Algorithms for Processing Massive Data at Network Line Speeds

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Joint work with S. Muthukrishnan

Outline

- What's the problem?
- What's hot and what's not?
- What's new?
- What's next?

Data is Massive

Data is growing faster than our ability to store or process 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) of routers!

Massive Data Analysis

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Must analyze this massive data:

- System management (spot faults, drops, failures)
- Customer research (association rules, new offers)
- For revenue protection (phone fraud, service abuse)
- Scientific research (Climate Change, SETI etc.)

Else, why even measure this data?

Focus: Network Data

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- Networks are sources of massive data: the metadata per hour per router is gigabytes
- 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

Network Data Questions

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Network managers ask questions that often map onto "simple" functions of the data.

- How many distinct host addresses?
- Destinations using most bandwidth?
- Address with biggest change in traffic overnight?

The complexity comes from space and time restrictions.

Data Stream Algorithms

- Recent interest in "*data stream algorithms*“ from theory: small space, one pass approximations

- Alon, Matias, Szegedy 96: frequency moments
  Henzinger, Raghavan, Rajagopalan 98 graph streams

- In last few years:
  Counting distinct items, finding frequent items, quantiles, wavelet and Fourier representations, histograms...

The Gap

A big gap between theory and practice: many good theory results aren't yet ready for primetime.

Approximate within $1 \pm \varepsilon$ with probability $> 1-\delta$. Eg: AMS sketches for F_2 estimation, set $\varepsilon=1\%$, $\delta=1\%$

- Space $O(1/\varepsilon^2 \log 1/\delta)$ is approx 10^6 words = 4Mb
  Network device may have 100k-4Mb space *total*
- Each data item requires pass over whole space
  At network line speeds can afford a few dozen memory accesses, perhaps more with parallelization

Bridging the Gap

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My work sets out to bridge the gap: the Count-Min sketch and change detection data structures.

- Simple, small, fast data stream summaries which have been implemented to solve several problems
- Some subtlety: to beat $1/\varepsilon^2$ lower bounds, must explicitly avoid estimating frequency moments
- Here: Application to fundamental problems in networks and beyond, finding heavy hitters and large changes

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1. Heavy Hitters

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- Focus on the Heavy Hitters problem: Find users (IP addresses) consuming more than 1% of bandwidth
- In algorithms, "Frequent Items": Find items and their counts when count more than ϕN
- Two versions:
  a) arrivals only : models most network scenarios
  b) arrivals and departures : applicable to databases

Prior Work

Heavily studied problem (for arrivals only):

- Sampling, keep counts of certain items:
  Gibbons, Matias 1998
  Manku, Motwani 2002
  Demaine, Lopez-Ortiz, Munro 2002
  Karp, Papadimitriou, Shenker 2003

- Filter or sketch based:
  Fang, Shivakumar, Garcia-Molina, Motwani, Ullman 1998
  Charikar, Chen, Farach-Colton 2002
  Estan, Varghese 2002

No prior solutions for arrivals and departures before this.

Stream of Packets

- Packets arrive in a stream. Extract from header:
  Identifier, i: Source or destination IP address
  Count: connections / packets / bytes

- Stream defines a vector a[1..U], initially all 0
  Each packet increases one entry, a[i].
  In networks $U = 2^{32}$ or 2^{64}, too big to store

