

Estimating Dominance Norms of Multiple Data Streams Graham Cormode graham@dimacs.rutgers.edu

Joint work with S. Muthukrishnan

Data Stream Phenomenon



- Data is being produced faster than our ability to process it
- Leads to the data stream paradigm: process the data as it arrives, don't store or communicate the full data
- Motivated by networks (Gb per hour per router), also applied to databases, scientific data feeds, sensor networks and so on
- Theoretically leads to search for one pass, online algorithms with poly-log space and time per item in the stream

Multiple Signals



Previous work considers only a single signal at a time

Many data streams consist of multiple signals from several distributions, from which we want to extract some global information

Examples:

- financial transactions from many different individuals
- web clickstreams from many users registered on different machines
- multiple readings from multiple sensors in atmospheric monitoring

Prior Work



- Growing body of work on data stream processing in algorithms, database and network fields
- Many computations possible on streams notably, finding frequency moments, Lp norms, quantiles, wavelet representation and so on
- Babcock Babu Datar Motwani Widom 02, Garofalakis, Gehrke, Rastogi 02, Muthukrishnan 03 give surveys from different perspectives
- But almost exclusively focus is on single massive streams, not many massive streams!

Data Stream Model



- Model data streams as simply structured series of items
- n items in the stream S=(i, a[i,j]) means a[i,j] is the value of distribution j at location i
- Assume: a[i,j] is bounded by polynomial in n
- Don't assume that j is made explicit in stream or that we see updates for every [i,j] pair

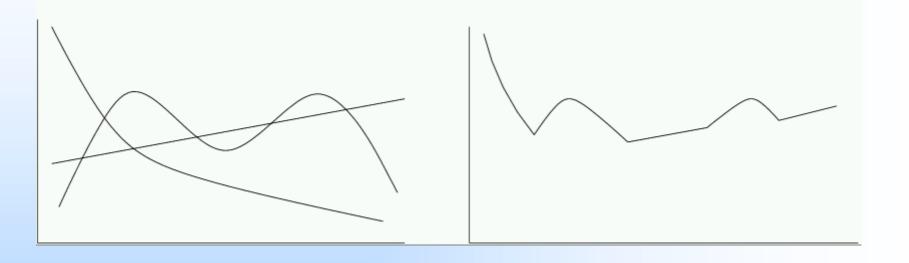
Dominance Norm



- The dominance norm measures the "worst case influence" of the different signals
- Defined as $Dom(S) = \Sigma_i \max_{i} \{a[i,j]\}$
- Can think of this as the L₁ norm of the upper-envelope of the signals,
- Alternatively, as a function of the marginals of a matrix of the signal values





