Mining Data Streams (Part 1)

A. Farzindar
farzinda@usc.edu

Mining of Massive Datasets
Jure Leskovec, Anand Rajaraman, Jeff Ullman Stanford University http://www.mmds.org

Topic: Infinite Data

High dim. data	Graph data	Infinite data	Machine learning	Apps
Locality sensitive hashing	PageRank, SimRank	Filtering data streams	SVM	Recommender systems
Clustering	Community Detection	Queries on streams	Decision Trees	Association Rules
Dimensionality reduction	Spam Detection	Web advertising	Perceptron, kNN	Duplicate document detection

Data Streams

- **In many data mining situations, we do not know the entire data set in advance**
- **Stream Management** is important when the input rate is controlled **externally:**
  - Google queries
  - Twitter or Facebook status updates,
- We can think of the **data** as **infinite** and **non-stationary** (the distribution changes over time).

The Stream Model

- Input **elements** enter at a **rapid rate**,
at one or more input ports (i.e., **streams**)
  - **We call elements of the stream tuples**
- **The system cannot store the entire stream accessibly**
- **Q: How do you make critical calculations about the stream using a limited amount of (secondary) memory?**

Side note: SGD is a Streaming Alg.

- **Stochastic Gradient Descent (SGD) is an example of a stream algorithm**
- **In Machine Learning we call this: Online Learning**
  - Allows for **modeling problems** where we have a **continuous stream of data**
  - We want an algorithm to **learn** from it and slowly **adapt** to the changes in data
- **Idea: Do slow updates to the model**
  - **SGD** (SVM, Perceptron) makes small updates
  - **So:** First **train the classifier** on training data
  - **Then:** For every example from the stream, we slightly **update the model** (using small learning rate).

Stream data processing

- Stream of **tuples** arriving at a **rapid rate**
  - In contrast to **traditional DBMS** where all tuples are stored in secondary storage

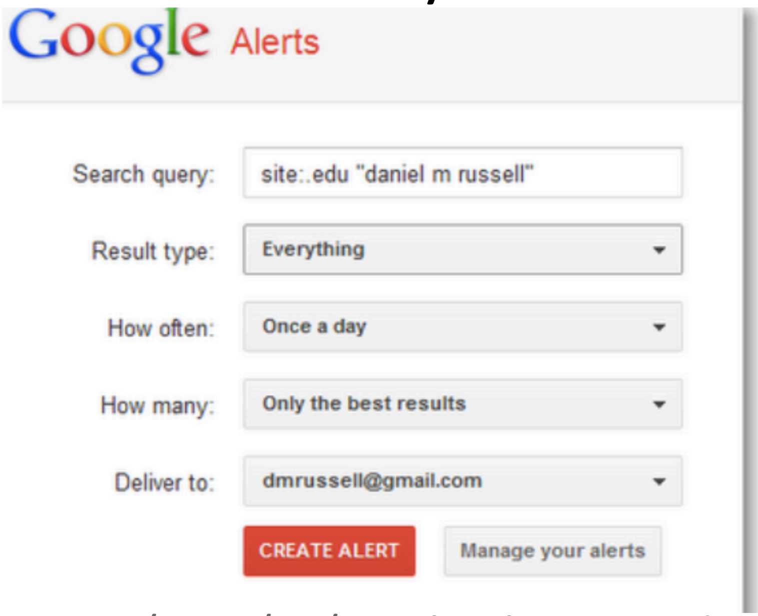
- Infeasible to **use all tuples** to answer queries
  - Can not store them all in **main memory**
  - Too much **computation**
  - Query response **time critical**.

Query types

- **Standing** queries
  - Executed whenever a **new tuple arrives**
  - e.g., report each **new maximum value** ever seen in the stream
- **Ad-hoc** queries

Standing queries

- **Google Alerts--standing queries to monitor the world**
  - Google Alerts are basically "standing queries." You write a Google query, then decide **how often you want it to run** and over what body of content (news, web sites, etc.).