- Heavy Hitters are those i's where $a[i] > \phi N$
  Maintain N = sum of counts

Arrivals Only Solution

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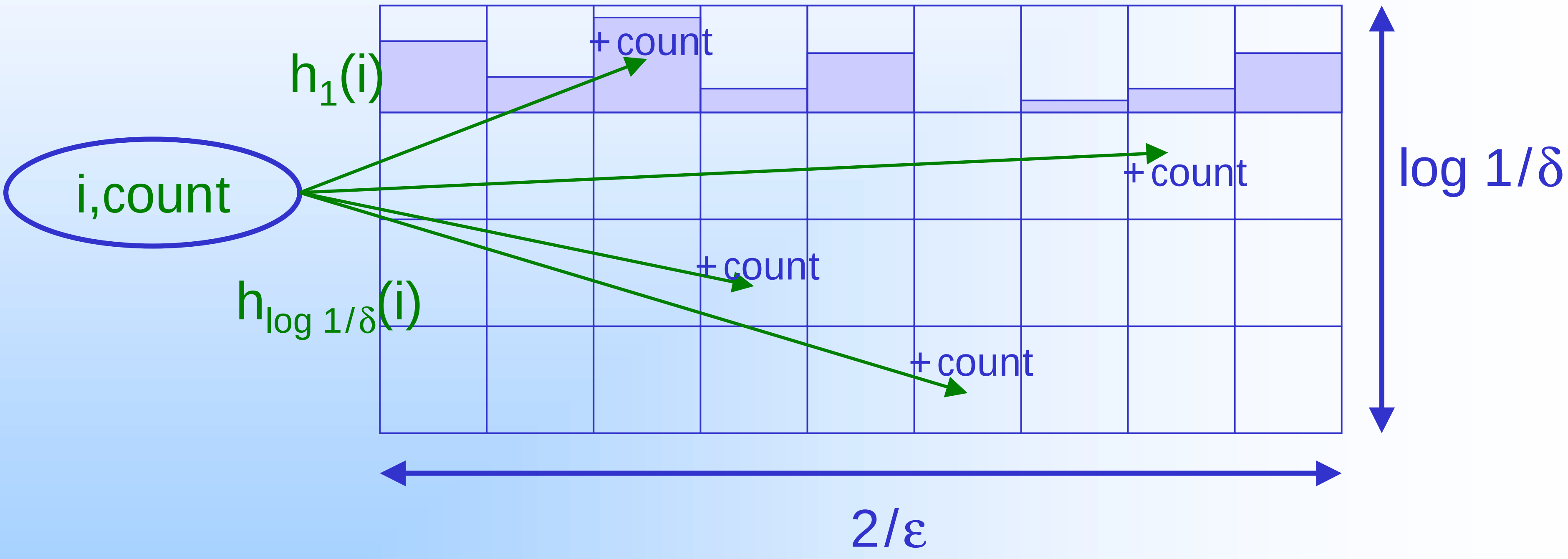
Naive solution: keep the array a and for every item in stream, test if $a[i] > \phi N$. Keep heap of items that pass since item can only become a HH following insertion.

Solution here: replace $a[i]$ with a small data structure which approximates all $a[i]$ upto εN with prob $1-\delta$

Ingredients:

- Universal hash fns $h_1..h_{\log 1/\delta}$ $\{1..U\} \rightarrow \{1..2/\varepsilon\}$
- Array of counters $CM[1..2/\varepsilon, 1..\log_2 1/\delta]$

Update Algorithm



Count-Min Sketch

Approximation

Approximate $\hat{a}[i] = \min_j CM[h_j(i),j]$

Analysis: In j'th row, $CM[h_j(i),j] = a[i] + X_{i,j}$

$$X_{i,j} = \Sigma\, a[k] \mid h_j(i) = h_j(k)$$

$$\begin{aligned} E(X_{i,j}) &= \Sigma\, a[k]*Pr[h_j(i)=h_j(k)] \\ &\leq Pr[h_j(i)=h_j(k)] * \Sigma\, a[k] \\ &= \varepsilon N/2 \text{ by pairwise independence of } h \end{aligned}$$

Analysis

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$$\Pr[X_{i,j} \geq \varepsilon N] = \Pr[X_{i,j} \geq 2E(X_{i,j})]$$
$$\leq 1/2$$ by Markov inequality

Hence, $\Pr[\hat{a}[i] \geq a[i] + \varepsilon N] = \Pr[\forall j.\ X_{i,j} > \varepsilon N]$
$$\leq 1/2^{\log 1/\delta} = \delta$$

Final result:

with certainty $a[i] \leq \hat{a}[i]$ and

with probability at least $1-\delta$, $\hat{a}[i] < a[i] + \varepsilon N$

Results for Heavy Hitters

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- Solve the arrivals only problem by remembering the largest estimated counts (in a heap).
- Every item with count $> \phi N$ is output and with prob $1-\delta$, each item in output has count $> (\phi-\varepsilon)N$
- Space $= 2/\varepsilon \log_2 1/\delta$ counters $+ \log_2 1/\delta$ hash fns
  Time per update $= \log_2 1/\delta$ hashes
  (Universal hash functions are fast and simple)
- Fast enough and lightweight enough for use in network implementations

Implementation Details

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Implementations work pretty well, better than theory suggests: 3 or so hash functions suffice in practice

Running in AT&T's Gigascope, on live 2.4Gbs streams

– Each query may fire many instantiations of CM sketch, how do they scale?
– Should sketching be done at low level (close to NIC) or at high level (after aggregation)?
– Always allocate space for a sketch, or run exact algorithm until count of distinct IPs is large?

