data, and an empirical formula of the counter number is derived for efficiently maintaining Top-k items. Meanwhile, easily understandable proof manner is presented to prove the merging ability of Space-saving algorithm, and some experiments are conducted to affirm the effectiveness of the algorithm.

2020 – Harrison et al.



Carpe Elephants: Seize the Global Heavy Hitters

Rob Harrison
United States Military Academy
rob.harrison@westpoint.edu

Shir Landau Feibish
Princeton University
sfeibish@cs.princeton.edu

Arpit Gupta
UC Santa Barbara
arpitgupta@cs.ucsb.edu

Ross Teixeira
Princeton University
rapt@cs.princ

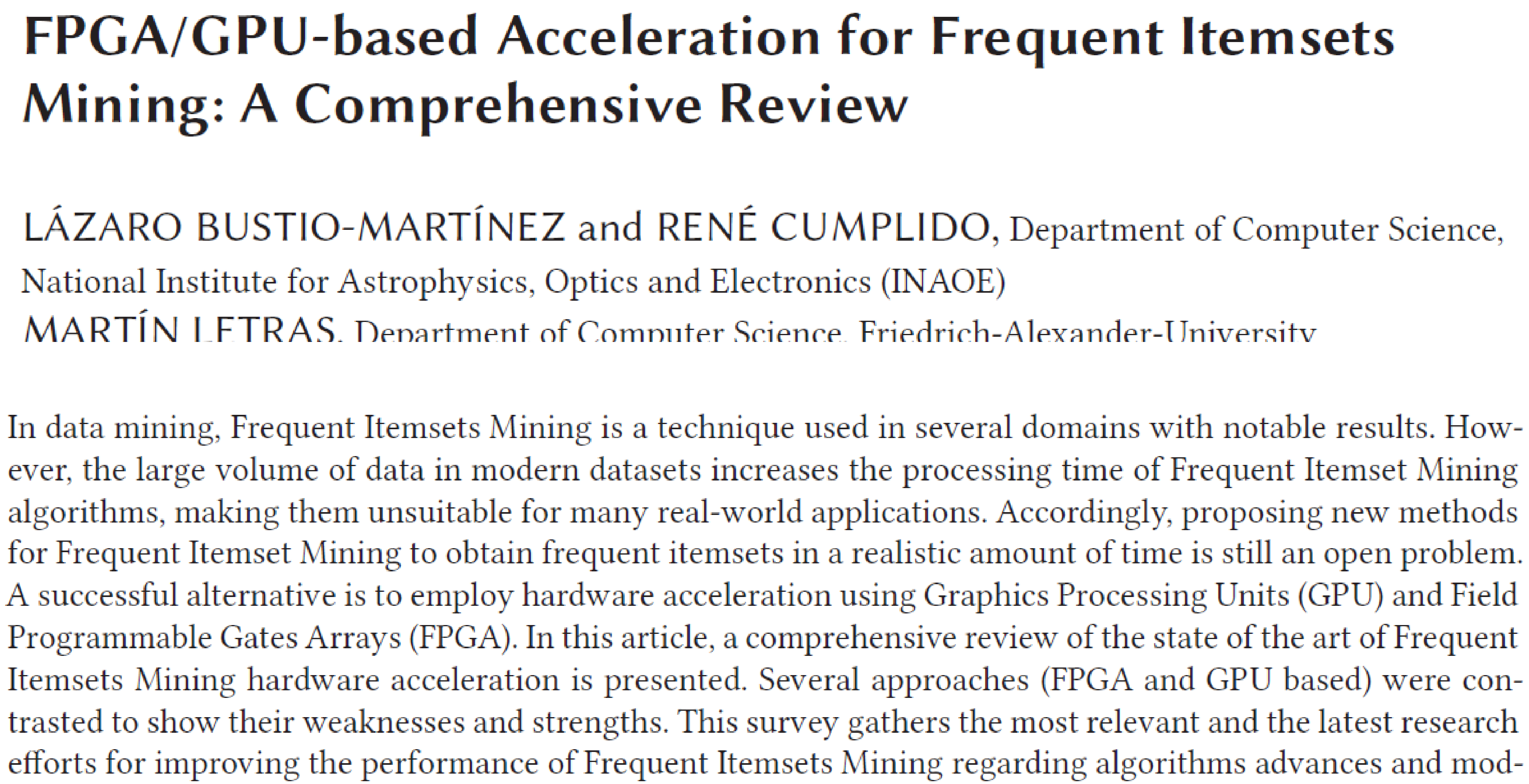
S. Muthukrishnan
Rutgers University

Jennifer Rexford
Princeton University
@cs.princeton.edu

ABSTRACT

Detecting "heavy hitter" flows is the core of many network security applications. While past work shows how to measure heavy hitters on a single switch, network operators often need to identify *network-wide* heavy hitters on a small timescale to react quickly to distributed attacks. Detecting network-wide heavy hitters efficiently requires striking a careful balance between the memory and processing resources required on each switch and the network-wide coordination protocol. We present Carpe, a distributed system for detecting network-wide heavy hitters with high accuracy under communication and state constraints. Our solution combines probabilistic counting techniques on the switches with probabilistic re-

