Analyzing Massive Data Sets

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Chapter 9: Data Streams

Data Streams

- **In many data analysis situations, we do not know the entire data set in advance**
- Instead, we get continuous sequences of data elements that are typically:
  - **Push-based** (data flow controlled by sources)
  - **Ordered** (e.g., by arrival time, or by explicit timestamps)
  - **Rapid** (e.g., ~ 100K messages/second in market data)
  - **Potentially unbounded** (may have no end)
  - **Time-sensitive** (usually representing real-time events)
  - **Time-varying/non stationary** (in content and speed)
  - **Unpredictable** (autonomous data sources)

Example Applications

- Financial Services

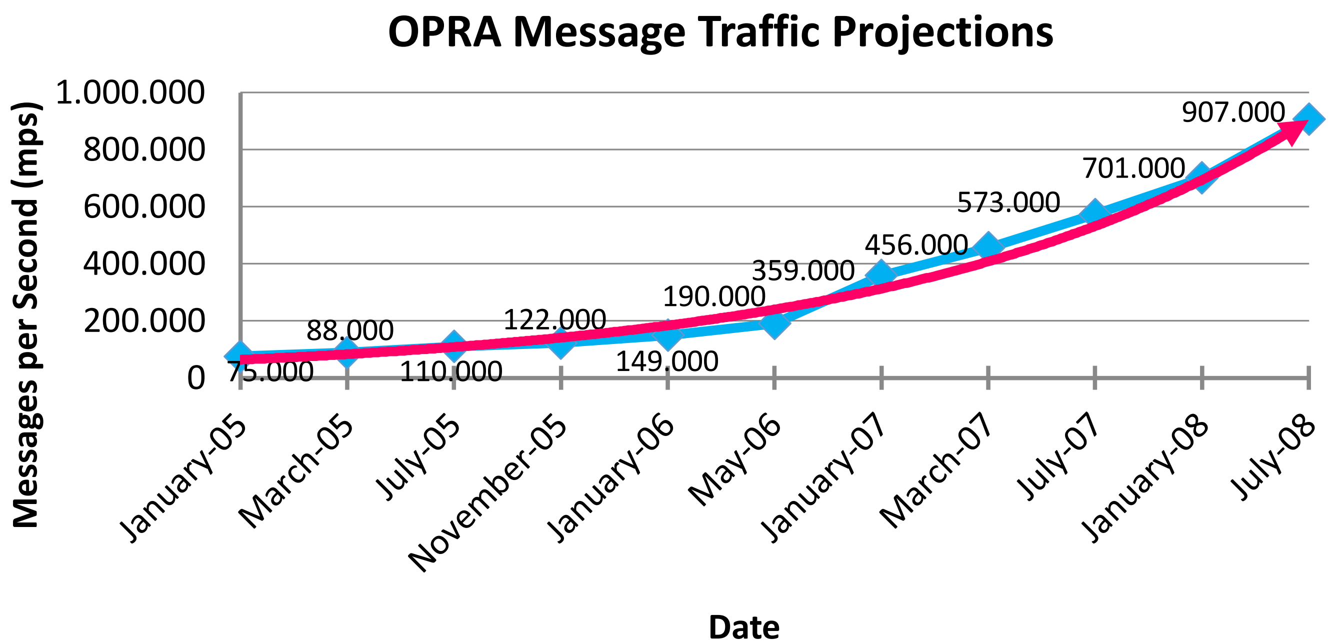
Example:

- Trades(time, symbol, price, volume)

Typical Applications:

- Algorithmic Trading
- Foreign Exchange
- Fraud Detection
- Compliance Checking

Financial Services: Skyrocketing Data Rates



[Source: Options Price Reporting Authority, http://www.opradata.com]

Some more up-to-date rates:

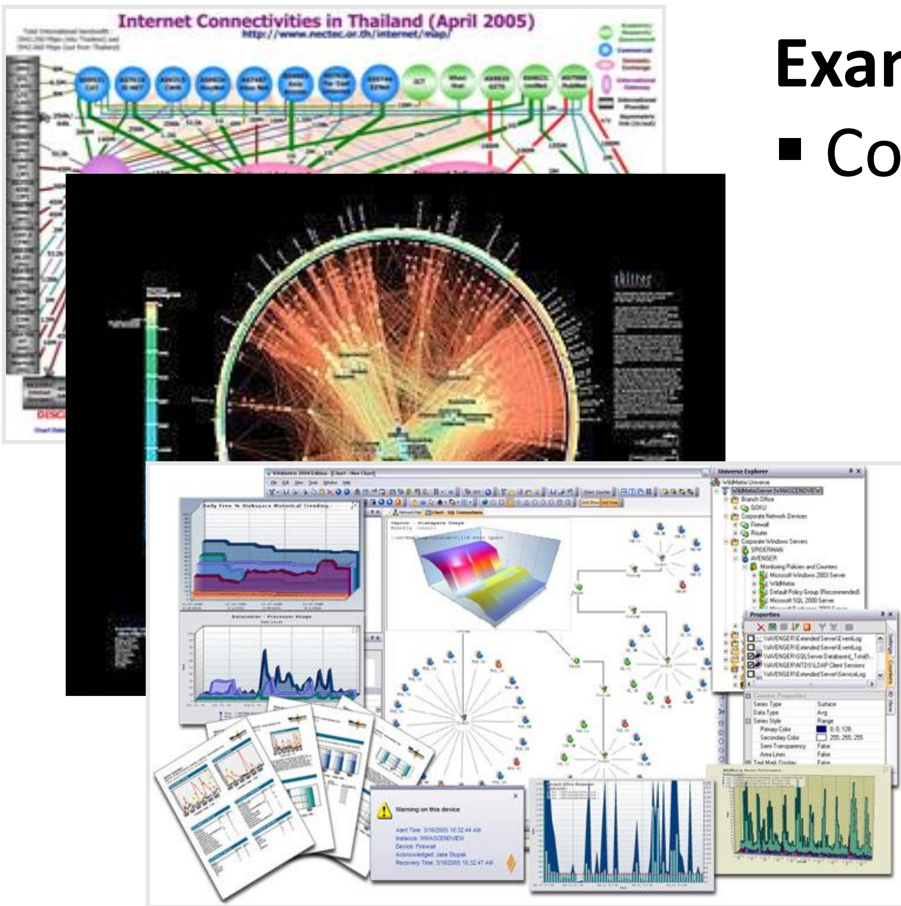
- 19.8M msg/s (Q4/2018)
- 4.2M msg/ 100msec (May 2019)

Low response time critical (think high frequency trading)!