Solutions with Departures

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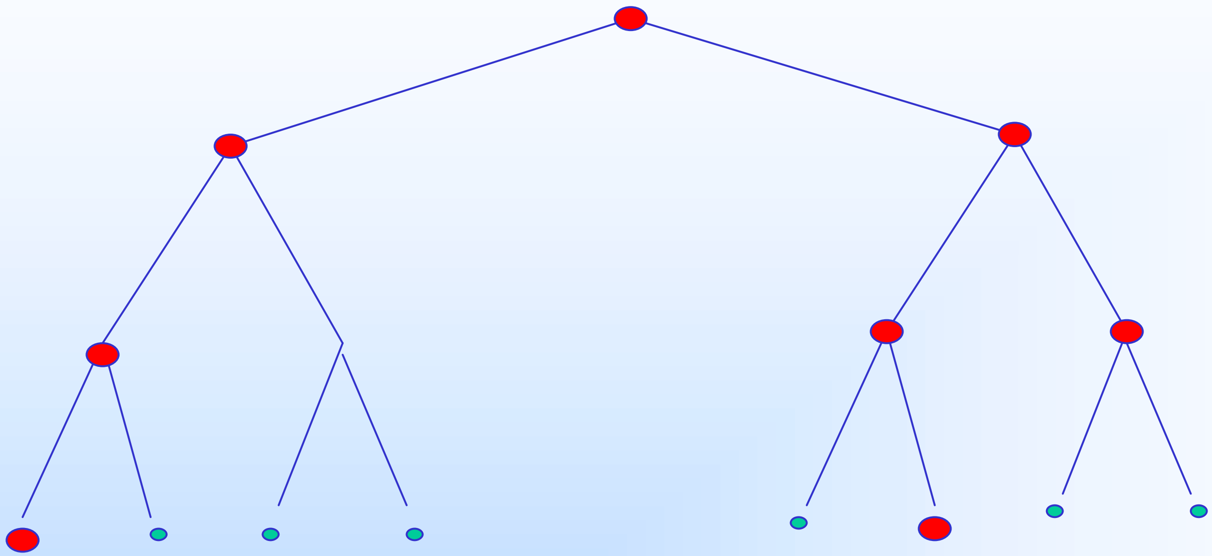
- When items depart (eg deletions in a database relation), finding heavy hitters is more difficult.
- Items from the past may become heavy, following a deletion, so need to be able to recover item labels.
- Impose a (binary) tree structure on the universe, nodes correspond to sum of counts of leaves.
- Keep a sketch for nodes in each level and search the tree for frequent items with divide and conquer.

Search Structure



Find all items with count > ϕN by divide and conquer
(play off update and search time by changing degree)

Sketch structure is an oracle for *adaptive group testing*

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2. Change Detection

- Find items with big change between streams x and y
  Find IP addresses with big change in traffic overnight
- "Change" could be absolute difference in counts, or large ratio, or large variance...
- Absolute difference: find large values in $|a(x) - a(y)|$
  Relative difference: find large values $a(x)[i]/a(y)[i]$
- CM sketch can approximate the differences, but how to find the items without testing everything?
  Divide and conquer (adaptive testing) won't work here!

Change Detection

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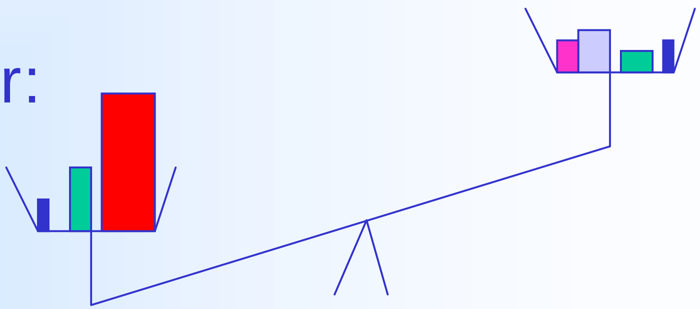
- Use Non-Adaptive Group Testing: will pick groups of items in a randomized fashion
- Within each group, test for "deltoids": items that have shown a large change in behavior
- Must keep more information than just counts to recover identity of deltoids.
- We separate the structure of the groups from the tests, and consider each in turn.