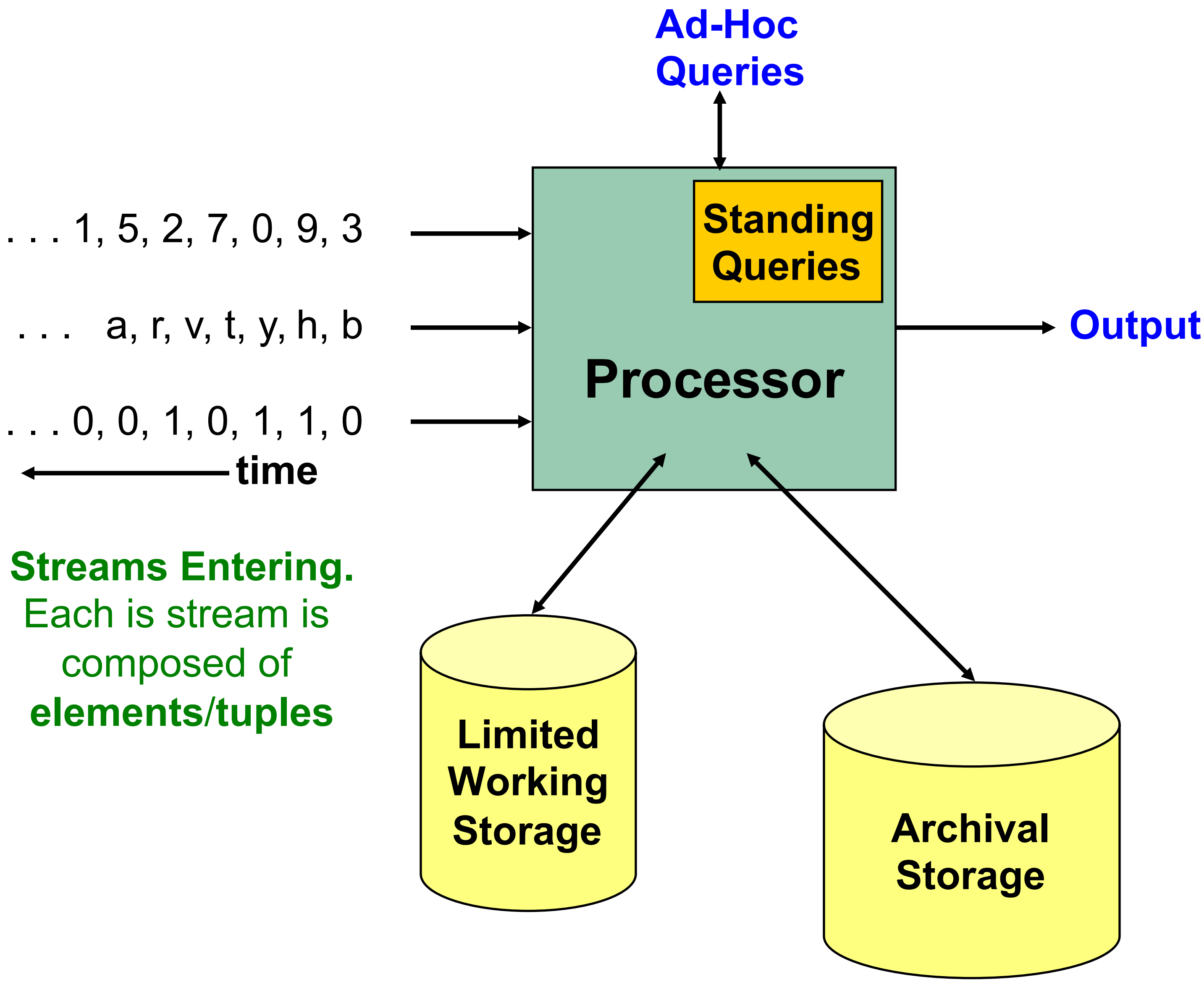


- http://searchresearch1.blogspot.com/2012/01/google-alerts-standing-queries-to.html

Query types

- **Standing** queries
  - Executed whenever a **new tuple arrives**
  - e.g., report each **new maximum value** ever seen in the stream
- **Ad-hoc** queries
  - Normal queries asked **one time**
  - **Ad hoc** comes from Latin which means "for the purpose"
  - E.g., what is the **maximum value so far**?

General Stream Processing Model



Example: Running averages

- Given a window of size N
  - **report the average of values in the window** whenever **a value arrives**
  - **N is so large** that we can not store all tuples in the window

- How to do this?

Example: running averages

- First N inputs, accumulate sum and count
  - Avg = sum/count

- A new element i
  - Change the average by adding (i-j)/N
  - j is the oldest element in the window.