2021 – FPGA/GPU-based methods

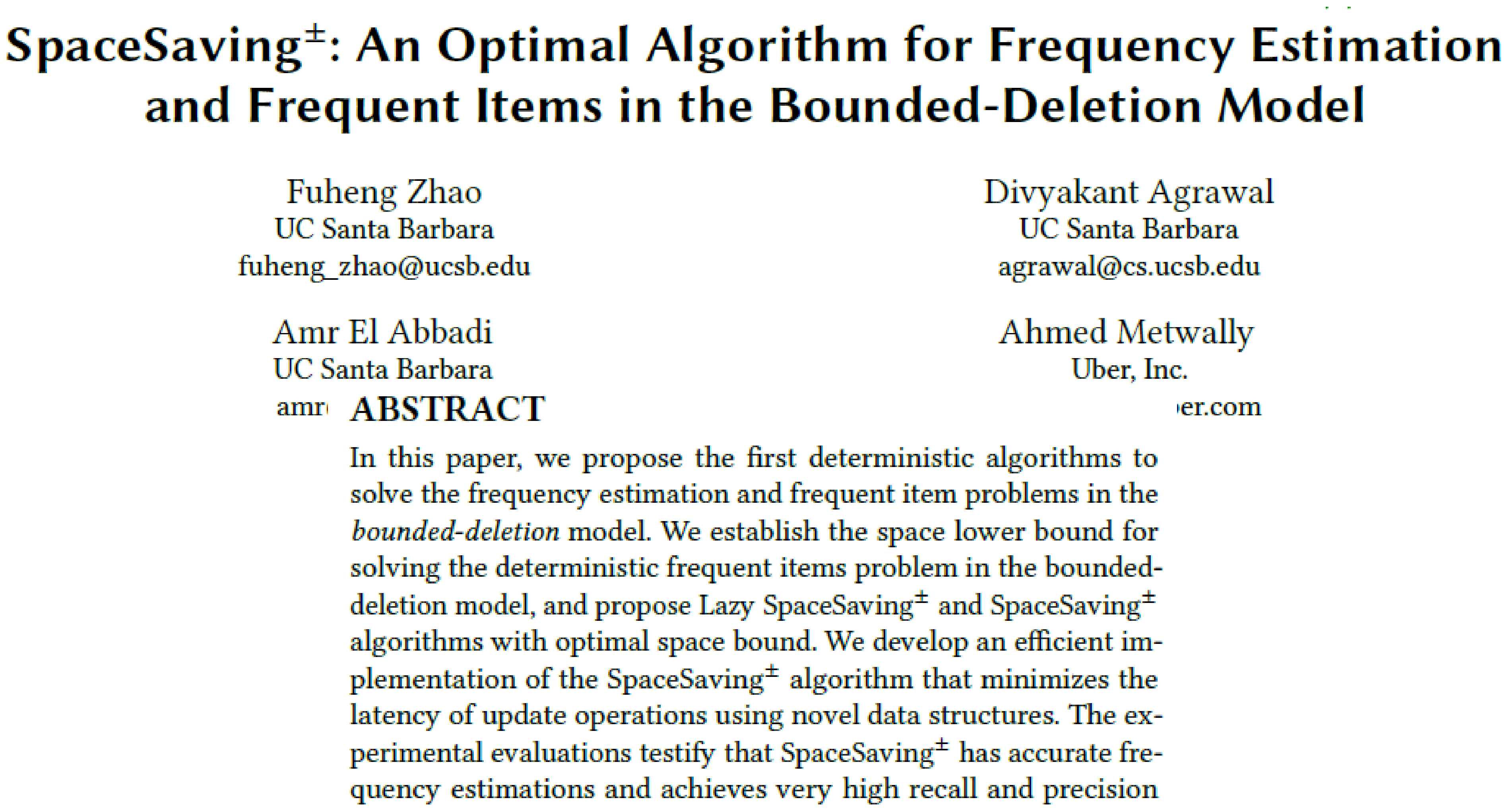


FPGA/GPU-based Acceleration for Frequent Itemsets Mining: A Comprehensive Review

LÁZARO BUSTIO-MARTÍNEZ and RENÉ CUMPLIDO, Department of Computer Science, National Institute for Astrophysics, Optics and Electronics (INAOE)
MARTÍN LETRAS, Department of Computer Science, Friedrich-Alexander-University

In data mining, Frequent Itemsets Mining is a technique used in several domains with notable results. However, the large volume of data in modern datasets increases the processing time of Frequent Itemset Mining algorithms, making them unsuitable for many real-world applications. Accordingly, proposing new methods for Frequent Itemset Mining to obtain frequent itemsets in a realistic amount of time is still an open problem. A successful alternative is to employ hardware acceleration using Graphics Processing Units (GPU) and Field Programmable Gates Arrays (FPGA). In this article, a comprehensive review of the state of the art of Frequent Itemsets Mining hardware acceleration is presented. Several approaches (FPGA and GPU based) were contrasted to show their weaknesses and strengths. This survey gathers the most relevant and the latest research efforts for improving the performance of Frequent Itemsets Mining regarding algorithms advances and mod-

2022 – SpaceSaving+-



SpaceSaving$^{\pm}$: An Optimal Algorithm for Frequency Estimation and Frequent Items in the Bounded-Deletion Model

