COMP9313: Big Data Management

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Course web site: http://www.cse.unsw.edu.au/~cs9313/

Chapter 6.1: Mining Data Streams

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)

Characteristics of Data Streams

- Traditional DBMS: data stored in *finite, persistent data sets*
- Data Streams: distributed, continuous, unbounded, rapid, time varying, noisy, . . .
- Characteristics
  - Huge volumes of continuous data, possibly infinite
  - Fast changing and requires fast, real-time response
  - Random access is expensive—single scan algorithm (can only have one look)
  - Store only the summary of the data seen thus far

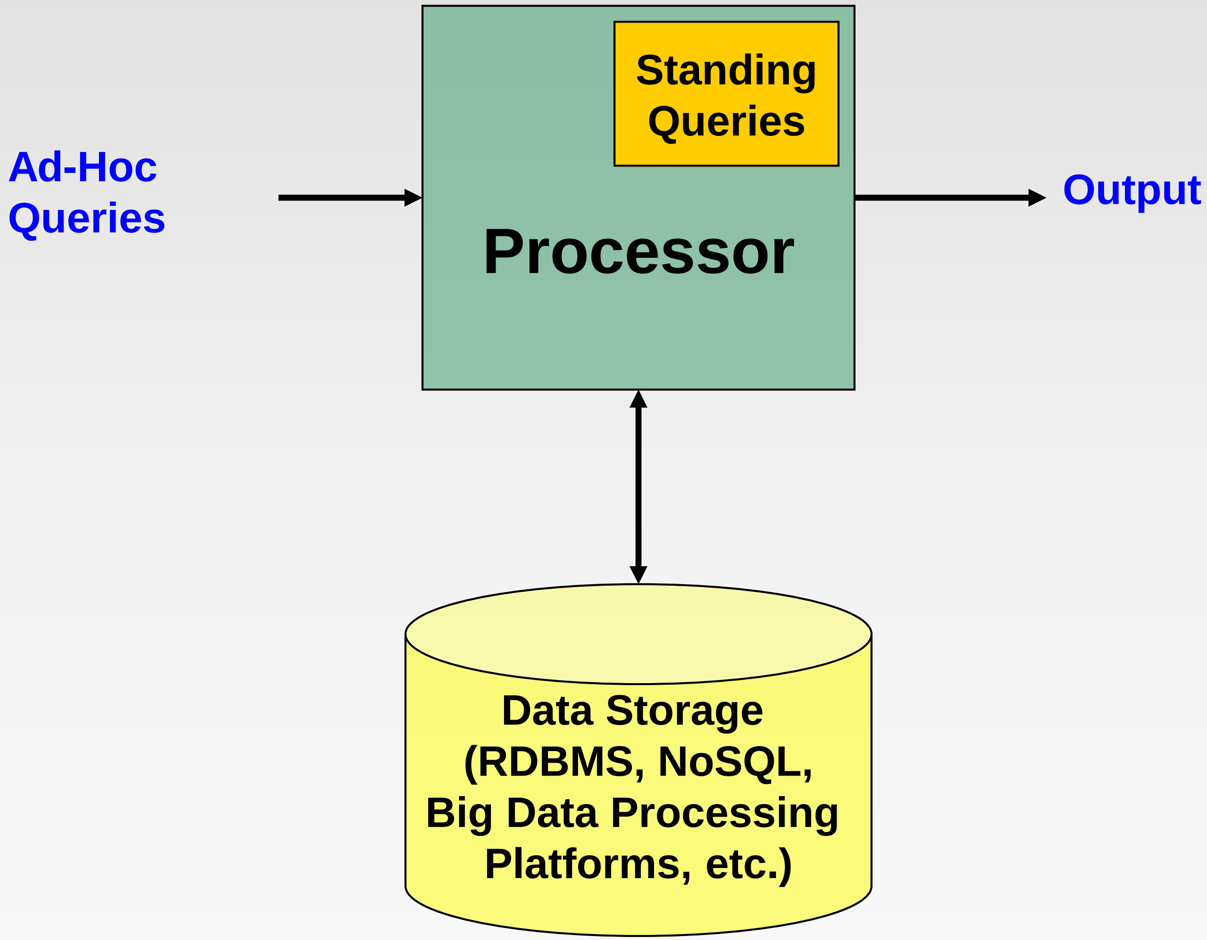
Massive Data Streams

- Data is *continuously growing* faster than our ability to store or index it
- There are 3 Billion Telephone Calls in US each day,
  30 Billion emails daily, 1 Billion SMS, IMs
- Scientific data: NASA's observation satellites generate billions of readings each per day
- IP Network Traffic: up to 1 Billion packets per hour per router. Each ISP has many (hundreds) routers!
- … …