Problems on Data Streams

- **Types of queries one wants on answer on a data stream:**
  - **Queries over sliding windows**
    - Number of items of type ***x*** in the last ***k*** elements of the stream
  - **Sampling data from a stream**
    - Construct a random sample.

Problems on Data Streams (2)

- **Types of queries one wants on answer on a data stream:**
  - **Filtering a data stream**
    - Select elements with property ***x*** from the stream
  - **Counting distinct elements**
    - Number of distinct elements in the last ***k*** elements of the stream
  - **Estimating moments**
    - Estimate avg./std. dev. of last ***k*** elements
  - **Finding frequent elements.**

Applications

- **Mining query streams**
  - Google wants to know what queries are **more frequent** today than yesterday
- **Mining click streams**
  - Yahoo wants to know which of its pages are getting an **unusual number of hits** in the past hour
- **Mining social network news feeds**
  - E.g., look for **trending topics** on Twitter, Facebook.

Queries over a (long) Sliding Window

Sliding Windows

- A useful model of stream processing is that queries are about a ***window*** of length ***N*** – the ***N*** **most recent elements received**

- **Interesting case:** ***N*** is **so large** that the data cannot be stored in memory, or even on disk
  - Or, there are so many streams that windows for all cannot be stored
- **Amazon example:**
  - For **every product X** we keep 0/1 stream of whether that product was sold in the **n-th transaction**
  - We want answer queries, how many times have we **sold X in the last k sales**.

Sliding Window: 1 Stream

- **Sliding window on a single stream:** **N = 6**

q w e r t y u i o p a s d f g h j k l z x c v b n m

q w e r t y u i o p a s d f g h j k l z x c v b n m

q w e r t y u i o p a s d f g h j k l z x c v b n m

q w e r t y u i o p a s d f g h j k l z x c v b n m

Past Future

Counting Bits

- **Problem:**
  - Given a stream of **0**s and **1**s
  - Be prepared to answer queries of the form
    How many 1s are in the last *k* bits? where $k \leq N$
- **Obvious solution:**
  Store the most recent N bits
  - When new bit comes in, discard the $N+1^{st}$ bit

0 1 0 0 1 1 0 1 1 1 0 1 0 1 0 1 1 0 $\boxed{1\ 1\ 0\ 1\ 1\ 0}$ Suppose N=6

← Past Future →

Counting Bits (2)

- Obvious solution: store the most recent *N* bits
- But answering the query will take O(k) time
  - Very possibly too much time
- And the space requirements can be too great
  - Especially if there are many streams to be managed in **main memory at once**, or N is huge.

Counting Bits (3)

- **You can not get an exact answer without storing the entire window**

- **Real Problem:**
  What if we cannot afford to store *N* bits?
  - **E.g.,** we're processing 1 billion streams and **_N_ = 1 billion**

0 1 0 0 1 1 0 1 1 1 0 1 0 1 0 1 1 0 ~~1 1 0 1 1 0~~

← Past Future →

- **But we are happy with an approximate answer.**

An attempt: Simple solution

- **Q: How many 1s are in the last *N* bits?**
- A simple solution that does not really solve our problem: **Uniformity assumption**

← *N* →

0 1 0 0 1 1 1 0 0 0 1 0 1 0 0 1 0 0 0 1 0 1 1 0 1 1 0 1 1 1 0 0 1 0 1 0 1 1 0 0 1 1 0 1 0

← Past Future →

- **Maintain 2 counters:**
  - ***S***: number of 1s from the beginning of the stream
  - ***Z***: number of 0s from the beginning of the stream
- **How many 1s are in the last N bits?** $N \cdot \frac{S}{S+Z}$
- **But, what if stream is non-uniform?**
  - What if distribution changes over time?