- 150 us avg end-to-end latency

Example Applications

- System and Network Monitoring



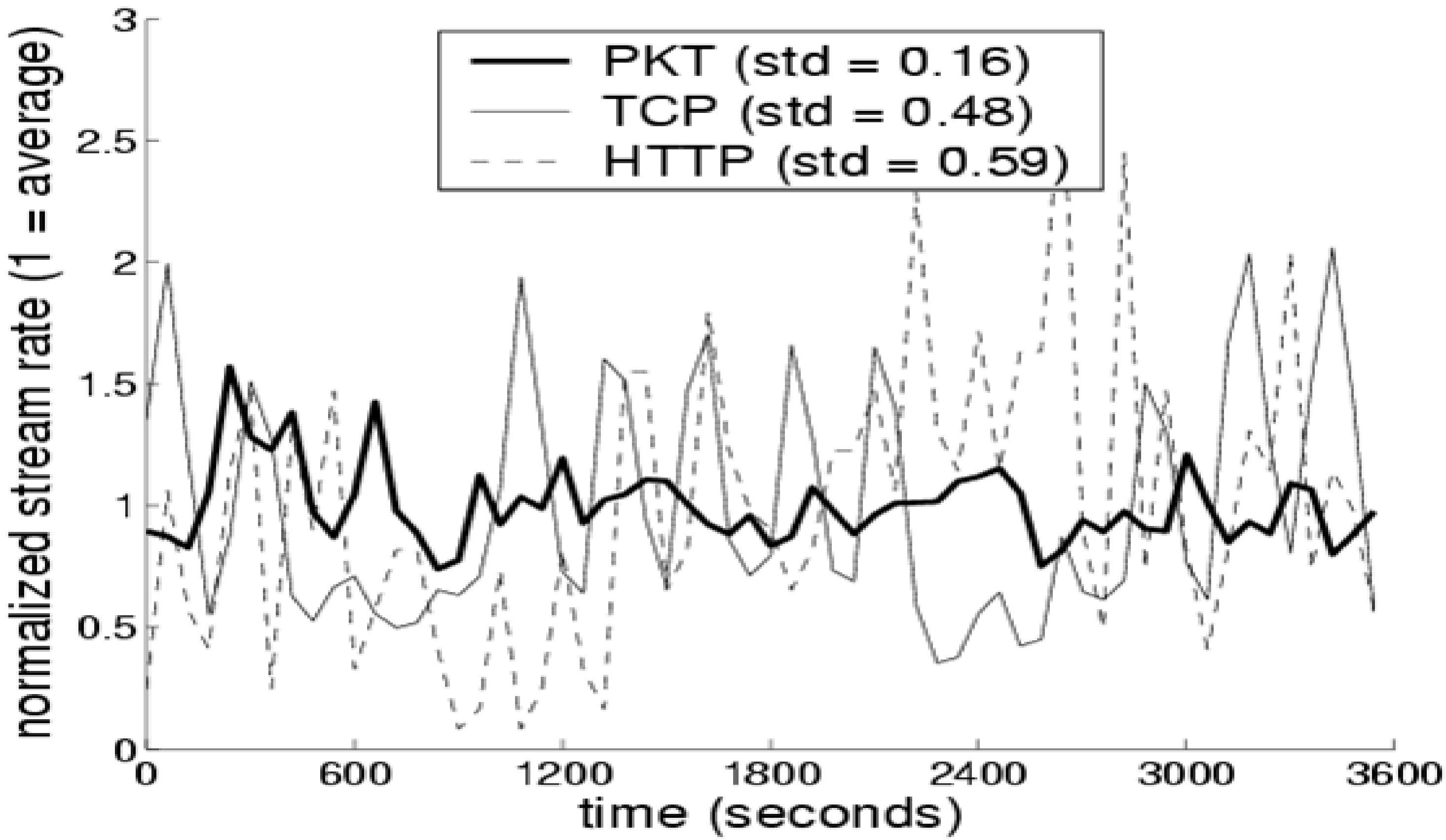
Example:

- Connections(time, srcIP, destIP, destPort, status)

Typical Applications:

- Server load monitoring
- Network traffic monitoring
- Detecting security attacks
  - Denial of Service
  - Intrusion

Network Monitoring: Bursty Data Rates



[Source: Internet Traffic Archive, http://ita.ee.lbl.gov/]

Example Applications

•Sensor-based Monitoring

Example:

- CarPositions(time, id, speed, position)