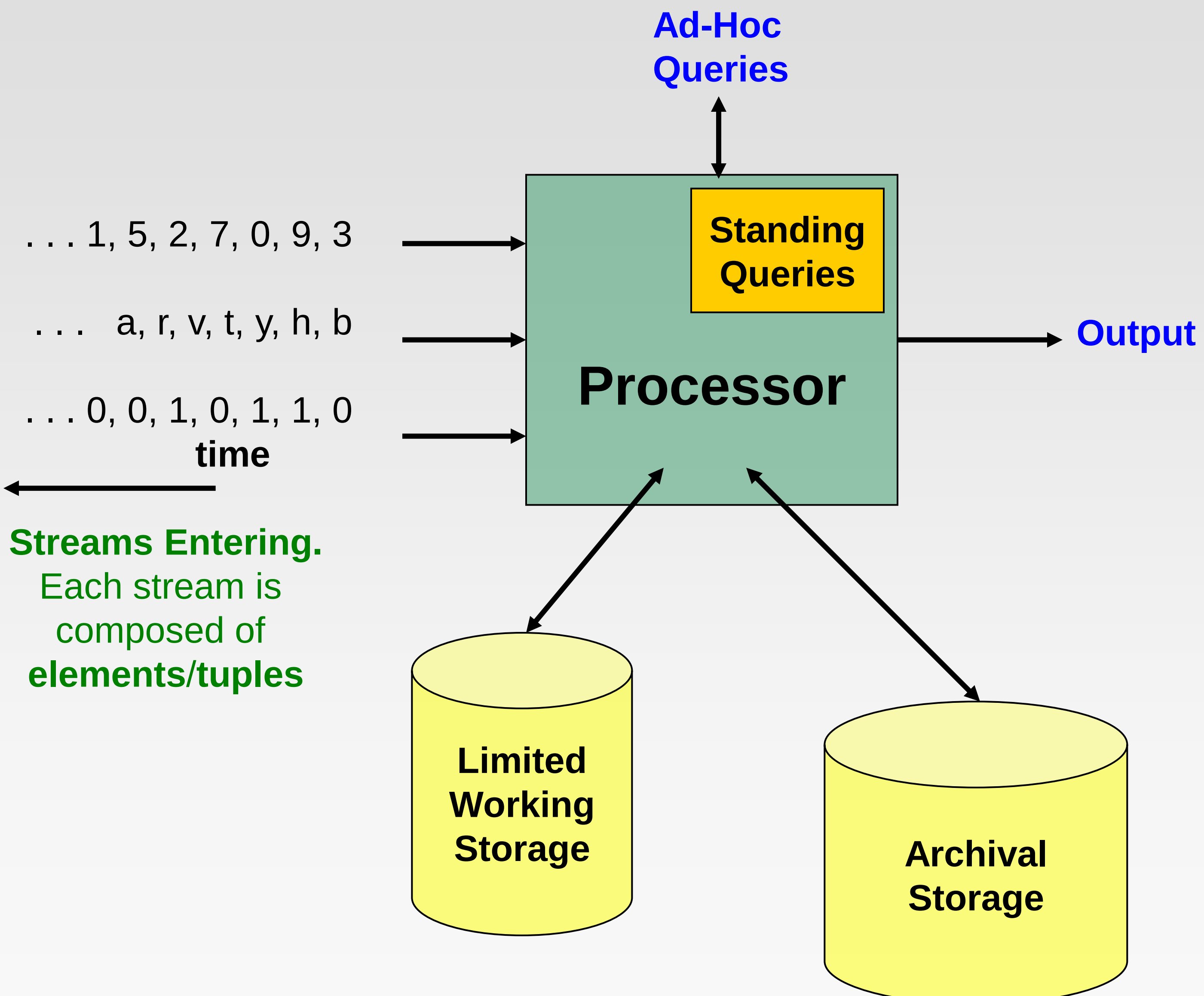
The Stream Model

- 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 memory?**

Database Management System (DBMS) Data Processing

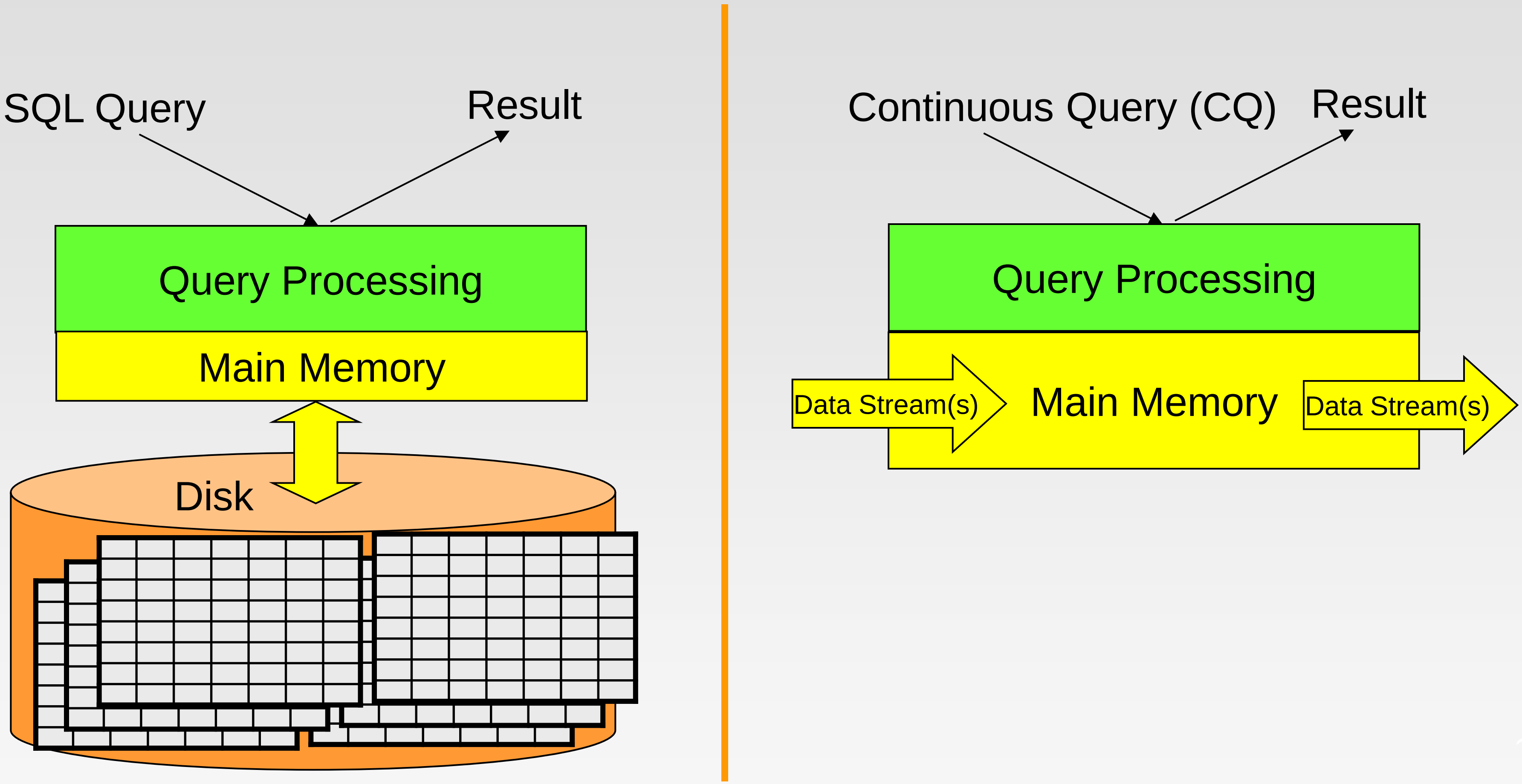


General Data Stream Management System (DSMS) Processing Model



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

DBMS vs. DSMS #1



DBMS vs. DSMS #2

- Traditional DBMS:
  - stored sets of relatively static records with no pre-defined notion of time
  - good for applications that require persistent data storage and complex querying

- DSMS:
  - support on-line analysis of rapidly changing data streams
  - data stream: real-time, continuous, ordered (implicitly by arrival time or explicitly by timestamp) sequence of items, too large to store entirely, no ending
  - continuous queries

DBMS vs. DSMS #3

DBMS

- Persistent relations
  (relatively static, stored)
- One-time queries
- Random access
- “Unbounded” disk store
- Only current state matters
- No real-time services
- Relatively low update rate
- Data at any granularity
- Assume precise data
- Access plan determined by query processor, physical DB design

DSMS

- Transient streams
  (on-line analysis)
- Continuous queries (CQs)
- Sequential access
- Bounded main memory
- Historical data is important
- Real-time requirements
- Possibly multi-GB arrival rate
- Data at fine granularity
- Data stale/imprecise
- Unpredictable/variable data arrival and characteristics