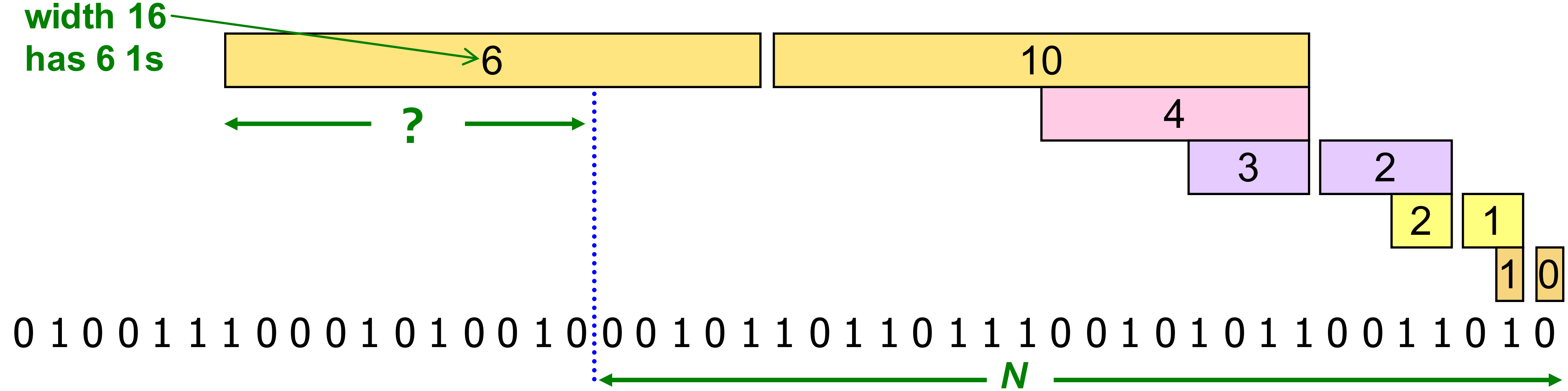
DGIM Method

[Datar, Gionis, Indyk, Motwani]

- Name refers to the inventors:
  - Datar, Gionis, Indyk, and Motwani.
  - DGIM solution that does not assume uniformity
- We store $O(\log^2 N)$ bits per stream
- **Solution gives approximate answer, never off by more than 50%**
  - Error factor can be reduced to any fraction > 0, with more complicated algorithm and proportionally more stored bits.

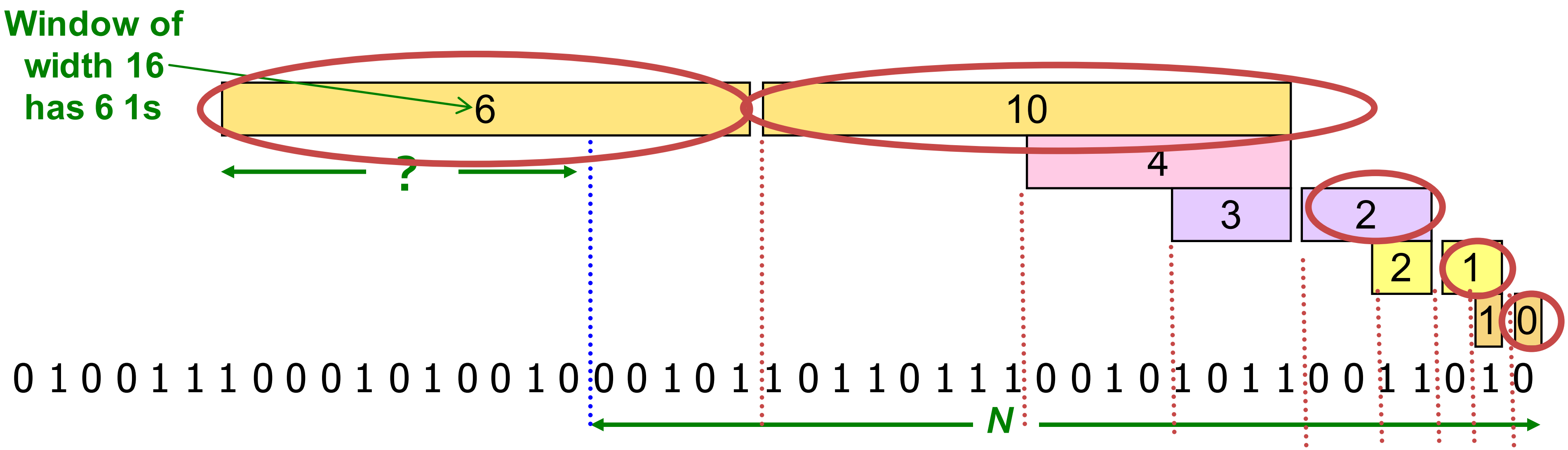
Idea: Exponential Windows

- **Solution that doesn't (quite) work:**
  - Summarize **exponentially increasing** regions of the stream, looking backward
  - Drop small regions if they begin at the same point as a larger region



We can reconstruct the count of the last ***N*** bits, except we are not sure how many of the last **6 1s** are included in the ***N***

Example (count.)



