# Data Mining and Analysis Streaming Data

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### Resources

MMDS Chapter 4 + slides

http://infolab.stanford.edu/~ullman/mmds/ch4.pdf

http://www.mmds.org/mmds/v2.1/ch04streams1.pdf

http://www.mmds.org/mmds/v2.1/ch04streams2.pdf

Carlos Castillo course on Data Mining [https://github.com/chatox/data-mining-course]

### What is a data stream?

A potentially infinite sequence of data points

### **Examples:**

Web click-stream data

Stock quotes

Sensor data (e.g., temperature, air pressure)

Network monitoring data

. . .

# **Key Properties**

#### **Unbounded size**

Data cannot be persisted on disk

Only summaries can be stored

#### **Transient**

Single pass over the data

Sometimes real-time processing is needed

### **Dynamic**

May require incremental updates

May require forgetting old data

Concepts "drift"

**Temporal order** is often important

# **Applications**

### Mining query streams

A search engine wants to know what queries are more frequent today than yesterday

### Mining click streams

Amazon wants to know when one of its pages starts getting an unusual number of hits per hour

### Mining social network news feeds

Twitter or Facebook wants to show trending topics

# **Applications**

#### **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

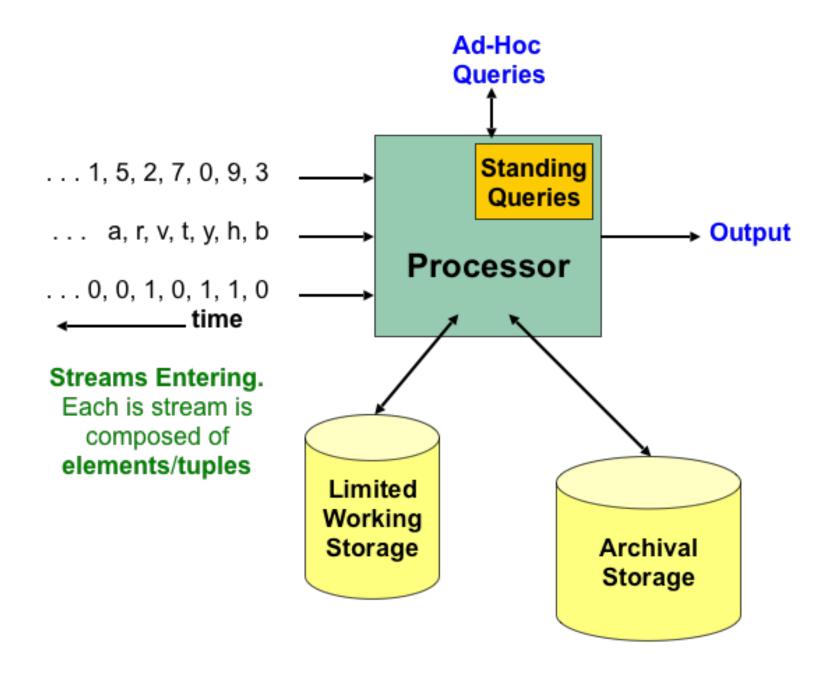
Gather information for optimal routing

Detect denial-of-service attacks

# Why do we need new algorithms?

	Traditional	Stream
passes	multiple	single
processing time	unlimited	restricted
memory	disk	main memory
results	typically accurate	approximate
distributed	typically not	often

# General Stream Processing Model



### Problems on Data Streams?

Sampling data from a stream

Queries over sliding windows

Filtering a data stream

Counting distinct elements

Finding frequent elements

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# Filtering Data Streams

Each element of data stream is a tuple

Given a list of keys S

Determine which tuples of stream are in S?

**Bloom filters!** 

# Sampling a fixed proportion

# Sampling a fixed proportion

Example stream: <user, query, timestamp> from a search engine query log

Suppose we have space to store 1/r of the stream

E.g., 1/10th, 1/100th, 1/1000th, ...

### Naive solution:

Generate uniform random number in 0 ... (r-1)

If the number is 0, keep the item

# What can we do with this sample?

Estimate the most frequent query

Pick the most frequent in the sample

Estimate the frequency of a query

Multiply the observed frequency by r

Do people ask query q?