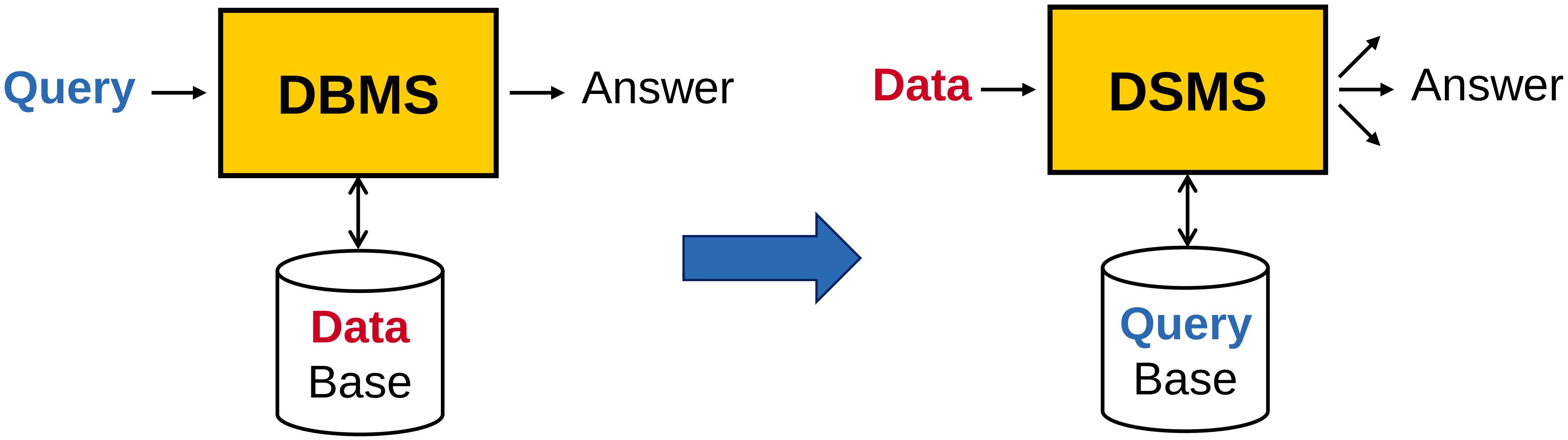
Typical Applications:

- Monitoring congested roads
- Route planning
- Rule violations
- Tolling

Example Applications: User-Centric Web

- **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

A Paradigm Shift in Data Processing Models



Traditional Data Management

Data Stream Management

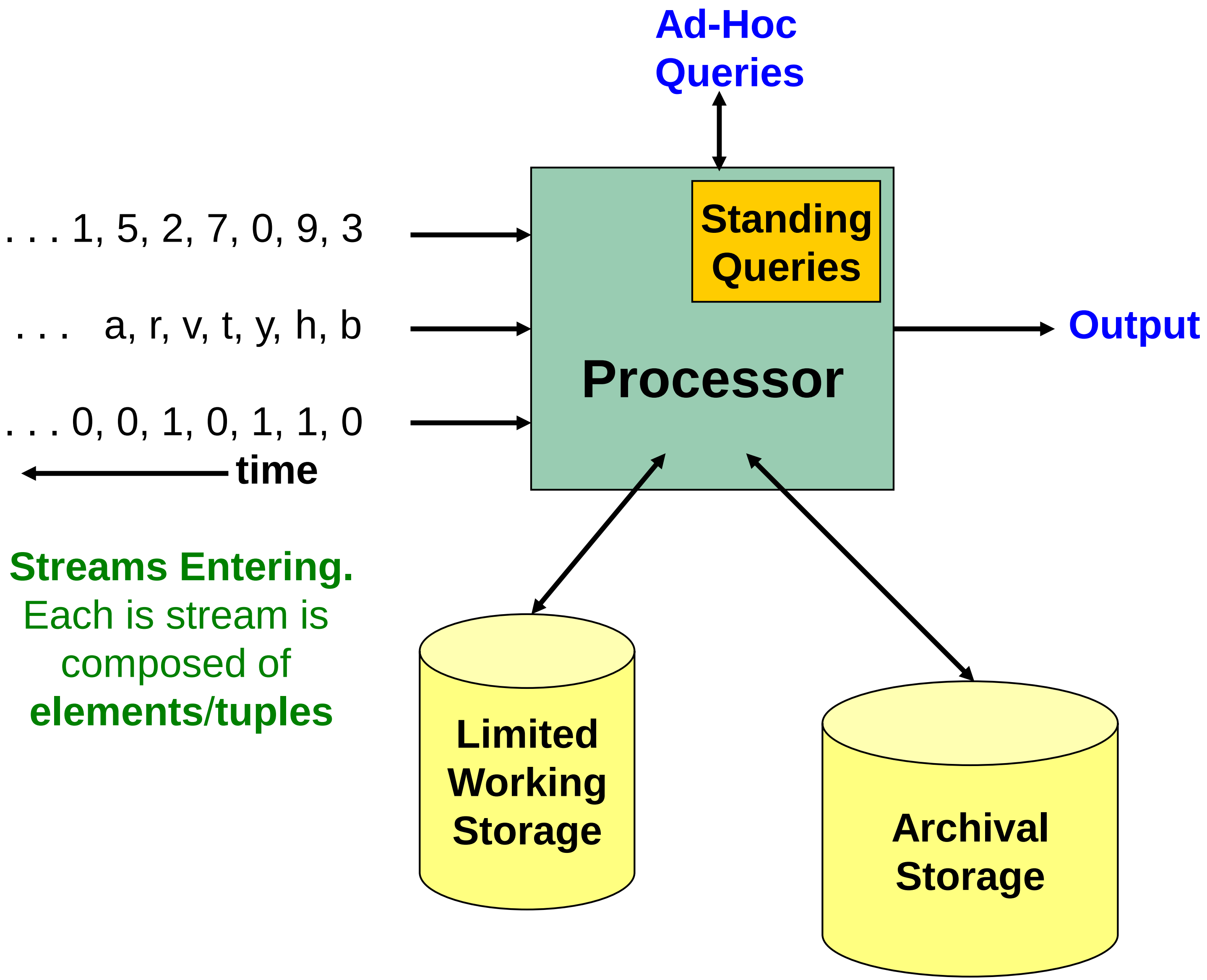
The Stream Model

- 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?**

General Stream Processing Model



Streams Entering. Each is stream is composed of **elements/tuples**

Impact of Operation Semantics

- How much effort is a filter (a.price > 50)?
  - Only current element
  - Also applies to projections, "map" function applications, …
  - Grouping/Splitting can often also be expressed this way
- What about a simple aggregate (max(price))?
  - Need storage for one number, if we report every time
- What about average?
  - Two number, might overflow
- What about
  - median, percentiles,
  - Joins, Set operations, Duplicate elimination, …

Dealing with stateful processing

Precise answers over **infinite input** not possible for **generic expressions**:

- Infinite State
- Blocking Operations

Two commons design directions:

1. Exact answers within bounded periods:
   - Window Processing
   - Allows all operations for finite data (e.g., SQL)
2. Approximate anwers over arbitrary periods
   - Summary-based Processing
   - Limited to commonly useful operations

Window-Based Processing

Window-based Processing

- Windows are finite excerpts of a potentially unbounded stream.
- Most streaming applications are interested in the readings of the recent past.
- Windows help us unblock operators such as aggregates.
- Windows help us bound the memory usage for operators such as joins.