We can reconstruct the count of the last ***N*** bits, except we are not sure how many of the last **6 1s** are included in the ***N***

6/16 x 5=30/16 ~ 2

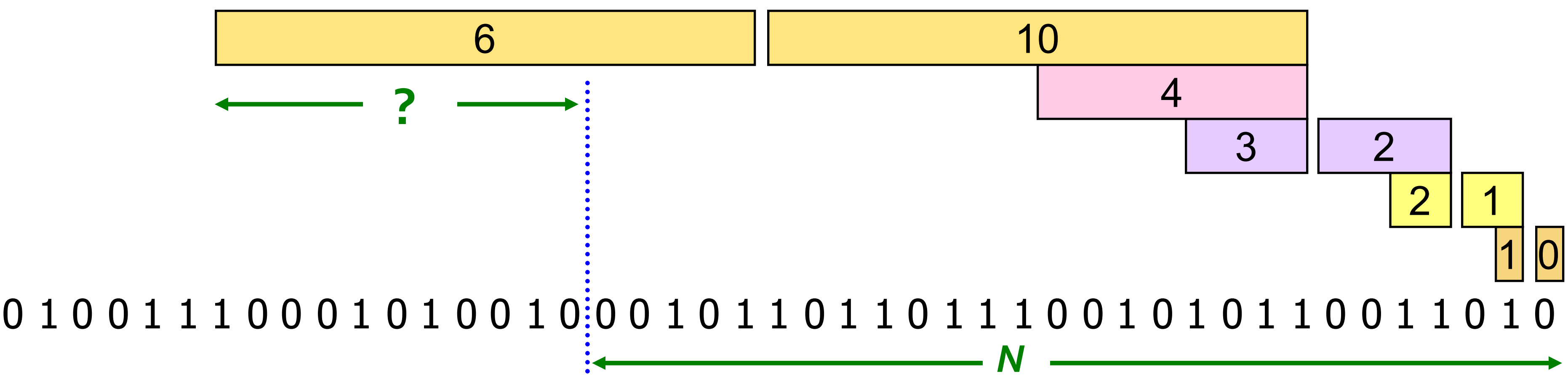
0+1+2+10=13 **+2=15**

What's Good?

- **Stores only $O(\log^2 N)$ bits**
  - $\boldsymbol{O}(\log \boldsymbol{N})$ counts of $\log_2 \boldsymbol{N}$ bits each
- **Easy update as more bits enter**
- Error in count no greater than the number of **1s** in the "**unknown**" area.

What's Not So Good?

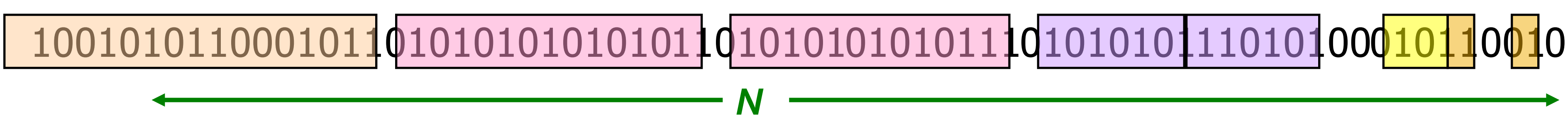
- As long as the **1s** are fairly evenly distributed, the error due to the unknown region is small – **no more than 50%**
- But it could be that **all the 1s are in the unknown area** at the end
- In that case, **the error is unbounded!**



Fixup: DGIM method

- **Idea:** Instead of summarizing fixed-length blocks, summarize blocks with specific number of **1s**:
  - Let the block ***sizes*** (number of **1s**) increase exponentially

- **When there are few 1s in the window, block sizes stay small, so errors are small**