Fuheng Zhao
UC Santa Barbara
fuheng_zhao@ucsb.edu

Divyakant Agrawal
UC Santa Barbara
agrawal@cs.ucsb.edu

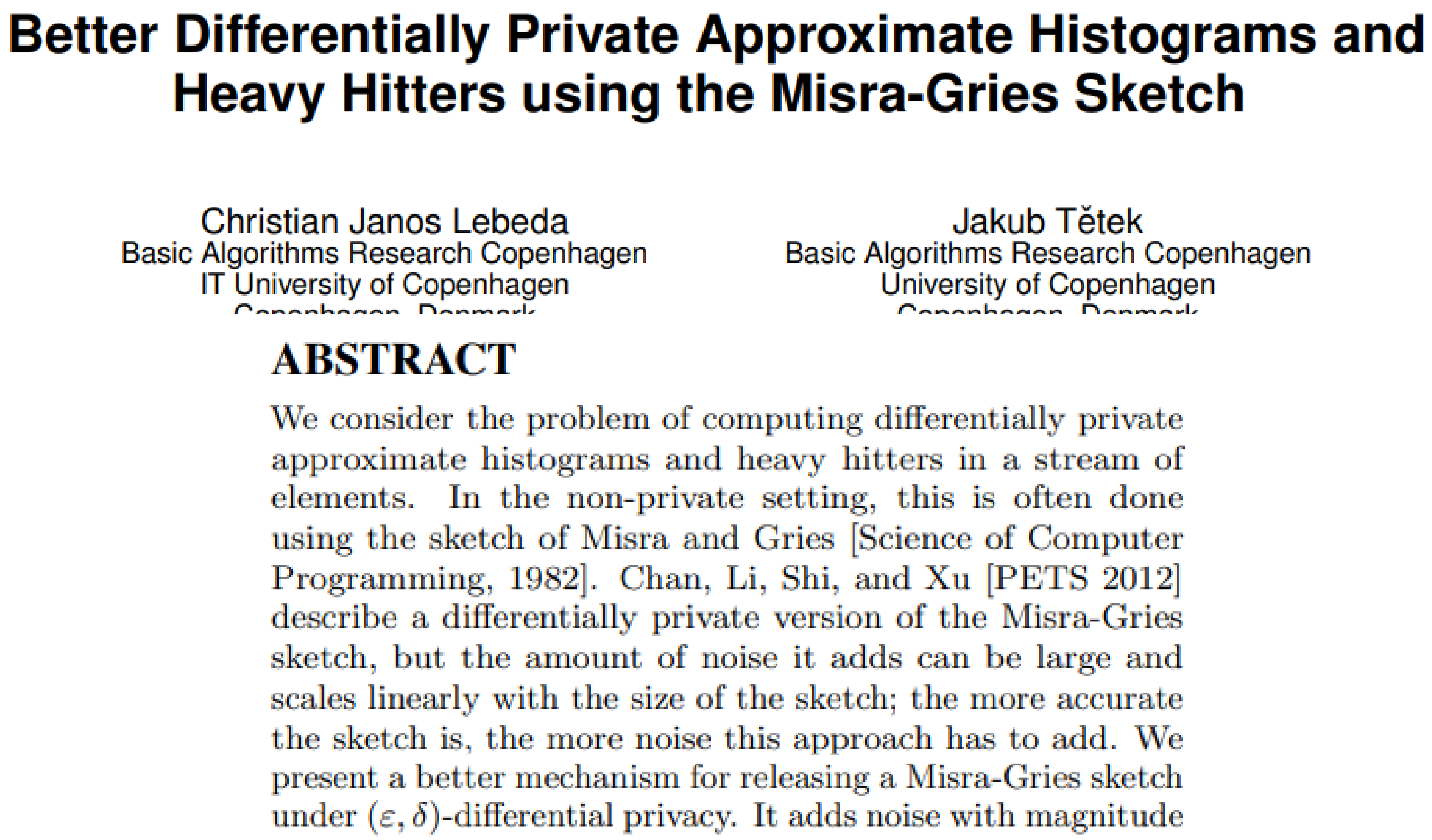
Amr El Abbadi
UC Santa Barbara
amr

Ahmed Metwally
Uber, Inc.
er.com

ABSTRACT

In this paper, we propose the first deterministic algorithms to solve the frequency estimation and frequent item problems in the *bounded-deletion* model. We establish the space lower bound for solving the deterministic frequent items problem in the bounded-deletion model, and propose Lazy SpaceSaving$^{\pm}$ and SpaceSaving$^{\pm}$ algorithms with optimal space bound. We develop an efficient implementation of the SpaceSaving$^{\pm}$ algorithm that minimizes the latency of update operations using novel data structures. The experimental evaluations testify that SpaceSaving$^{\pm}$ has accurate frequency estimations and achieves very high recall and precision

2024 – Privacy & Misra-Gries



Better Differentially Private Approximate Histograms and Heavy Hitters using the Misra-Gries Sketch

Christian Janos Lebeda
Basic Algorithms Research Copenhagen
IT University of Copenhagen

Jakub Tětek
Basic Algorithms Research Copenhagen
University of Copenhagen

ABSTRACT

We consider the problem of computing differentially private approximate histograms and heavy hitters in a stream of elements. In the non-private setting, this is often done using the sketch of Misra and Gries [Science of Computer Programming, 1982]. Chan, Li, Shi, and Xu [PETS 2012] describe a differentially private version of the Misra-Gries sketch, but the amount of noise it adds can be large and scales linearly with the size of the sketch; the more accurate the sketch is, the more noise this approach has to add. We present a better mechanism for releasing a Misra-Gries sketch under (ε, δ)-differential privacy. It adds noise with magnitude

REFERENCES

References

- R. Boyer & J. Moore, MJRTY – A fast majority vote algorithm, in *Automated Reasoning: Essays in Honor of Woody Bledsoe*, Springer, 1991

- J. Misra & D. Gries, Finding repeated elements, *Science of Computer Programming*, Vol. 2, 1982

- G. Cormode & M. Hadjieleftheriou, Finding the frequent items in streams of data, *Commun. ACM*, Vol. 52, N. 10, 2009