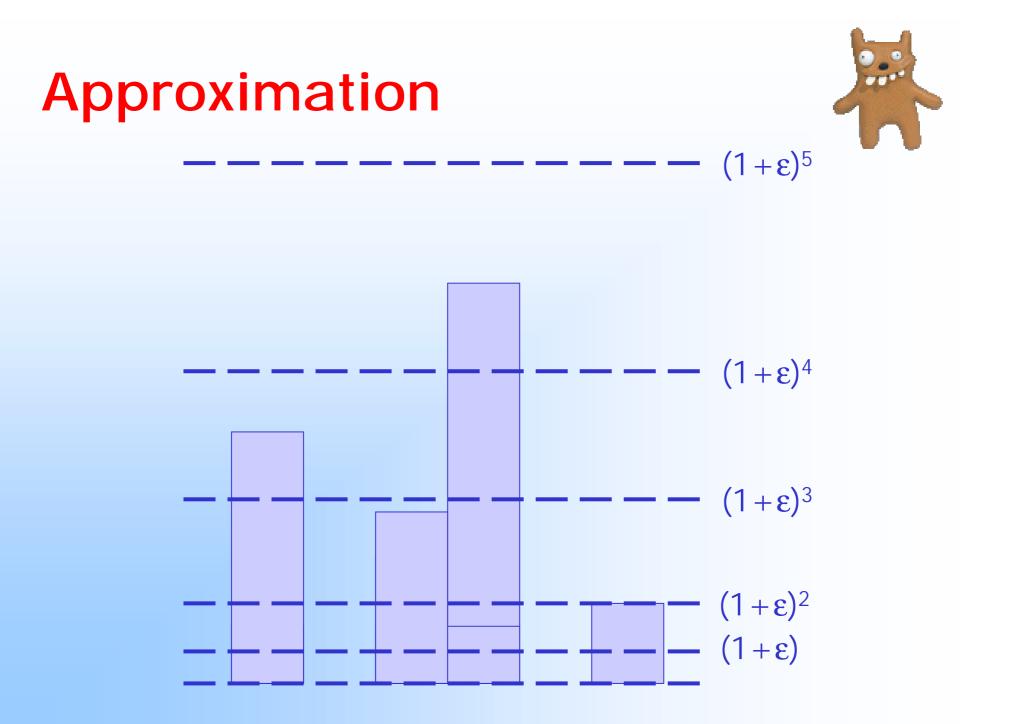


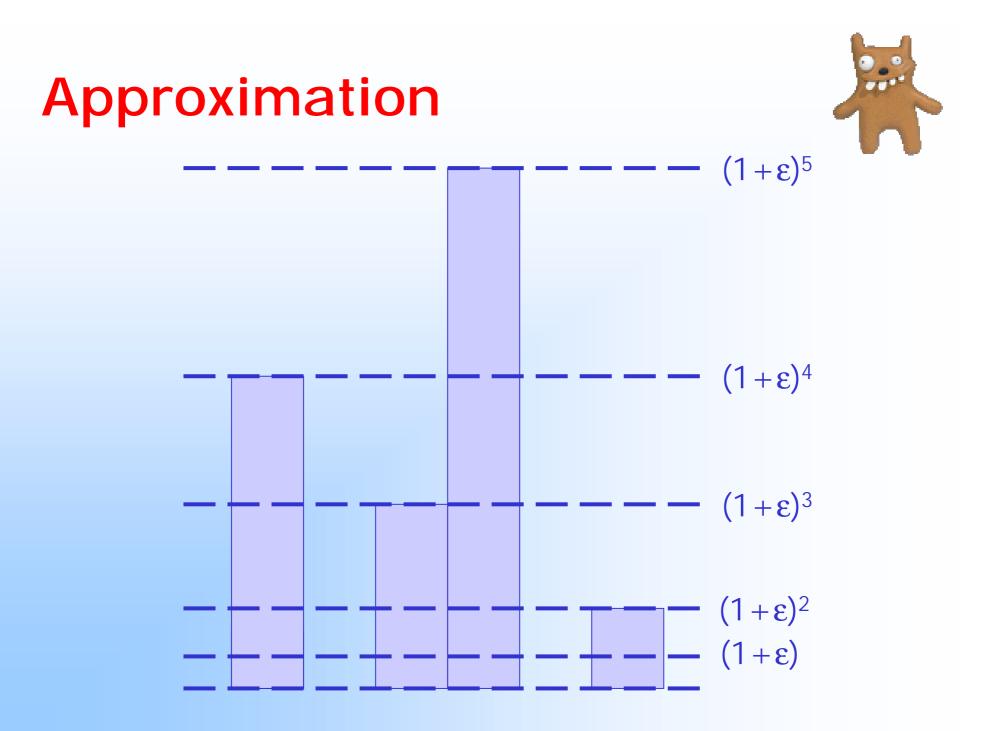
- Maximum possible utilization of a resource
- Applied in financial applications, electrical grid
- Treat as an indicator of actionable events

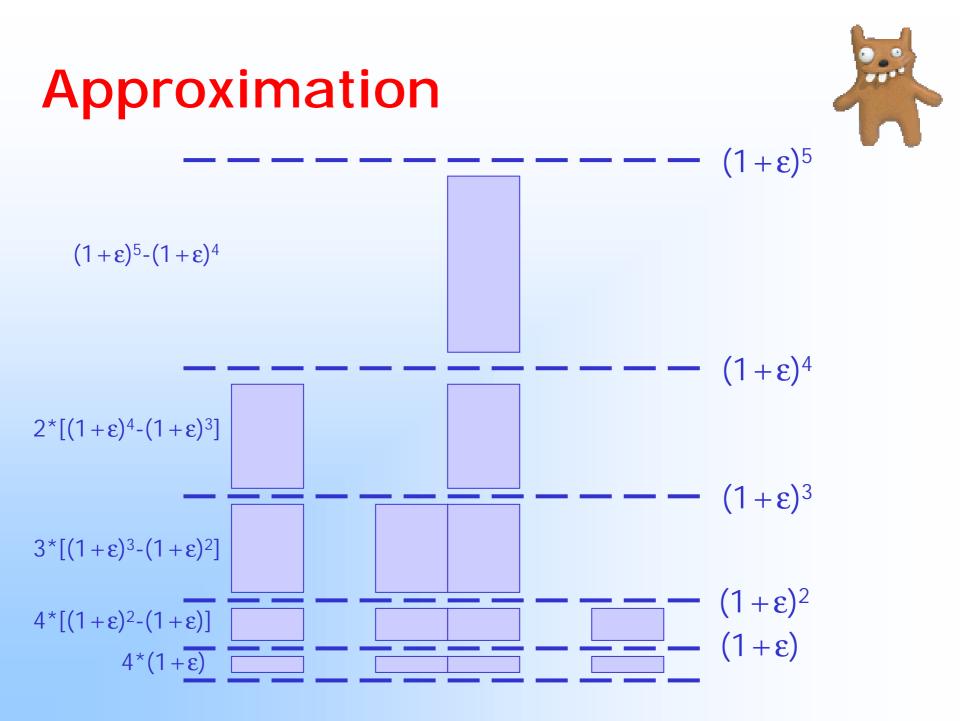
Dominance Norm



- Suppose each a[i,j] is 0 or 1
- Consider each signal to be a set X_j , then $Dom(S) = |U_j X_j|$
- This can be solved using existing stream algorithms for finding unions of multiple sets
- Can also be thought of as counting the number of distinct items i in the stream
- Can this be generalized for arbitrary a[i,j]?