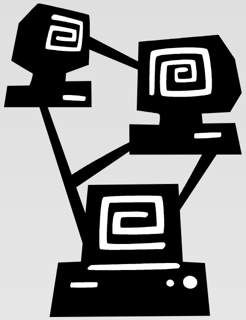
Problems on Data Streams

- Types of queries one wants on answer on a data stream: (we'll learn these today)
  - 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
  - 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
  - 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
- Sensor Networks
  - Many sensors feeding into a central controller
- Telephone call records
  - Data feeds into customer bills as well as settlements between telephone companies
- IP packets monitored at a switch
  - Gather information for optimal routing

Example: IP Network Data

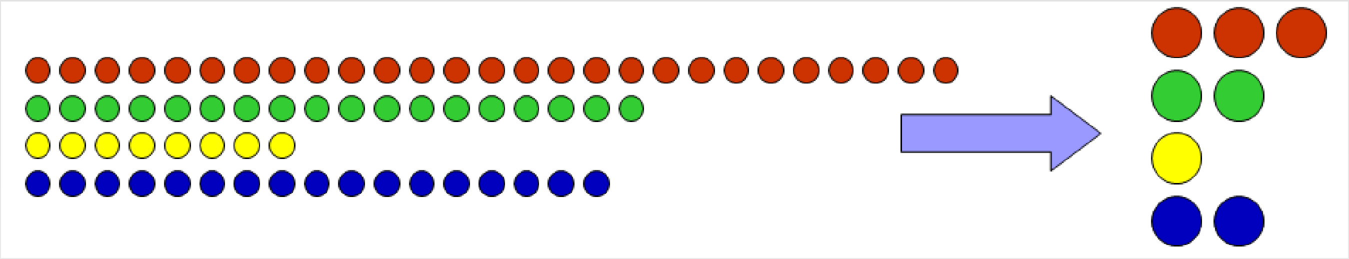


- Networks are sources of massive data: the metadata per hour per IP router is gigabytes
- Fundamental problem of data stream analysis:
  - Too much information to store or transmit
- So process data as it arrives
  - One pass, small space: the data stream approach
- **Approximate answers** to many questions are OK, if there are guarantees of result quality

Part 1: Sampling Data Streams

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)
    - As the stream grows the sample also gets bigger
  - **(2)** Maintain a **random sample of fixed size** over a potentially infinite stream
    - As the stream grows, the sample is of fixed size
    - At any "time" ***t*** we would like a random sample of ***s*** elements
      - **What is the property of the sample we want to maintain?** For all time steps ***t***, each of ***t*** elements seen so far has equal probability of being sampled

Sampling a Fixed Proportion

- 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** $\frac{\frac{d}{100}}{\frac{x}{10}+\frac{d}{100}+\frac{18d}{100}} = \frac{d}{10x+19d}$ **≠*d*/(*x*+*d*)**

Solution: Sample Users

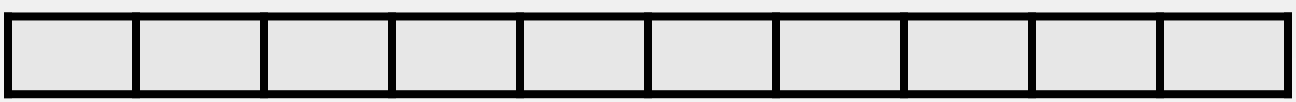
Solution:

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

- Use a hash function that hashes the username or user id uniformly into 10 buckets
  - We hash each username to one of ten buckets, 0 through 9
  - If the user hashes to bucket 0, then accept this search query for the sample, and if not, then not.

Generalized Problem and Solution

- Problem: Give a data stream, take a sample of fraction a/b.
- 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***



How to generate a 30% sample?

Hash into b=10 buckets, take the tuple if it hashes to one of the first 3 buckets

Sample Operator in Spark

- sample(withReplacement, fraction, seed)
  - Return a sampled subset of this RDD.
  - withReplacement: can elements be sampled multiple times
  - fraction: expected size of the sample as a fraction of this RDD's size without replacement
    - This is not guaranteed to provide exactly the fraction specified of the total count of the given
  - seed: seed for the random number generator

```
scala> val rdd = sc.parallelize(1 to 100)
rdd: org.apache.spark.rdd.RDD[Int] = ParallelCollectionRDD[90] at parallelize at <console>:31

scala> var sample1 = rdd.sample(true, 0.4, 2).collect
sample1: Array[Int] = Array(5, 5, 15, 19, 26, 27, 29, 38, 40, 45, 48, 48, 49, 50, 52, 54, 57, 58, 58,
59, 61, 67, 68, 68, 71, 73, 78, 82, 83, 83, 85, 88, 89, 89, 92, 95, 99)

scala> sample1.size
res7: Int = 37

scala> var sample2 = rdd.sample(false, 0.4, 2).collect
sample2: Array[Int] = Array(4, 5, 6, 7, 15, 21, 23, 26, 27, 36, 41, 42, 43, 44, 49, 50, 51, 52, 54, 61
, 62, 66, 68, 77, 82, 86, 91, 93, 96)

scala> sample2.size
res8: Int = 29
```

Maintaining a Fixed-size Sample

- 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.