Window Example

- Two basic parameters: size and slide
- Example: **`Trades(time, symbol, price, volume)`**

size = 10 min

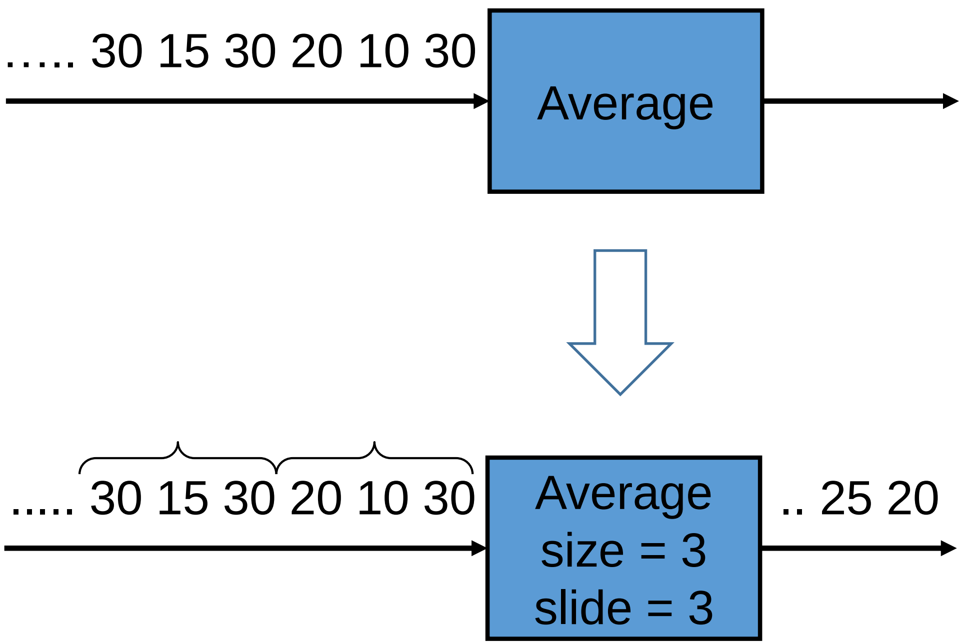
slide by 5 min

```
(10:00, "IBM",   20, 100)
(10:00, "INTC",  15, 200)
(10:00, "MSFT",  22, 100)
(10:05, "IBM",   18, 300)
(10:05, "MSFT",  21, 100)
(10:10, "IBM",   18, 200)
(10:10, "MSFT",  20, 100)
(10:15, "IBM",   20, 100)
(10:15, "INTC",  20, 200)
(10:15, "MSFT",  20, 200)
```

.

.

Windows: Unblocking Aggregate Operation



- **Problem:**

No results can be produced until the stream ends.

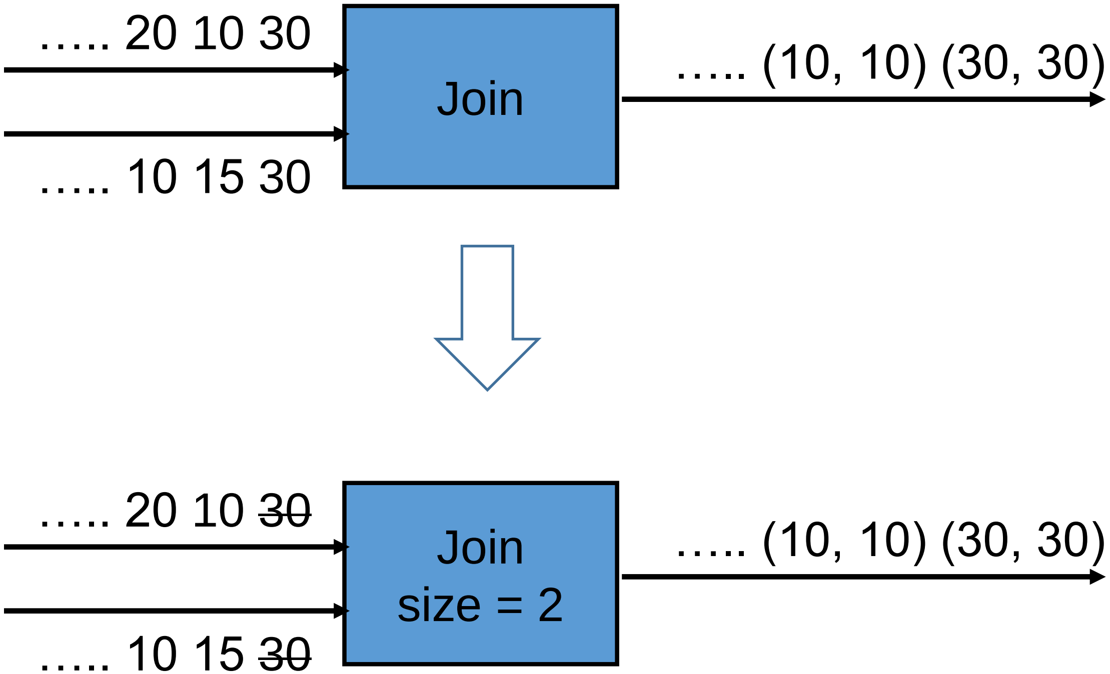
➢ Average is "blocked".

