Mining Data Streams

Sommerakademie St. Johann im Ahrntal — AG 4
Introduction to streams and stream processing

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PROBABILITY PROBABILITY HASHING MANAGEMENT SAMPLING
MARTIN ESTIMATES ELEMENTS DISTINCT BIGDATA SENSORS FILTERING
SENSORS ALGORITHM HASHING ESTIMATES QUERIES FREQUENCY MOMENTS FILTERING TRAFFIC
DISTINCT PROBABILITY STREAMING WEB
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STREAMING SAMPLING BIGDATA BIGDATA HASHING HASHING
FLAJOLET TRAFFIC QUERIES MARTIN MARTIN SENSORS
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DISTINCT BIGDATA FLAJOLET ESTIMATES MANAGEMENT STREAMING

Outline

Section 1

Introduction

Motivation

Problem Monitor network links for quantities such as

- Elephant flows (e.g., traffic engineering),
- Number of distinct flows or average flow size,
- Flow size distribution,
- Per-flow traffic volume,
- Entropy of the traffic,
- Traffic matrix estimation or others

Challenge

Network monitoring at high speed is challenging:

- Packets arrive every 25 ns on a 40 Gbps link
- DRAM cannot be used due to speed limitations
- We need to use SRAM for per-packet processing
- The per-flow state is too large for the SRAM
- Traditional solution not accurate enough

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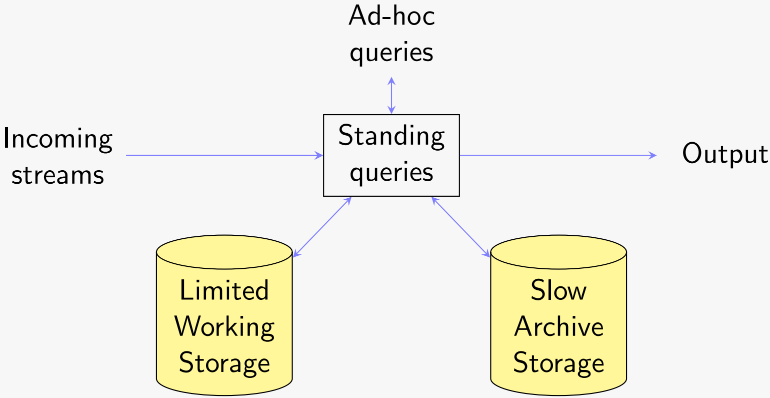
- Input records (tuples) enter at a rapid rate
- We have one or more input ports (possible streams)
- We are not able to store the entire stream
- The system may be required to scale (more streams, more frequent)

Illustration



Stream sources

- Sensors (GPS, IoT, ...)

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- Simulations (Results, Steps, ...)

Section 2

Sampling

Sliding window

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- Or if we have too many streams to handle (velocity)?

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- In practice not as simple, since the query might require more information

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- By considering each n-th record we get

$$\tilde{f} = n \frac{d}{ns + (2n-1)d} \leq f \tag{2}$$

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- If user is known and tracked, then store the query
- If user is known and not tracked, discard
- Otherwise determine by random chance, n-th user
- Now we obtain

$$\tilde{f} = \frac{d}{n} \frac{n}{s + d} = f \tag{3}$$

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- No need to store user and status, only query

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Filtering

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- The Bloom filter is the algorithm of choice

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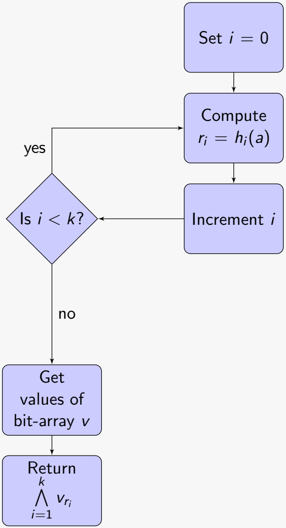
- Storing S or matching against every element is not possible
- Use a bit-array v with n entries as lookup table
- Initialize the bit-array: Enable entries at $h_i(a)$ for $a \in S$, $i \in [1, k]$

