MADALGO – CENTER FOR MASSIVE DATA ALGORITHMICS

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Continuous Monitoring of Distributed Data Streams over a Time-based Sliding Window

Motivation

Suppose a set of routers are monitoring a network. To allow an early detection of a Distributed Denial-of-service (DDoS) attack, we need to answer *at any time*:

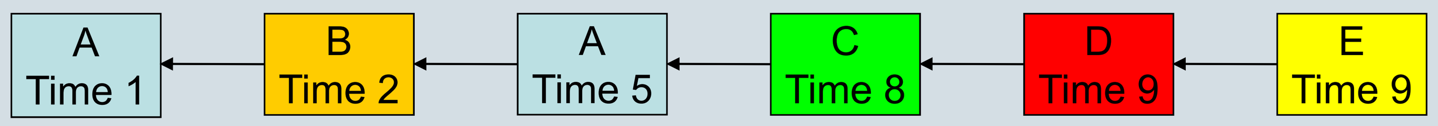
In the IP packets received by all the routers over the last hour, does there exist any frequent destination address?

The problem is to *minimize the communication overhead* to maintain such statistics.

Distributed Data Stream Model

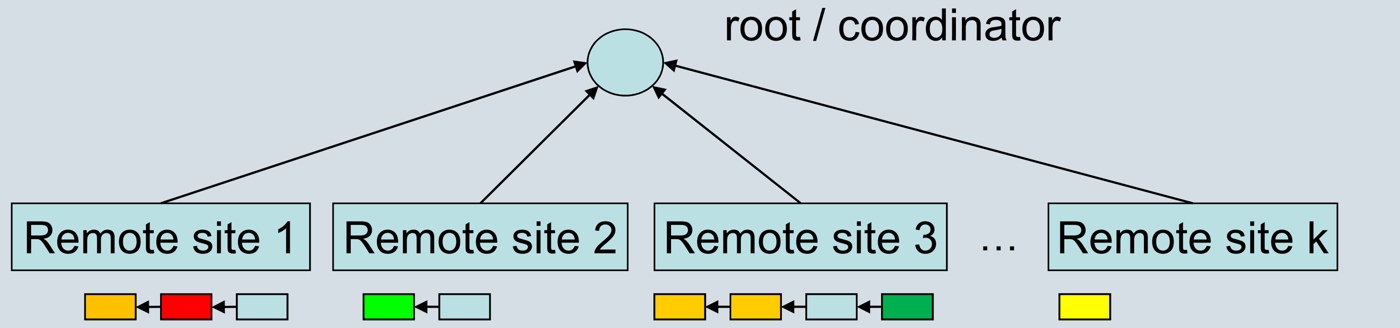
We have $k \geq 1$ remote sites and a single root (or coordinator) distant apart.

- **Each remote site** is monitoring a *stream of items*, where each item contains an item label and a timestamp.



As the stream contains a massive volume of data items, the remote site cannot store the whole stream for processing, and hence each remote site can only maintain an *approximation of some stream statistics* on its own stream.

- **The root** is required to compute the (approximate) *global statistics* on the union of the k streams.



- Only communication between the root and each remote site is allowed; remote sites cannot communicate with each other. This restriction is practical; e.g., in a sensor network, the sensors are cheap devices with limited processing power and memory, and they cannot communicate with each other.

Algorithms in this model are *communication protocols* for the root and remote sites. They can be classified into two types:

- **Two-way algorithms**: bi-directional communication between the root and remote sites are allowed.
- **One-way algorithms**: only the remote sites are allowed to communicate with the root and the root cannot send message to any remote site.

One-way algorithms are usually simple and thus easy to implement, as each remote site has only local information about its own stream; the best the remote site can do is to update the root if its local statistics deviate too much from the one it previously sent to the root.

Two-way communication allows more sophisticated algorithm. Thus, *it is believed that two-way algorithms are more communication-efficient than one-way algorithms.*

Stream Statistics

We study algorithms that enable the root to answer the following classical ε-approximate queries, where $0 < \varepsilon \leq 1$ is a user-specified error bound. Let c be the total count of all items in the stream.

Basic Counting: Estimate the total count c with absolute error εc.

Frequent Items: Let $0 < \phi \leq 1$ be a user-specified threshold. The query asks for *a set of items,* which contains

- all *frequent items* appearing at least $\phi\, c$ times.
- some items appearing at least $(\phi - \varepsilon)\, c$ times.

It is well-known that to return frequent items, it suffices to answer **Approximate Counting**: Estimate the count of any item with absolute error εc.

Quantiles: Given any $0 < \phi \leq 1$, in the sorted order of all items in the stream, return an item with rank in $[(\phi - \varepsilon)\, c, (\phi + \varepsilon)\, c]$.

Stream statistics can be computed over

- **whole data stream**
- a **sliding window** of recent items: all items with timestamps in the *most recent W* time units, where W is the window size.

Sliding window is more difficult to handle as items will expire.

Previous and Our Results

All previous work focuses on the *whole data stream* setting.
Let N be the number of items in all the k streams.