- **Solution:**

Average can be computed on sliding windows.

➢ Average is "unblocked".

Windows: Bounding (Join) State



- **Problem:**
  Join must buffer its inputs until both streams end.
  ➢Join state is “unbounded”.

- **Solution:**
  Join must only buffer the latest window on its inputs.
  ➢Join state is “bounded”.

Common Window Types

- Sliding window
  - A window that slides (i.e., both of its end-points move) as new stream tuples arrive.
- Tumbling window
  - A sliding window for which window size = window slide (i.e., consecutive windows do not overlap).
- Landmark window
  - A window which is moving only on one of its end-points (usually the forward end-point).

Common Window Types

- Tuple-based window (a.k.a., count-based window)
  - A window whose size and content is determined by the number of tuples arrived.
  - Note: The actual size is always fixed.
- Time-based window
  - A window whose size and content is determined by tuples that arrived within a "time period".
  - Note: The actual size of such a window may depend on the stream arrival rate.
- Semantic window (a.k.a., predicate-based window)
  - A window whose size and content is determined by the tuple contents.
  - Note: Time-based window is a very simple form of semantic window when the time field carried in the tuple is used for windowing.

Sampling-based processing

Summary-based approaches (1)

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

Summary-based approaches (2)

- **Types of queries one wants on answer on a data stream:** (next slide set)
  - **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**

Sampling from a Data Stream:
Sampling a fixed proportion

As the stream grows the sample also gets bigger

Sampling from a Data Stream

- Since **we can not store the entire stream**, one obvious approach is to store a **sample**
- **Two different problems:**
  - **(1)** Sample a **fixed proportion** of elements in the stream (say 1 in 10)
  - **(2)** Maintain a **random sample of fixed size** over a potentially infinite stream
    - At any "time" ***k*** we would like a random sample of ***s*** elements
    - **What is the property of the sample we want to maintain?** For all time steps ***k***, each of ***k*** elements seen so far has equal prob. of being sampled

Problem 1: Sampling fixed proportion

- **Scenario:** Search engine query stream
  - **Stream of tuples:** (user, query, time)
  - **Answer questions such as: How often did a user run the same query in a single days**
  - Have space to store **1/10th** of query stream
- **Naïve solution:**
  - Generate a random integer in **[0..9]** for each query
  - Store the query if the integer is **0**, otherwise discard

Problem with Naïve Approach

- **Simple question: What fraction of queries by an average search engine user are duplicates?**
  - Suppose each user issues ***x*** queries once and ***d*** queries twice (total of ***x*+2*d*** queries)
    - **Correct answer:** ***d*/(*x*+*d*)**
  - **Proposed solution: We keep 10% of the queries**
    - Sample will contain ***x*/10** of the singleton queries and **2*d*/10** of the duplicate queries at least once
    - But only ***d*/100** pairs of duplicates
      - **d/100 = 1/10 · 1/10 · d**
    - Of ***d*** "duplicates" ***18d/100*** appear exactly once
      - **18d/100 = ((1/10 · 9/10)+(9/10 · 1/10)) · d**
  - **So the sample-based answer is** $\frac{\frac{d}{100}}{\frac{x}{10}+\frac{d}{100}+\frac{18d}{100}} = \frac{d}{10x+19d}$

Solution: Sample Users

Solution:

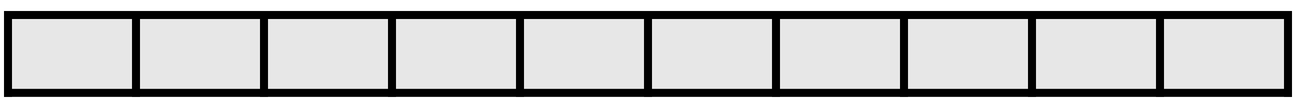
- Pick **1/10th** of **users** and take all their searches in the sample

- Possible problem: we need to keep track of all users, even those that are not picked
- Solution: Use a hash function that hashes the user name or user id uniformly into 10 buckets

Generalized Solution

- **Stream of tuples with keys:**
  - Key is some subset of each tuple's components
    - e.g., tuple is (user, search, time); key is **user**
  - Choice of key depends on application

- **To get a sample of *a/b* fraction of the stream:**
  - Hash each tuple's key uniformly into ***b*** buckets
  - Pick the tuple if its hash value is at most ***a***



Hash table with **b** buckets, pick the tuple if its hash value is at most **a.**
How to generate a 30% sample?
Hash into b=10 buckets, take the tuple if it hashes to one of the first 3 buckets

Sampling from a Data Stream: Sampling a fixed-size sample

As the stream grows, the sample is of fixed size

Problem 2: Fixed-size sample

- **Suppose we need to maintain a random sample *S* of size exactly *s* tuples**
  - E.g., main memory size constraint
- **Why?** Don't know length of stream in advance
- **Suppose at time *n* we have seen *n* items**
  - **Each item is in the sample *S* with equal prob. *s/n***

How to think about the problem: say s = 2

Stream: a x c y z k c d e g…

At **n= 5,** each of the first 5 tuples is included in the sample **S** with equal prob.

At **n= 7,** each of the first 7 tuples is included in the sample **S** with equal prob.