Existence check for incoming a



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- Probability for a false positive is given by

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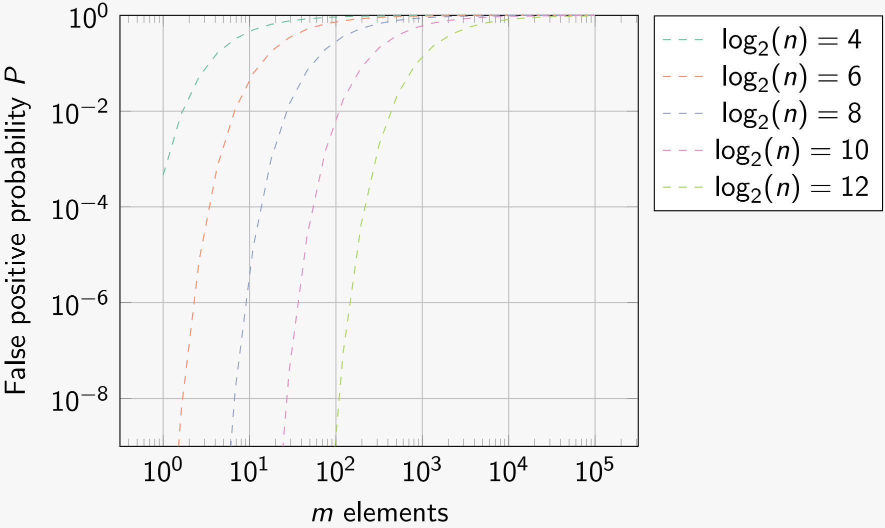
- We can also try to optimize n, the length of the bit-array

False positive probability



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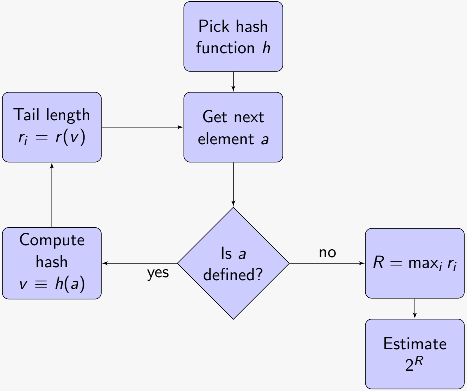
- The Flajolet-Martin algorithm describes this procedure

Flajolet-Martin algorithm [Flajolet, Martin (1985)]



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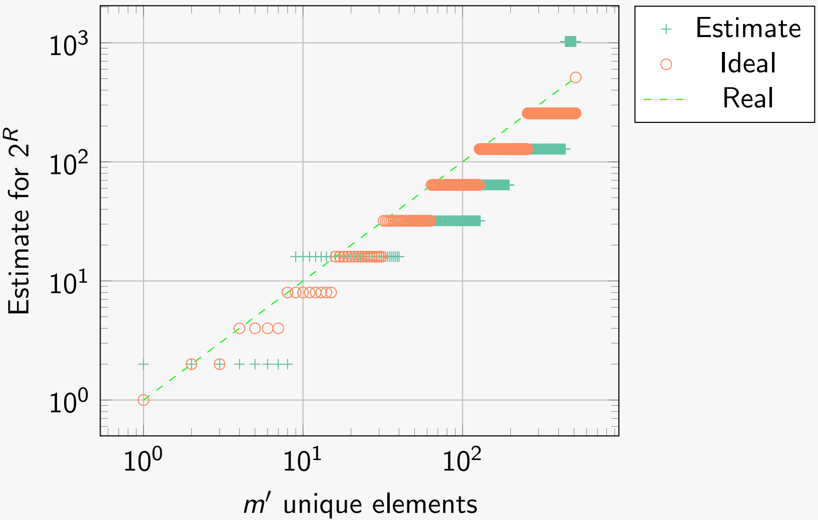
- Count the number of distinct elements
- Use ordinary string hashing function

Sample estimates



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- Use random reservoir only if probabilities are obvious
- Embrace hash functions for randomness
- Determine if approximations are sufficient
- Always think about scaling

Thank you!