Groups: Simple Case

- Suppose there is just one large item, i, whose "weight" is more than half the weight of all items.
- Use a pan-balance metaphor: this item will always be on the heavier side



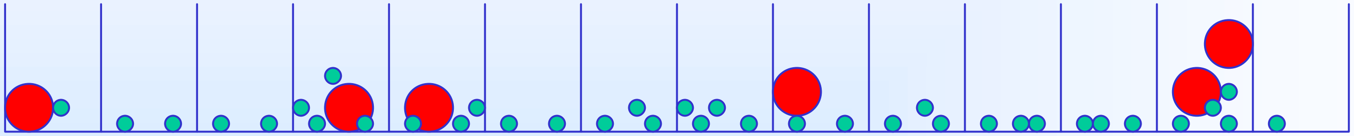
- Assume we have a test which tells us which group is heavy. The large item is always in that group.
- Arrange these tests to let us identify the deltoid.

Solving the simple case

- Keep a test of items whose identifier is odd, and for even: result of test tells whether i is odd or even
- Similarly, keep tests for every bit position.
- Then can just read off the index of the heavy item
- Now, turn original problem into this simple case…

Spread into Buckets

Allocate items into buckets:



- With enough buckets, we expect to achieve the simple case: each deltoid lands in a bucket where the rest of weight is small
- Repeat enough times independently to guarantee finding all deltoids

Group Structure

Formalize the scheme to find deltoids with weight at least $\phi - \varepsilon$ of total amount of change:

- Use a universal hash function to divide the universe into $2/\varepsilon$ groups, repeat $\log 1/\delta$ times.
- Keep a test for each group to determine if there is a deltoid within it. Keep $2\log U$ subgroups in each group based on the bit positions to identify deltoids.

Update procedure: for each update, find the groups the items belongs to and update the corresponding tests.

Group Testing

- Searching: For each group whose test is positive, read results of tests of subgroups: if test j is positive, bit $j = 1$, test j' positive, bit $j=0$
- Avoid false positives: If test j and j' both positive, there are two deltoids in same group, so reject the group (also if j and j' both negative).
- Avoid false positives: Check the recovered item belongs to that group. If so, output it as a deltoid.
- Result: Find all deltoids, if tests gave correct results.

Tests

- How to construct a test for the presence of a deltoid?
- Naively, could keep sketch for each group, but space blows up ($1/\varepsilon^2$ or worse)
- For absolute change deltoids, keeping counts of items suffices, proof similar to CM sketch
- For relative change, appropriate counts also suffice, new proof needed.

Relative Change Test

Keep different information for each stream.

- For stream x, keep $T(x)[j] = \Sigma_{h(i) = j}\, a(x)[i]$
  sum counts of items in the group
- For stream y, keep $T(y)[j] = \Sigma_{h(i) = j}\, (1/a(y)[i])$
  sum reciprocal of counts of items in the group
- Test: if $T(x)[j]*T(y)[j] > \phi\, \Sigma\, (a(x)[i]/a(y)[i])$
  test if product of counts exceeds threshold
- Must be able to find $(1/a(y)[i])$ – open problem to remove this restriction

Relative Change Test

- Test has one-sided error, will always say yes if

  $$(a(x)[i]/a(y)[i]) > \phi \, \Sigma \, (a(x)[i]/a(y)[i])$$

- To bound false positives, and ensure true positives are not obscured by noise, need to argue that each test gives good enough estimate of $(a(x)[i]/a(y)[i])$

- In full paper, show that expected error is $\frac{1}{2} \varepsilon \, \|a(x)\|_1 \, \|1/a(y)\|_1$. So with constant probability this is good estimate of the change.