Note that the same item is treated as different tuples at different timestamps

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:

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

- 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*** $= \frac{s}{n}\cdot\frac{n}{n+1}=\frac{s}{n+1}$

takeSample Operator in Spark

- takeSample(withReplacement, num, seed=None)
  - Return a fixed-size sampled subset of this RDD.
  - withReplacement: can elements be sampled multiple times
  - num: sample size
  - This method should only be used if the resulting array is expected to be small, as all the data is loaded into the driver's memory.

```
scala> val rdd = sc.parallelize(1 to 100)
rdd: org.apache.spark.rdd.RDD[Int] = ParallelCollectionRDD[95] at parallel
ize at <console>:31

scala> var sample1 = rdd.takeSample(true, 20, 1)
sample1: Array[Int] = Array(67, 72, 29, 2, 37, 86, 16, 42, 68, 100, 46, 4,
 83, 67, 51, 69, 92, 24, 97, 8)

scala> sample1.size
res10: Int = 20
```

Part 2: Querying Data Streams

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 = 7

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 (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 1 1 0 1 1 0

Suppose N=7

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**

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?

The Datar-Gionis-Indyk-Motwani (DGIM) Algorithm

- Maintaining Stream Statistics over Sliding Windows (SODA'02)

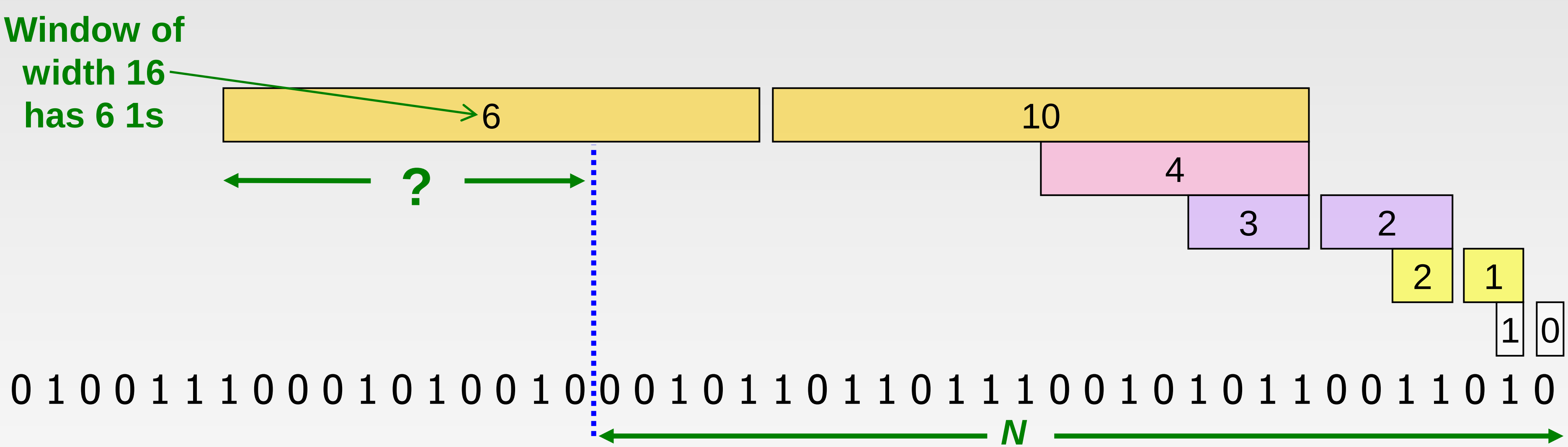
- DGIM solution that does not assume uniformity

- We store $\boldsymbol{O}(\log^2 \boldsymbol{N})$ bits per stream
  - If $\boldsymbol{N}$ = 2^16 (64KB), log (log $\boldsymbol{N}$) = log (16) = 4

- 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?

