Data Stream Mining

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The book

Reference book.

1. Gama, Joao. Knowledge discovery from data streams. Chapman and Hall/CRC, 2010.
2. Aggarwal, Charu C., ed. Data streams: models and algorithms. Vol. 31. Springer Science & Business Media, 2007.

Data Streams

Definition

A data stream is an ordered (not necessarily always) and potentially infinite sequence of data points.

$$x_1, x_2, x_3, \ldots,$$

where x_i could be anything such as numbers, words, sequences, etc.

Such streams are ubiquitous and we are always around them. For example:

- Click streams
- Sensor measurements
- Satellite imaging data
- Power grid electricity distribution
- Banking/e-commerce transactions

Examples of Data Streams : YouTube comments

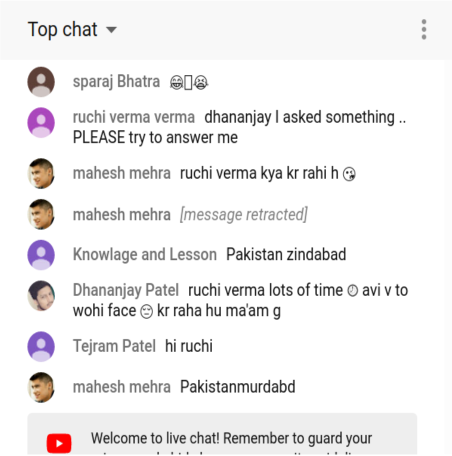

Figure: Youtube live comments

Data Stream Mining Algorithms

Various kinds of tasks:

- Classification
- Clustering
- Frequent pattern mining
- Anomaly Detection
- Change/Concept drift detection
- Mining multiple streams
- Database operations such as indexing, aggregation, and so on

Characteristics of data streams

A data stream has several distinguishing features such as:

- Unbounded Size
  - Transient (that means it lasts for only few seconds or minutes)
  - Single-pass over data
  - Only summaries can be stored
  - Real-time processing (in-memory)
- Data streams are not static
  - Incremental/decremental updates
  - Concept Drifts
- Temporal order may be important

Why can't use traditional algorithms?

- Using SQL/relational DB for storing
- K-mean for clustring?
- Naive-bayes for classification?
- Aprior algorithm for frequent pattern mining?

Relational DB and Data Streams

Table: Source:Babock et al., (2002)

Relational DB	**Data Streams**
Persistent	Transient
Multiple passes	single-pass
unlimited memory	limited memory
low update rate	stream
not real-time	real-time

Traditional Algorithms vs. DS Algorthms

	Traditional	**Data Streams**
passes	multiple	single
processing time	unlimited	limited
realt-time	no	yes
memory	disk	main memory
results	accurate	approximate
distributed	no	yes

Research Issues in Data Stream Management Systems (DSMS)

- Approximate query processing
- Sliding window query processing
- Sampling

Basic Streaming Methods

Most of the streaming methods are approximate. (Why?) So, need good approximation techniques such as:

- ϵ-approximation: answer is within some small fraction ϵ of the true answer.
- (ϵ, δ)-approximation: the answer is within $1 \pm \epsilon$ of the true answer with probability $1 - \delta$

Example 1: Counting the frequency of unique items in a stream

The Problem: Count frequency of A in the stream: A, B, C, A, A, C,...?

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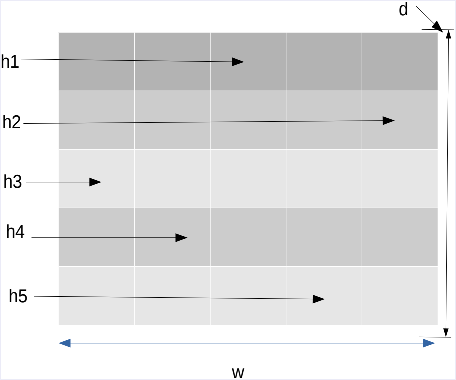
Count-Min Sketch



(c)

	h1	h2	h3	h4	h5
A	0	1	3	4	2
B	1	0	2	4	1
C	0	3	2	1	4

(d)

Example 2: Count unique values in a stream

Similar to numpy np.unique() function. Suppose the domain of the random variable is $\{0, 1, \ldots, M\}$ and stream looks like:

$$0, 1, 0, 0, 0, 1, 1, 2, 3, \ldots$$

Here $M = 3$. Trivial if you have space linear in M (why?). Can you do better? e.g. using space only $\log(M)$. Answer: Use Flajolet and Martin Algorithm (1985).

Flajolet and Martin Algortihm

Algorithm 1: Flajolet and Martin (FM) Algorthm

Input: stream M

Output: Cardinality of M

initialization: BITMAP OF L bits initialized to 0.;

for *each x in M* **do**

1. Calculate hash function $h(x)$.;
2. get binary representation of hash output, call it $bin(h(x))$.;
3. Calculate the index i such that $i = \rho(bin(h(x)))$, where $\rho()$ is such that it outputs the **position** of the least-significant set bit,i.e., position of 1.;
4. set BITMAP[i] = 1.;

end

Let R denote the smallest index i such that BITMAP[i] = 0;

Cardinality of M is $2^R/\phi$ where $\phi \approx 0.77351$;

Intuition

The basic idea behind FM algorithm is that of using a hash function that maps the strings in the stream to uniformly generated random integers in the range $[0, \ldots, 2^L - 1]$. Thus we expect that:

- 1/2 of the numbers will have their binary representation end in 0 (divisible by 2)
- 1/4 of the numbers will have their binary representation end in 00 (divisible by 4)
- 1/8 of the numbers will have their binary representation end in 00 (divisible by 8)
- In general, $1/2^R$ of the numbers will have their binary representation end in 0^R

Then the number of unique strings will be approx. 2^R.(because using n bits, we can represent 2^n integers)

Working Example:

Assume stream M=$\{\ldots, 1, 1, 2, 3, 1, 4, 2, \ldots\}$ and the hash function $h(x) = (2x+1)\%5$.
Then,

$$h(M) = \{3, 3, 0, 2, 3, 4, 0\}$$

and

$$\rho(h(M)) = \{0, 0, 0, 1, 0, 2, 0\}$$

and BITMAP looks like

$$BITMAP = 0|0|0|1|1|1$$

so we see the largest integer has number of 0s as 2. So $R = 2$ and unique integers are $2^2 = 4$ approx.
HW: Try finding unique numbers in $M = \{5, 10, 15, 20, \ldots$ with any hash function.
Extensions:$\log\log$ and $Hyper \log\log$

Bibliography I