- The group structure amplifies this probability to $1-\delta$

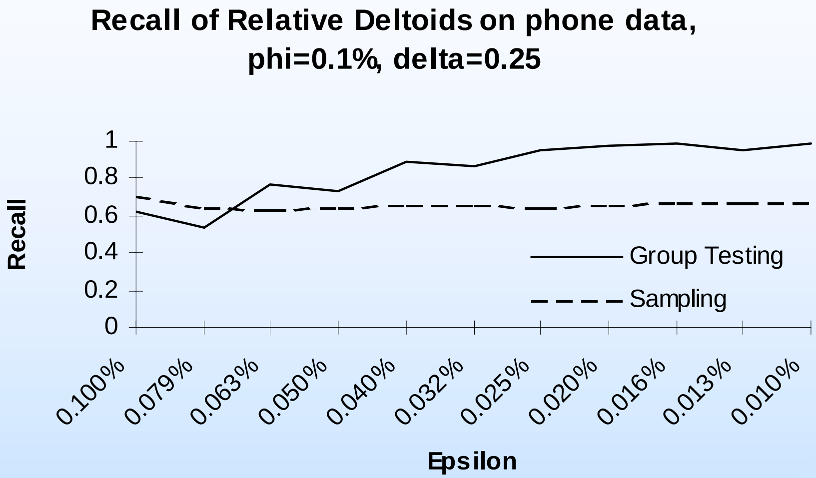
Results

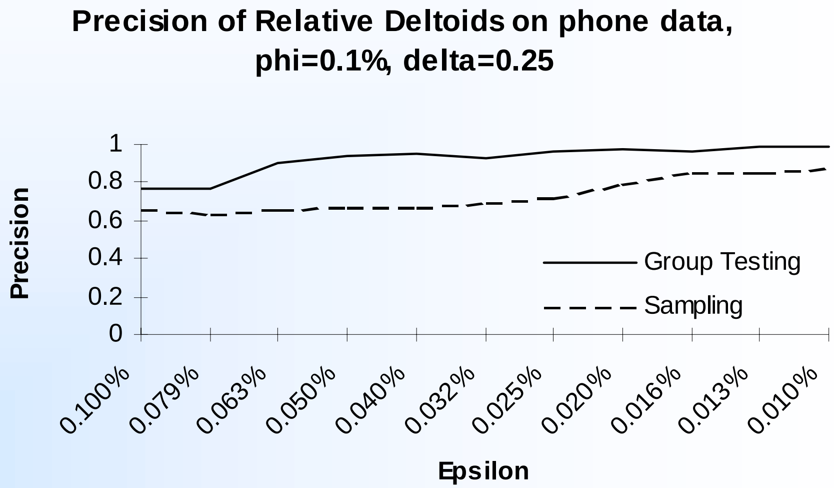
- With probability $1-\delta$, all deltoids are found, no items which are far from being deltoids

- Space is $O(1/\varepsilon \log U \log 1/\delta)$
  Update time is $O(\log U \log 1/\delta)$ per item
  Time to search is linear in the space used

- The same group structure works for different objective functions, if there is an efficient test.

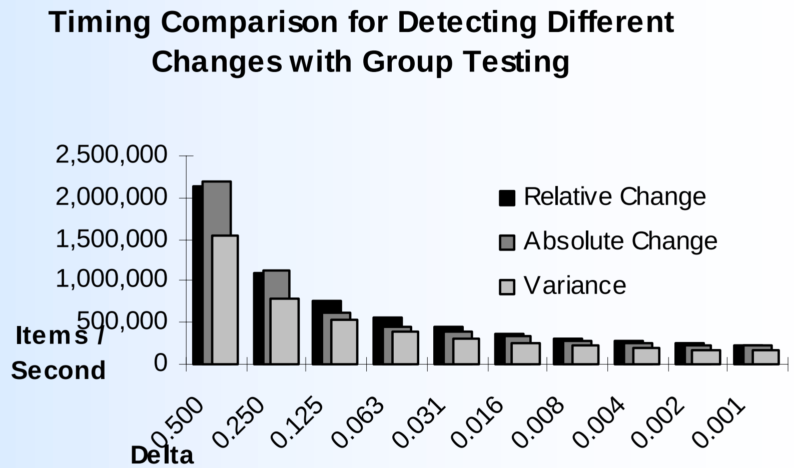
Experiments





Recall = fraction of deltoids found

Precision = fraction of returned items that are deltoids



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Other Applications

These techniques can be applied to several other fundamental data analysis problems:

– Range Sum and Inner Product Estimation

– Finding Approximate Quantiles

– Wavelets and Histograms…

Limited (pairwise) independence suffices for all

Group testing approach is fundamental

Ongoing Work

Agenda: Move other data mining methods from the theoretical to the practical for massive data, in similar and new domains:

- Burst detection on many (large) texts
- Items in hierarchies, eg IP addresses, geographic data
- Massive geometric data — many points from mobile clients.
- Massive Graphs — eg call graphs, web graph

References

- "What's Hot and What's Not: Tracking Most Frequent Items Dynamically" Principles of Database Systems (PODS) 2003
- "An improved data stream summary: the Count-Min sketch and its applications" Journal of Algorithms, 2004
- "What's New: Finding Significant Differences in Network Data Streams" INFOCOM 2004

(all joint work with S. Muthukrishnan)

Code for these algorithms and others is publicly available
http://www.dimacs.rutgers.edu/~graham/code/

http://www.dimacs.rutgers.edu/~graham/
Or web search for "Graham Cormode"