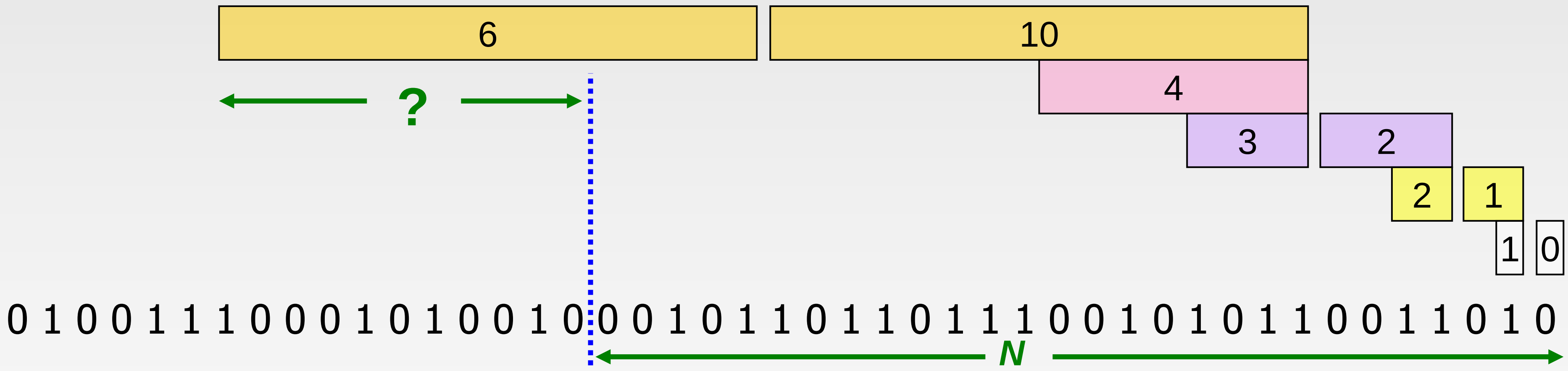
- Stores only $\boldsymbol{O}(\log^{2} \boldsymbol{N})$ bits
  - $\boldsymbol{O}(\log \boldsymbol{N})$ counts of $\log_{2}\boldsymbol{N}$ bits each

- 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?

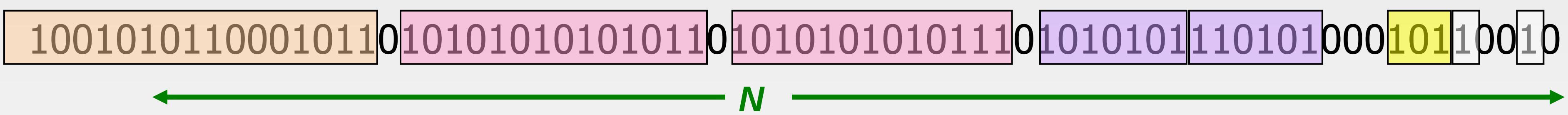
- As long as the **1s** are fairly evenly distributed, the error due to the unknown region is small – **no more than 50%**
- But it could be that all the 1s are in the unknown area at the end
- In that case, the error is unbounded!
  - Because that the number of 1's in the known regions could be 0!



Fixup: DGIM Algorithm

- **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



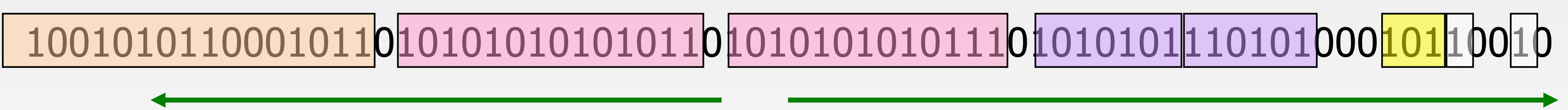
DGIM: Timestamps

- Each bit in the stream has a timestamp, starting from **1**, **2,** …
- Record timestamps modulo ***N*** (**the window size**), so we can represent any **relevant** timestamp in $\boldsymbol{O}(\log_2 \boldsymbol{N})$ bits
  - E.g., given the windows size 40 (***N***), timestamp 123 will be recorded as 3, and thus the encoding is on 3 rather than 123

DGIM: Buckets

- A bucket in the DGIM method is a record consisting of:
  - (A) The timestamp of its end [$\boldsymbol{O}(\log \boldsymbol{N})$ bits]
  - (B) The number of 1s between its beginning and end [$\boldsymbol{O}(\log\log \boldsymbol{N})$ bits]