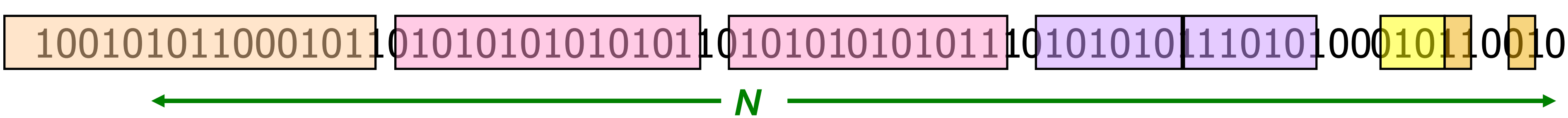


DGIM: Timestamps

- Each bit in the stream has a ***timestamp***, starting **1**, **2,** …
- Record timestamps modulo ***N*** (**the window size**), so we can represent any **relevant** timestamp in $\boldsymbol{O(log_2 N)}$ bits.

DGIM: Buckets

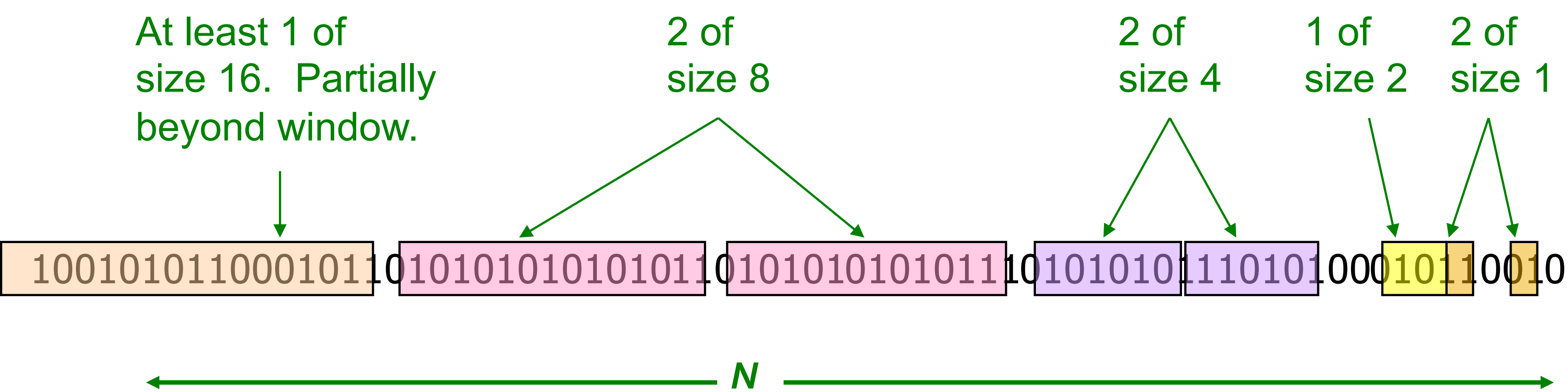
- A ***bucket*** in the DGIM method is a record consisting of:
  - **(A) The timestamp of its end [O(log *N*) bits]**
  - **(B) The number of 1s between its beginning and end [O(log log *N*) bits]**
- **Constraint on buckets:**
  Number of **1s** must be a power of **2**
  - That explains the **O(log log *N*)** in **(B) above**



Representing a Stream by Buckets

- Either **one** or **two** buckets with the same **power-of-2 number** of **1s**
- **Buckets do not overlap in timestamps**
- **Buckets are sorted by size**
  - Earlier buckets are **not smaller than later buckets**
- Buckets **disappear** when their **end-time** is **>** ***N*** time units in the past.

Example: Bucketized Stream



Three properties of buckets that are maintained:

- Either **one** or **two** buckets with the same **power-of-2** number of **1s**
- Buckets do not overlap in timestamps
- Buckets are sorted by size.

Updating Buckets (1)

- When a new bit comes in, **drop the last (oldest) bucket** if its **end-time is prior to *N*** time units before the current time
- **2 cases:** Current bit is **0** or **1**
- **If the current bit is 0:**
  no other changes are needed.