Approximate answer (with some error)

## **Question Time**

We want to tell if we have seen item q
Suppose we have seen n items so far
We have sampled a fraction 1/r
Suppose item q appears with prob p(q)
What is the probability of:

False positive? (item q was not in the stream but we said it was)

ZERO

False negative? (item q was in the stream but we said it was not)  $(1-p(q))^{n/r}$ 

# But there are questions we cannot answer with the naive approach

Example: What fraction of queries by an average search engine user are duplicates?

Suppose each user issues

x queries once and d queries twice

In total: x + 2d queries

Correct answer = d/(x+d)

### Proposed solution: We keep 1/10th of the queries

Sample will contain x/10 of the singleton queries at least once

Sample will contain 2d/10 of the duplicate queries at least once

Sample will contain d/100 pairs of duplicates

$$d/100 = 1/10 * 1/10 * d$$

Of the d duplicates, 18d/100 will be seen once

$$18d/100 = ((1/10 * 9/10) + (9/10 * 1/10)) * d$$

So the sample answer is:

Observed duplicates 
$$\frac{d}{100}$$
  $=$   $\frac{d}{10x+19d}$  WRONG!  $\frac{x}{10}+\frac{18d}{100}+\frac{d}{100}$  Observed singletons Observed duplicates

# Solution: Sample users!

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

How?

### **Hashing**

Given <user, query, timestamp>

Compute h(user) —> 0, 1, ... (r-1)

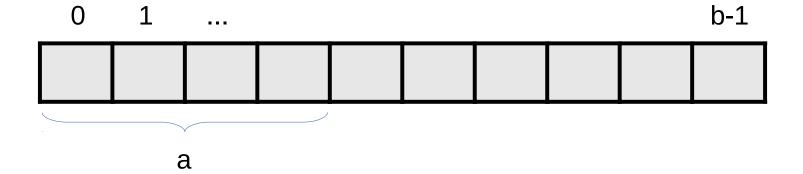
Keep tuple if hash value is 0

# In general

To sample a/b of a stream by key

Compute hash(key) -> 0, 1, (b-1)

Keep if h(key) < a



# Sampling a fixed-size sample

# A fixed size sample

We normally do not know the stream size

We just know how much storage space we have

Suppose we have storage space s and want to maintain a random sample S of size s=|S|

**Requirement:** after seeing n items, each of the n items should be in our sample with probability s/n

No item should have an advantage or disadvantage

## **Bad solutions**

Suppose stream = <a, f, e, b, g, r, u, ...>

Requirement: after seeing n items, each of the n items should be in our sample with probability s/n

Suppose s=2

Always keep first two? No, because then p(a) = 1, while p(e) = 0

Always keep last two? No, because then p(a) = 0, while p(u) = 1

Sample some? But which? Then evict some? But which?

# Reservoir sampling

Elements  $x_1, x_2, x_3, ..., x_i, ...$ 

- 1. Store all first s elements  $x_1, x_2, ..., x_s$
- 2. Suppose element x<sub>n</sub> arrives

With probability 1-s/n, ignore this element

With probability s/n:

Discard a random element from the reservoir

Insert element x<sub>n</sub> into the reservoir

# Example

Input is <a, b, c, ...>

Suppose s=2

We have just processed element 3 = "c"

What is:

Probability "a" is in the sample?

Probability "b" is in the sample?

Probability "c" is in the sample?

# Proof by induction

Inductive hypothesis: after n elements seen, each of them is sampled with probability s/n

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 seen, each of them is sampled with probability s/n

Inductive step: element x<sub>n+1</sub> arrives

What is the probability that an alreadysampled element x<sub>i</sub> stays in the sample?

$$\left(1 - \frac{s}{n+1}\right) + \left(\frac{s}{n+1}\right) \cdot \left(\frac{s-1}{s}\right) = \frac{n}{n+1}$$
 
$$\mathbf{x}_{\text{n+1}} \text{ not sampled} \quad \mathbf{x}_{\text{n+1}} \text{ sampled} \quad \mathbf{x}_{\text{i}} \text{ not evicted}$$

# Proof by induction

Tuple  $x_{n+1}$  is sampled with probability s/(n+1)

Tuples  $x_i$  with i <= n

Were in the sample with probability s/n

Stay in the sample with probability n/(n+1)

Hence, in the sample with probability

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