Impractical solution would be to store all the *n* tuples seen so far and out of them pick *s* at random

Solution: Fixed Size Sample

- **Algorithm (a.k.a. Reservoir Sampling)**
  - Store all the first ***s*** elements of the stream to ***S***
  - Suppose we have seen ***n-1*** elements, and now the n^{th} element arrives ($n > s$)
    - With probability s/n, keep the n^{th} element, else discard it
    - If we picked the n^{th} element, then it replaces one of the ***s*** elements in the sample ***S***, picked uniformly at random
- **Claim:** This algorithm maintains a sample ***S*** with the desired property:
  - After ***n*** elements, the sample contains each element seen so far with probability s/n

Proof: By Induction

- **We prove this by induction:**
  - Assume that after ***n*** elements, the sample contains each element seen so far with probability ***s/n***
  - We need to show that after seeing element ***n+1*** the sample maintains the property
    - Sample contains each element seen so far with probability ***s/(n+1)***
- **Base case:**
  - After we see **n=s** elements the sample **S** has the desired property
    - Each out of **n=s** elements is in the sample with probability ***s/s = 1***

Proof: By Induction

- **Inductive hypothesis:** After ***n*** elements, the sample ***S*** contains each element seen so far with prob. ***s/n***
- **Now element *n+1* arrives**
- **Inductive step:** For elements already in ***S***, probability that the algorithm keeps it in ***S*** is:

$$\underbrace{\left(1-\frac{s}{n+1}\right)}_{\text{Element n+1 discarded}}+\underbrace{\left(\frac{s}{n+1}\right)}_{\text{Element n+1 not discarded}}\underbrace{\left(\frac{s-1}{s}\right)}_{\text{Element in the sample not picked}}=\frac{n}{n+1}$$

- So, at time ***n,*** tuples in ***S*** were there with prob. **s/n**
- Time ***n→n+1,*** tuple stayed in ***S*** with prob. **n/(n+1)**
- So prob. tuple is in ***S*** at time ***n+1*** $= \frac{s}{n} \cdot \frac{n}{n+1} = \frac{s}{n+1}$

Queries over a (long) Sliding Window

Sliding Windows

- **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 $\boxed{\text{a s d f g h}}$ j k l z x c v b n m

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

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

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

← Past Future →

Counting Bits (1)

- **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*+1st** 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)

- **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**

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

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 →

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**

$\longleftarrow$ ***N*** $\longrightarrow$

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

$\longleftarrow$ Past Future $\longrightarrow$

- **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?

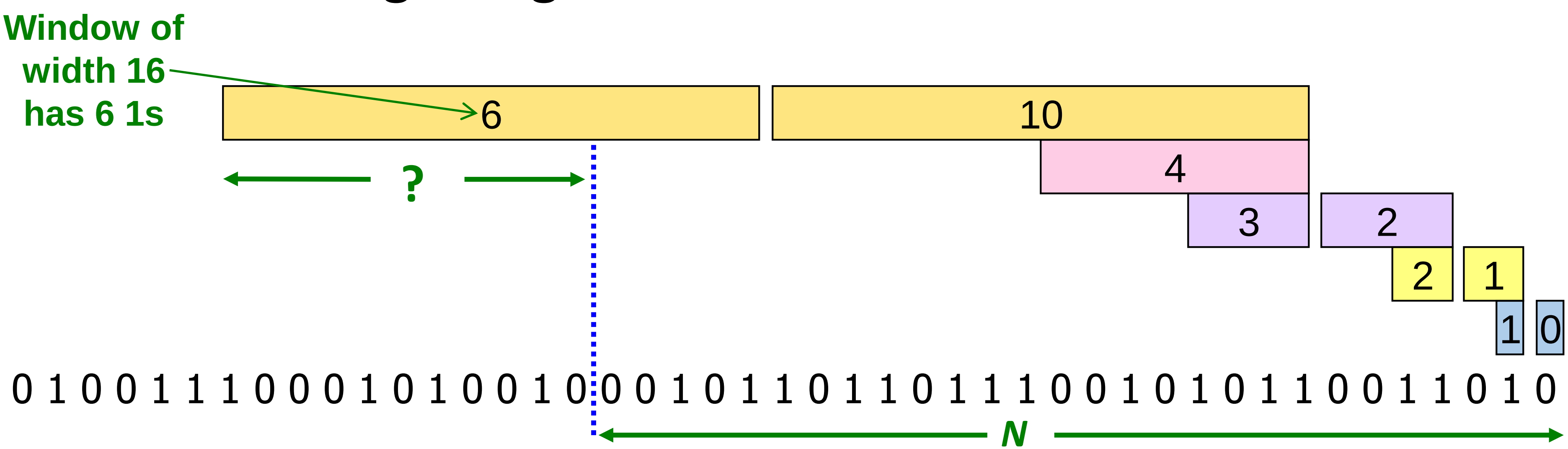
Datar, Gionis, Indyk, Motwani]

DGIM Method

- **DGIM solution that does not assume uniformity**
- We store $\boldsymbol{O}(\log^2 \boldsymbol{N})$ 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***

What's Good?

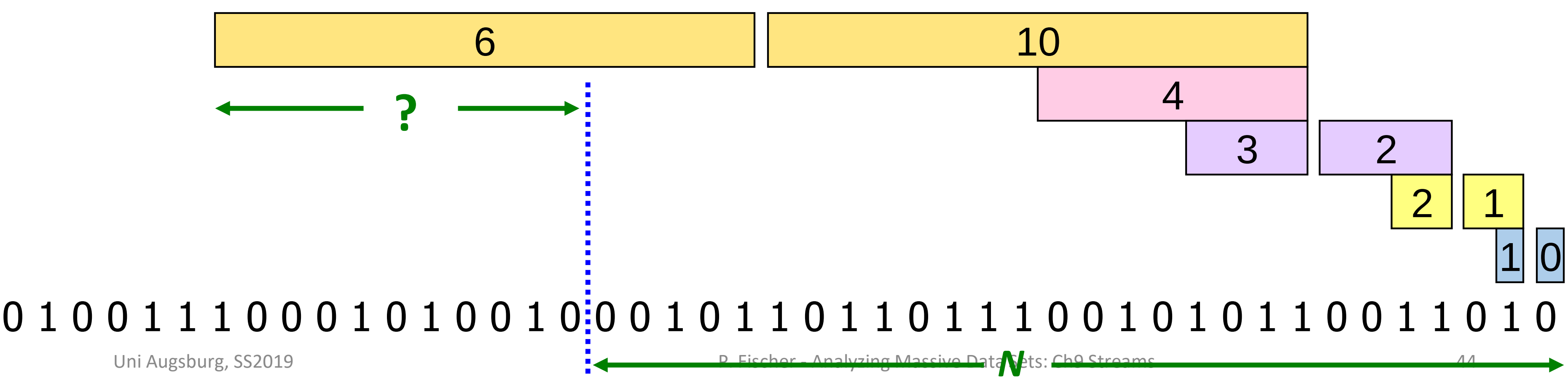
- **Stores only O(log^2*N*) bits**
  - $\boldsymbol{O}(\log \boldsymbol{N})$ counts of $\log_{\mathbf{2}}\boldsymbol{N}$ bits each