Updating Buckets (2)

- **If the current bit is 1:**
  - **(1)** Create a new bucket of size **1**, for just this bit
    - **End timestamp = current time**
  - **(2)** If there are now **three buckets of size 1**, **combine the oldest two into a bucket of size 2**
  - **(3)** If there are now **three buckets of size 2**, **combine the oldest two into a bucket of size 4**
  - **(4) And so on …**

Example: Updating Buckets

Current state of the stream:

10010101100010110101010101010101101010101010101111010101011010100010110010

Bit of value 1 arrives

001010110001011010101010101010110101010101010111101010101101010001011001 01

Two orange buckets get merged into a yellow bucket

0010101100010110101010101010101101010101010101111010101011010100010110010 1

Next bit 1 arrives, new orange bucket is created, then 0 comes, then 1:

010110001011010101010101010110101010101010111101010101101010001011001 01101

Buckets get merged…

010110001011010101010101010110101010101010111101010101101010001011001 01101

State of the buckets after merging

01011000101101010101010101011101010101010111101010101110101000101100101101

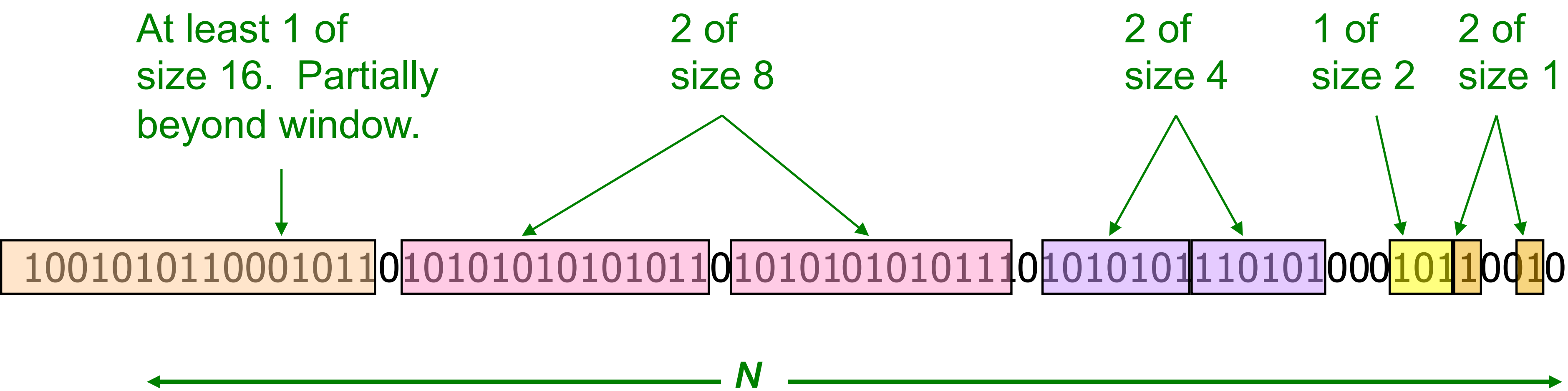
How to Query?

- **To estimate the number of 1s in the most recent *N* bits:**
  1. **Sum the sizes of all buckets but the last**

     (note "**size**" **means the number of 1s** in the bucket)
  2. **Add half the size of the last bucket**

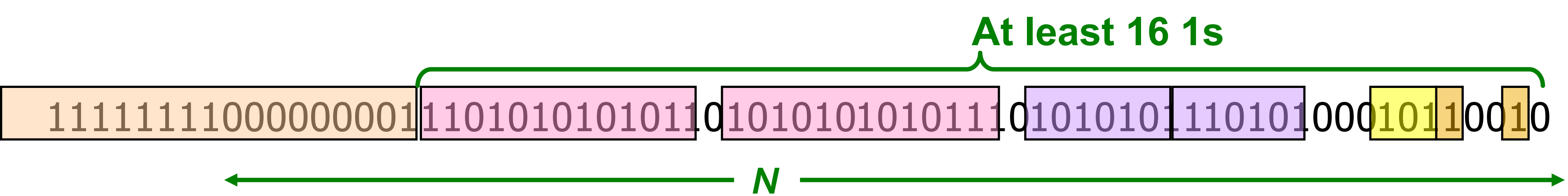
- **Remember:** We do not know how many **1s** of the last bucket are still within the wanted window.