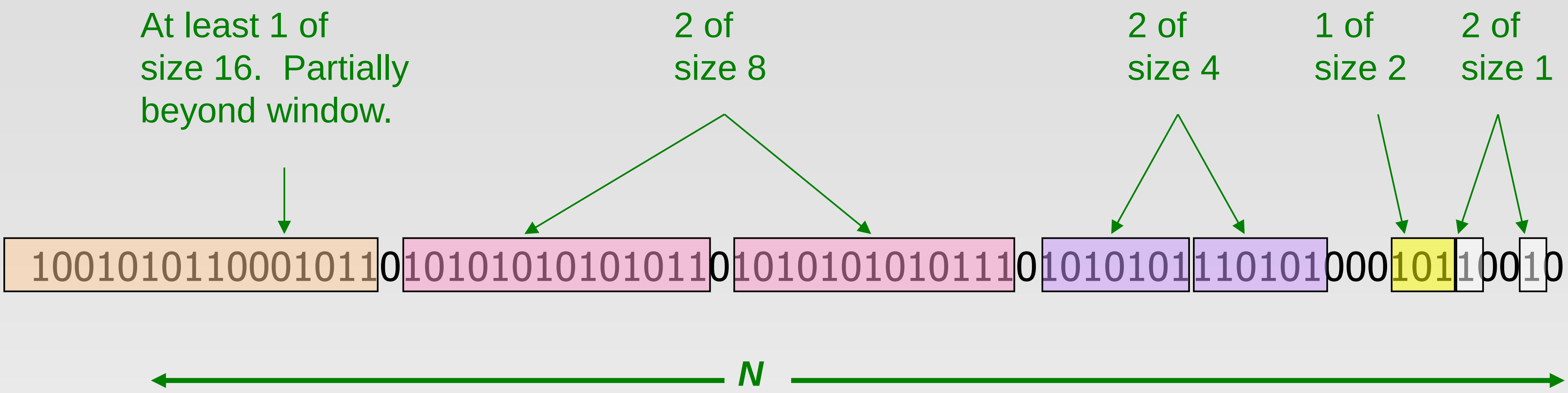
- Constraint on buckets:
  - Number of 1s must be a power of 2
  - That explains the $\boldsymbol{O}(\log\log \boldsymbol{N})$ in (B) above



Representing a Stream by Buckets

- The right end of a bucket is always a position with a 1
- Every position with a 1 is in some bucket
- 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

- 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
- 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:

1001010110001011010101010101011010101010101110101010111010100010110010

Bit of value 1 arrives

00101011000101101010101010101101010101010111010101011101010001011001001

Two white buckets get merged into a yellow bucket

00101011000101101010101010101101010101010111010101011101010001011001001

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

010110001011010101010101011010101010101110101010111010100010110010101101

Buckets get merged…

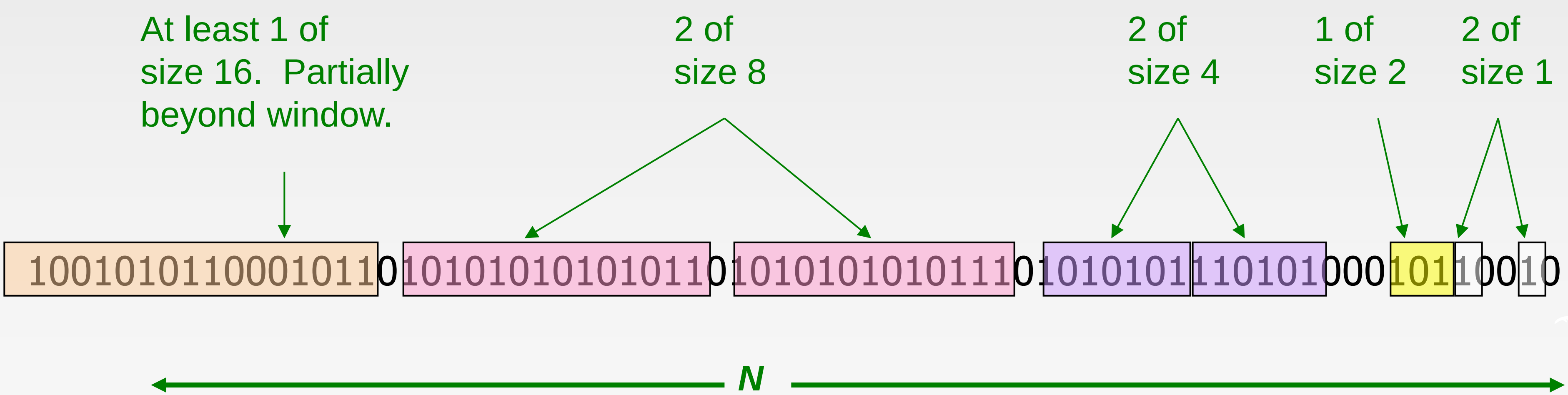
010110001011010101010101011010101010101110101010111010100010110010101101