- **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?

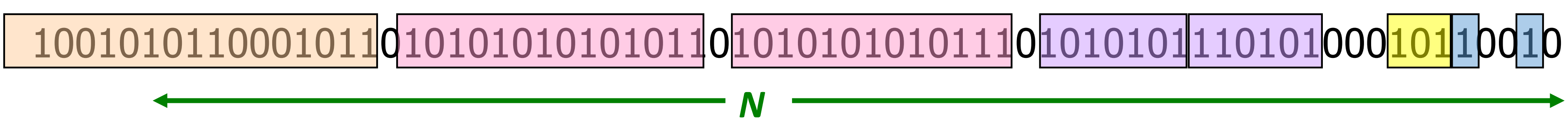
- As long as the **1s** are fairly evenly distributed, the error due to the unknown region is small – **no more than 50%**
- But it could be that all the **1s** are in the unknown area at the end
- In that case, **the error is unbounded!**



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

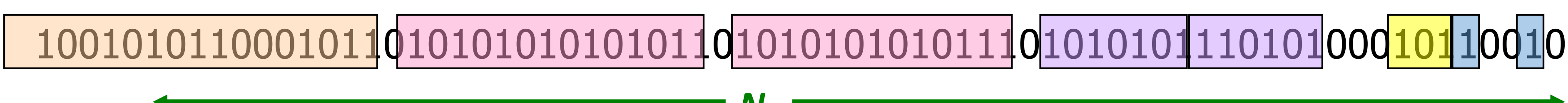
- Each bit in the stream has a ***timestamp***, starting **1**, **2,** …

- 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]**

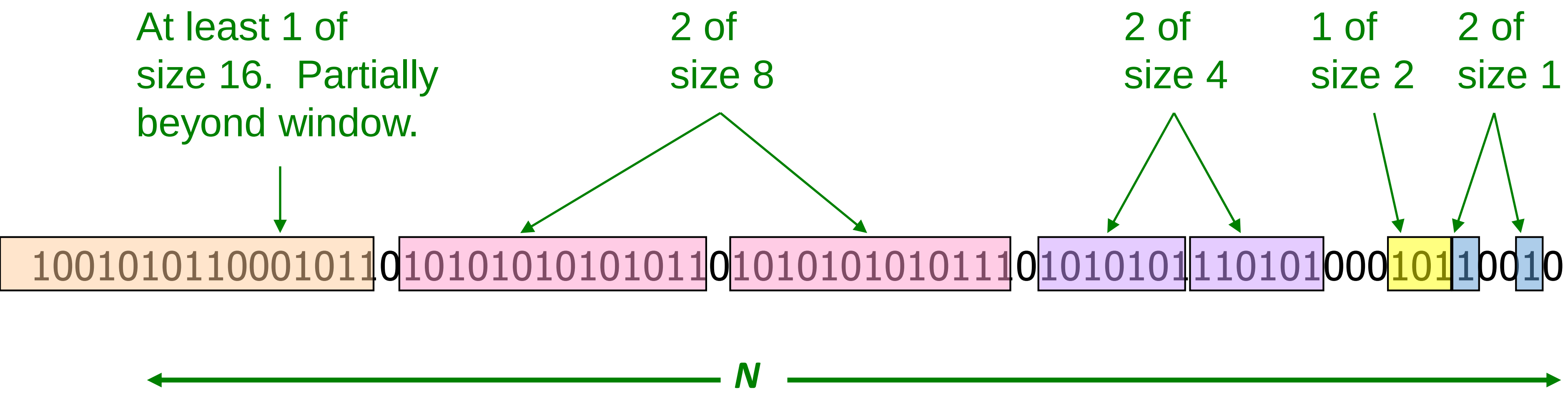
- **Constraint on buckets:**
  Number of **1s** must be a power of **2**
  - That explains the **O(log log *N*)** in **(B) above**



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 $\boldsymbol{N}$ 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:

10010101100010110101010101010101101010101010101110101010111010100010110010

Bit of value 1 arrives

001010110001011010101010101010110101010101010111010101011101010001011001011

Two blue buckets get merged into a yellow bucket

001010110001011010101010101010110101010101010111010101011101010001011001011

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

010110001011010101010101010110101010101010111010101011101010001011001011101

Buckets get merged…

010110001011010101010101010110101010101010111010101011101010001011001011101

State of the buckets after merging

010110001011010101010101010110101010101010111010101011101010001011001011101

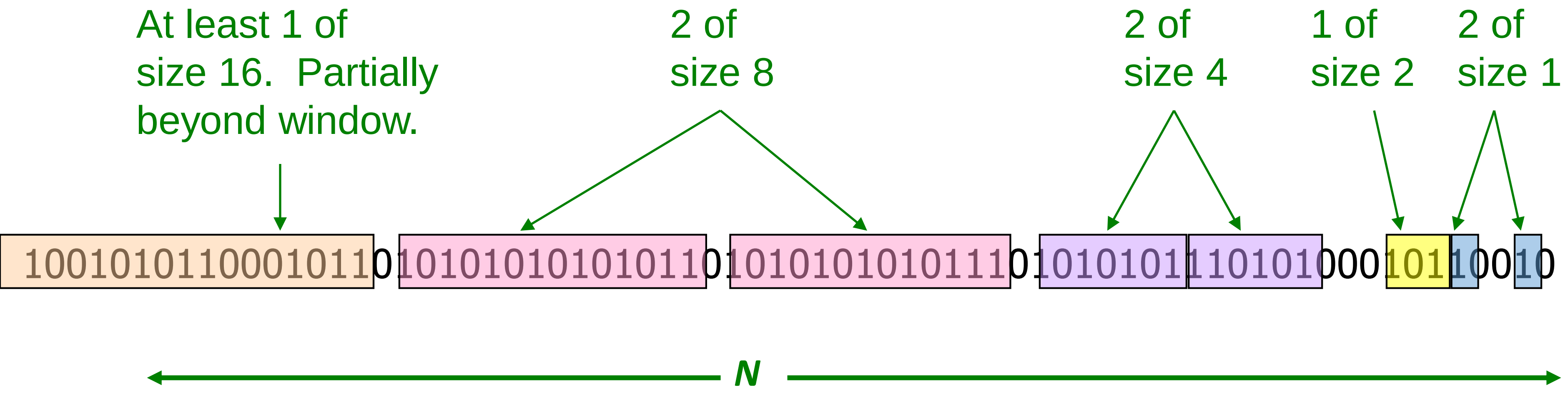
How to Query?

- **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**

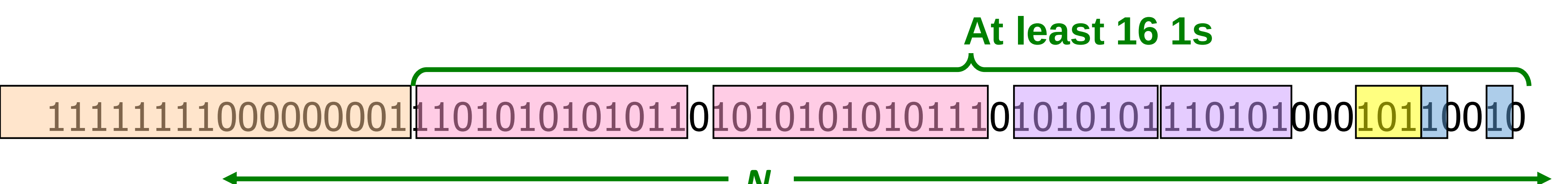
- **Remember:** We do not know how many **1s** of the last bucket are still within the wanted window

Example: Bucketized Stream



Error Bound: Proof

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

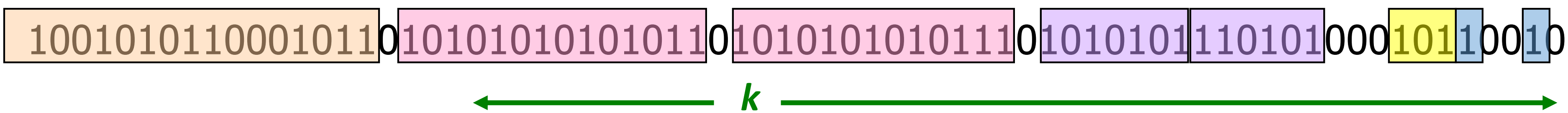


Further Reducing the Error

- Instead of maintaining **1** or **2** of each size bucket, we allow either ***r*-1** or ***r*** buckets (***r* > 2**)
  - 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**

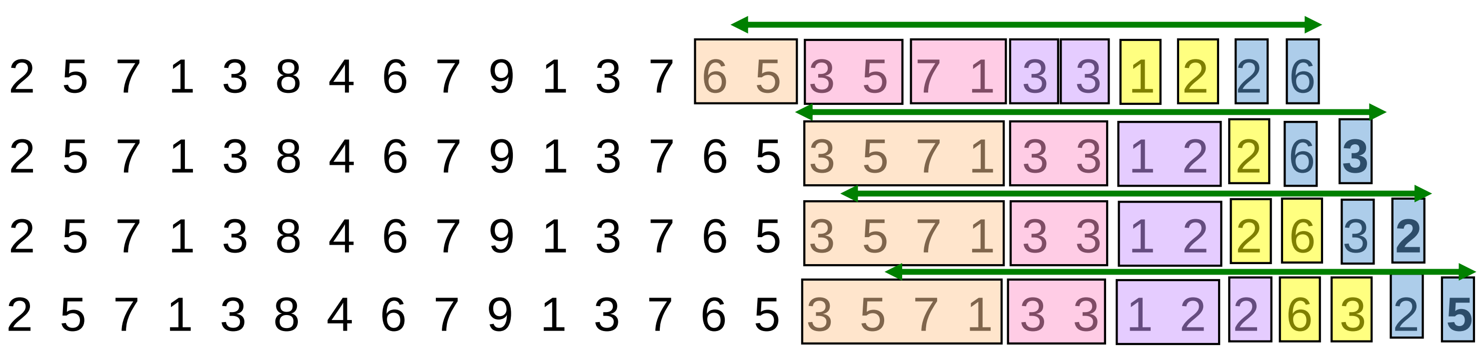


- **Can we handle the case where the stream is not bits, but integers, and we want the sum of the last *k* elements?**

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 $= \sum_{i=0}^{m-1} c_i 2^i$
  - **(2) Use buckets to keep partial sums**
    - **Sum of elements in size *b* bucket is at most 2^b**

c_i …estimated count for **i-th** bit



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

16	8	4	2	1

Summary

- **Window-based processing**
  - Allow exact operations on finite sub-sequences
- **Sampling a fixed proportion of a stream**
  - Sample size grows as the stream grows
- **Sampling a fixed-size sample**
  - Reservoir sampling
- **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