Example: Bucketized Stream



Error Bound: Proof

- **Why is error 50%?**
- Suppose the last bucket has size $\mathbf{2^{\mathit{r}}}$
- Then by assuming $\mathbf{2^{\mathit{r}-1}}$ (i.e., half) of its **1s** are still within the window, we make an error of at most $\mathbf{2^{\mathit{r}-1}}$
- Since there is at least one bucket of each of the sizes less than $\mathbf{2^{\mathit{r}}}$, the true sum is at least $\mathbf{1 + 2 + 4 + .. + 2^{r-1} = 2^{\mathit{r}} - 1}$
- Thus, **error at most 50%**

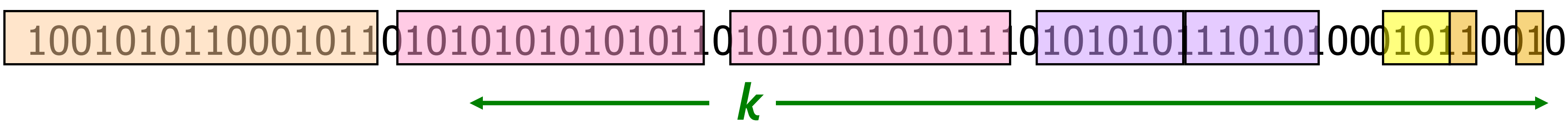


Further Reducing the Error

- Instead of maintaining **1** or **2** of each size bucket, we (r > 2) **allow either r-1 or r buckets**
  - Except for the largest size buckets; we can have any number between **1** and ***r*** of those
- **Error is at most $O(1/r)$**
- By picking ***r*** appropriately, we can tradeoff between **number of bits we store and the error.**

Extensions

- Can we use the same trick to answer queries **How many 1's in the last *k*?** where ***k* < *N***?
  - **A:** Find earliest bucket **B** that at overlaps with ***k***. Number of **1s** is the **sum of sizes of more recent buckets + ½ size of B**



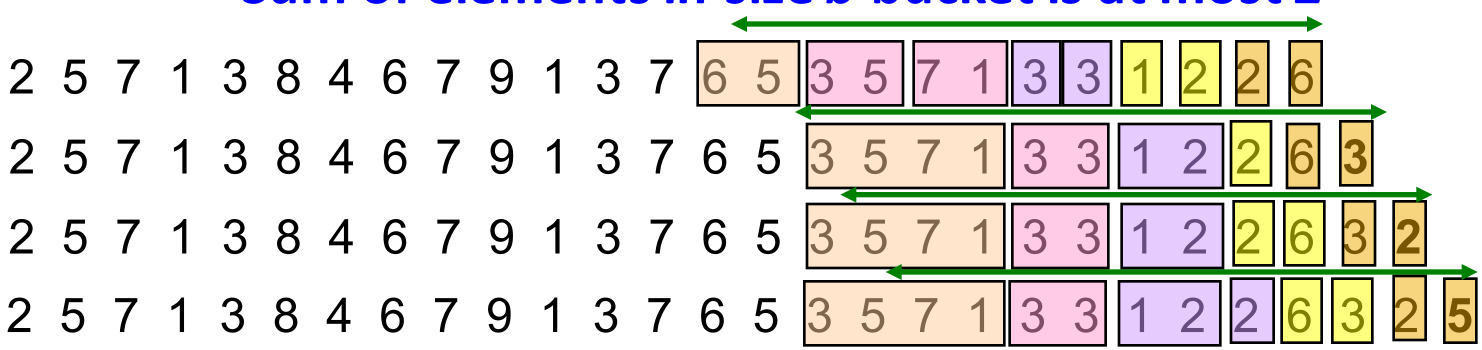
Can we handle the case where the stream is not bits, but integers, and we want the sum of the last *k* elements?

Extensions

- **Stream of positive integers**
- **We want the sum of the last *k* elements**
  - **Amazon:** Avg. price of last **k** sales
- **Solution:**
  - **(1) If you know all have at most *m* bits**
    - Treat ***m*** bits of each integer as a separate stream
    - Use DGIM to count **1s** in each integer
    - The sum is $= \sum_{i=0}^{m-1} c_i 2^i$

c_i …estimated count for **i-th** bit

  - **(2) Use buckets to keep partial sums**
    - **Sum of elements in size *b* bucket is at most 2^b**



Idea: Sum in each bucket is at most 2^b (unless bucket has only **1** integer)

Bucket sizes:

16	8	4	2	1

Summary

- **DBMS vs Stream Management**
- **Stream data processing** and **type of queries**
- **Counting the number of 1s in the last N elements**
  - Exponentially increasing windows
  - Extensions:
    - Number of 1s in any last k (k < N) elements
    - Sums of integers in the last N elements.