- Basic Counting: $O(\frac{k}{\varepsilon}\log\frac{N}{k})$ words *(one-way)* [2]
- Frequent Items / Approximate Counting:
  $O(\frac{k}{\varepsilon^2}\log\frac{N}{k})$ words *(one-way)* [1]; $O(\frac{k}{\varepsilon}\log\frac{N}{k})$ words *(two-way)* [4]
- Quantiles:
  $O(\frac{k}{\varepsilon^2}\log\frac{N}{k})$ words *(one-way)* [1]; $O(\frac{k}{\varepsilon}\log^2(\frac{1}{\varepsilon})\log\frac{N}{k})$ words *(two-way)* [4]

Our results [3] extend the above study to the *sliding window* setting. Let N be the number of items in all the k streams that *arrive or expire* within the current sliding window of W time units. We show *upper bounds of one-way algorithms* and *lower bounds for any two-way algorithms*.

- Basic Counting: $\Theta(\frac{k}{\varepsilon}\log\frac{\varepsilon N}{k})$ bits (this result also improves that in [2])
- Frequent Items / Approximate Counting:
  $O(\frac{k}{\varepsilon}\log\frac{N}{k})$ words $\quad \Omega(\frac{k}{\varepsilon}\log\frac{\varepsilon N}{k})$ words
- Quantiles:
  $O(\frac{k}{\varepsilon^2}\log\frac{N}{k})$ words $\quad \Omega(\frac{k}{\varepsilon}\log\frac{\varepsilon N}{k})$ words

Our upper bounds match or nearly match the lower bounds, which reveals that *for these statistics, two-way algorithms could not be much better than one-way algorithms in the worst case*.

Basic Counting

Algorithm. Let $\lambda=\varepsilon/9$.
Each remote site: keeps an λ-approximate local count.
Let c_{cur} and c_{old} be current estimate and the previously sent estimate.
At any time, it updates the root about c_{cur} if the following event occurs

- *Up* event: $c_{cur} - c_{old} > 4\lambda\, c_{old}$
- *Down* event: $c_{old} - c_{cur} > 4\lambda\, c_{old}$

The root: upon a query, returns the sum of all the k estimates received.

Analysis techniques. In a remote site, let n be the number of items arriving or expiring in the current sliding window $[t_1,t_2]$.
If items do not expire, only Up's occur. When an Up occurs, n increases by a fraction of $(1+\Theta(\varepsilon))$, so no. of Up's is $O(\log_{1+\varepsilon}\varepsilon n) = O(\frac{1}{\varepsilon}\log\varepsilon n)$.
Expiry of items destroys the monotonic property of n. Our idea is to define a *characteristic set* of items as a new measure of progress.

- *Up* event: The set is the items *arriving* from t_1 up to the time the Up occurs. When an Up occurs, the size of this set increases by a fraction of $(1+\Theta(\varepsilon))$, and thus the no. of Up's is $O(\frac{1}{\varepsilon}\log\varepsilon n)$.
- *Down* event: The set is the items *expiring* from t_1 up to the time the Down occurs. Similarly, the no. of Down's is $O(\frac{1}{\varepsilon}\log\varepsilon n)$.

The total no. of events is $O(\frac{k}{\varepsilon}\log\frac{\varepsilon N}{k})$. To reduce message size, we *restrict the estimates to a predefined set*, giving the required upper bound.

Approximate Counting

Algorithm. Let $\lambda=\varepsilon/11$.
Each remote site: keeps an λ-approximate item count $c_{cur}(j)$ for each item j, and an $\lambda/6$-approximate total count c_{cur}.
At any time, for each item j, it updates $c_{cur}(j)$ if the following event occurs

- *Up* event: $c_{cur}(j) - c_{old}(j) > 9\lambda\, c_{cur}$
- *Down* event: $c_{old}(j) - c_{cur}(j) > 9\lambda\, c_{cur}$

The root: upon a query on item j, returns the total estimate of j received.

Analysis techniques. Up's can be caused by a *big increase of item j*, or a small increase of j but *significant drop of c_{cur}*, which requires different characteristic set analysis. Furthermore, the communication cost would depend on the no. of possible items. We observe that if $c_{cur}(j) < 3\lambda\, c_{cur}$, we can treat $c_{cur}(j) = 0$ and stop updating j until $c_{cur}(j) \geq 3\lambda$. This keeps $O(\frac{1}{\varepsilon})$ *'active'* items at any time, leading to the required upper bound.

References

[1] Cormode, Garofalakis, Muthukrishnan, Rastogi. *Holistic aggregates in a networked world: distributed tracking of approximate quantiles.* SIGMOD 2005.

[2] Keralapura, Cormode, Ramamirtham. *Communication-efficient distributed monitoring of thresholded counts.* SIGMOD 2006.

[3] Chan, Lam, Lee, Ting. *Continuous monitoring of distributed data streams over a time-based sliding window.* STACS 2010.

[4] Yi, Zhang. *Optimal tracking of distributed heavy hitters and quantiles.* PODS 2009.