State of the buckets after merging

010110001011010101010101011010101010101110101010111010100010110010101101

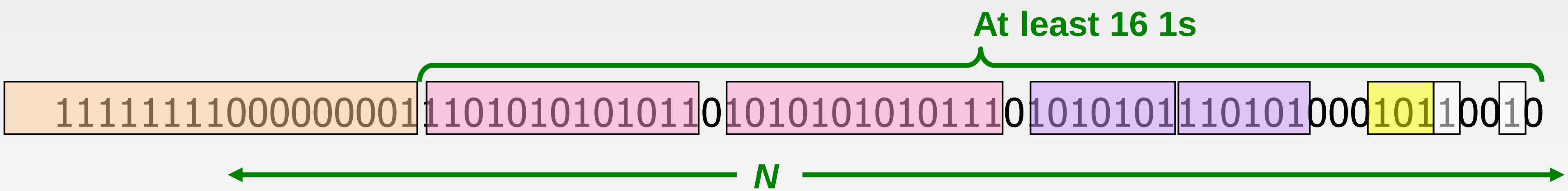
How to Query?

- To estimate the number of 1s in the most recent N bits:
  - Sum the sizes of all buckets but the last
    - (note “size” means the number of 1s in the bucket)
  - 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:



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*)**
  - ***WHY?***
- By picking ***r*** appropriately, we can tradeoff between number of bits we store and the error

Practice

- Suppose we are maintaining a count of 1s using the DGIM method. We represent a bucket by (i, t), where i is the number of 1s in the bucket and t is the bucket timestamp (time of the most recent 1).
  - Consider that the current time is 200, window size is 60, and the current list of buckets is: (16, 148) (8, 162) (8, 177) (4, 183) (2, 192) (1, 197) (1, 200). At the next ten clocks, 201 through 210, the stream has 0101010101. What will the sequence of buckets be at the end of these ten inputs?

Solution

- There are 5 1s in the stream. Each one will update to windows to be:
  - (1) (16, 148)(8, 162)(8, 177)(4, 183)(2, 192)(1, 197)(1, 200), (1, 202)

    => (16, 148)(8, 162)(8, 177)(4, 183)(2, 192)(2, 200), (1, 202)
  - (2) (16, 148)(8, 162)(8, 177)(4, 183)(2, 192)(2, 200), (1, 202), (1, 204)
  - (3) (16, 148)(8, 162)(8, 177)(4, 183)(2, 192)(2, 200), (1, 202), (1, 204), (1; 206)

    => (16, 148)(8, 162)(8, 177)(4, 183)(2, 192)(2, 200), (2, 204), (1, 206)

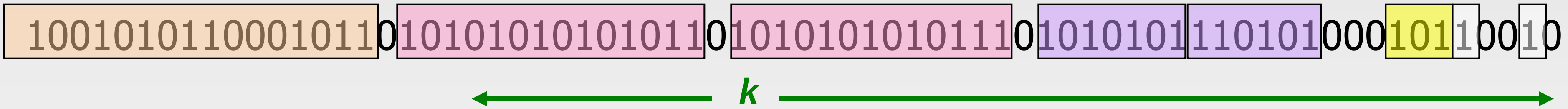
    => (16, 148)(8, 162)(8, 177)(4, 183)(4, 200), (2, 204), (1, 206)
  - (4) Windows Size is 60, so (16,148) should be dropped.

    (16, 148)(8, 162)(8, 177)(4, 183)(4, 200), (2, 204), (1, 206), (1, 208) => (8, 162)(8, 177)(4, 183)(4, 200), (2, 204), (1, 206), (1, 208)
  - (5) (8, 162)(8, 177)(4, 183)(4, 200), (2, 204), (1, 206), (1, 208), (1, 210)

    => (8, 162)(8, 177)(4, 183)(4, 200), (2, 204), (2, 208), (1, 210)

Extensions

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

2 5 7 1 3 8 4 6 7 9 1 3 7 6 5 3 5 7 1 3 3 1 2 2 6

2 5 7 1 3 8 4 6 7 9 1 3 7 6 5 3 5 7 1 3 3 1 2 2 6 3

2 5 7 1 3 8 4 6 7 9 1 3 7 6 5 3 5 7 1 3 3 1 2 2 6 3 2

2 5 7 1 3 8 4 6 7 9 1 3 7 6 5 3 5 7 1 3 3 1 2 2 6 3 2 5

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

Bucket sizes:

16	**8**	**4**	**2**	**1**

References

- Chapter 4, Mining of Massive Datasets.

End of Chapter 6.1