Space Cost



- $\log_{1+\epsilon}$ (max val / min val) distinct element algorithm instances = O(log (n) / ϵ)
- Space required is O(poly-log(n) / ε²) per instance using prior work
- Total space is $O(\text{poly-log}(n)/\epsilon^3)$
- Cubic space dependency on 1/ε is high can we do better?

Reducing Space



- Try to keep just 1 distinct element count algorithm, and so reduce space cost
- Need a more flexible algorithm and new analysis
- Make a new use of Stable Distributions, used before in stream processing
- See Indyk'00, CIKM'02, CDIM'03

Idealized Algorithm



Suppose there were a distribution X such that E(cX) = 1 (an impossible property

- Let x_{i,k} be values drawn from X.
- Set z = 0 initially
- For every (i,a[i,j]) in the stream,

$$z = z + \Sigma_{k=1}^{a[i,j]} x_{i,k}$$

 Then E(z) = Σ_i max_i {a[i,j]}, and can be used to estimate Dom(S)

Reduction to Norms



Fix the idealized algorithm and make it practical.

Replace impossible dbn X with stable distributions by turning problem into one of norm approximation.

Let b be the matrix with $b[i,k] = |\{j | k \le a[i,j]\}|$

- Define $||b||_p^p = \Sigma_{i,k} b^p$
- $Dom(S) = |\{i,k \mid b[i,k] > 0\}| = ||b||_0^0$

Approximate the value of $\|b\|_0^0$ with $\|b\|_p^p$ for suitably chosen small value of p.

Choosing the p-value



Absolute value of any entry in the matrix < n $\|\mathbf{b}\|_{0} = \Sigma \|\mathbf{b}_{i}\|^{0} \le \Sigma \|\mathbf{b}_{i}\|^{p} \le \Sigma B^{p} \|\mathbf{b}_{i}\|^{0} \le n^{p} \|\mathbf{b}\|_{0}$ Setting $n^p = (1 + \varepsilon)$ means $\|\mathbf{b}\|_{0} \leq \|\mathbf{b}_{i}\|_{0}^{p} \leq (1+\varepsilon) \|\mathbf{b}\|_{0}$ So setting $p = \epsilon / \log n$, allows approximation of L_0 by L_p – reducing p zeros in on L_0

Stable Distributions



Use stable distributions to approximate $\|b\|_p^p$ Stable distributions have property that $a_1X_1 + a_2X_2 + \dots a_nX_n \stackrel{\text{in dbn.}}{=} \|(a_1, a_2, \dots, a_n)\|_pX$

if $X_1 \dots X_n$ are stable with stability parameter p

Stable distributions exist and can be simulated for all parameters 0 .

Approximation Algorithm



- Let $x_{i,k}$ be values drawn from Stable Distribution with parameter $p = \epsilon/\log n$.
- Set z = 0 initially
- For every (i,a[i,j]) in the stream,

$$z = z + \Sigma_{k=1}^{a[i,j]} x_{i,k}$$

• Repeat independently in parallel $O(1/\epsilon^2 \log 1/\delta)$ times, take the median of |z|s as the answer

Approximation Result



- Each z distributed as ||b||_p X
- median $(|z|^p) = median(||b||_p^p |X|^p)$ = $||b||_p^p median(|X|^p)$

Result (with rescaling of ε): With probability at least 1- δ , $(1-\varepsilon)Dom(S) \leq median(|z|^p) \leq (1+\varepsilon)Dom(S)$ median(|X|^p)

Issues to Resolve



- What is the scale factor, median(|X|^p)?
- How to compute efficiently (faster than O(a[i,j]) per update?
- How to avoid storing x_{i,k} explicitly?
 - Use appropriate pseudo-random number generator to find x_{i,k} when needed
 - use standard transforms to draw from stable distributions via uniform distribution

Scale Factor



- Use result from stats: in the limit as $p \rightarrow 0$, $|X|^p$ is distributed as E⁻¹, inverse exponential distribution
- Cumulative density function of E⁻¹

 $F(x) = \exp(-1/x)$

- Median: $F(x) = \frac{1}{2} = \exp(-1/\text{median}(|X|^0))$
- So median($|X|^{0}$) = 1/ln 2

Efficient Computation



- Direct implementation means adding a[i,j] values to the counters for every update
- But, each value is drawn from a stable distribution, and we know sum of stables is a stable
- Use same trick as before, round to nearest power of $(1 + \varepsilon)$ and just add the O(log (n)/ ε) values to the counters
- So update time is $O(\log (n)/\epsilon^3)$

Full results



- Approximate the Dominance norm within $1 \pm \epsilon$ with probability at least $1-\delta$ using $O(1/\epsilon^2 \log (1/\delta))$ counters
- Time per update is $O(1/\epsilon^3 \log (1/\delta))$
- Possible to 'subtract off' the effect of earlier insertions – not possible with most distinct element algorithms
- A few other aspects not mentioned, full details in the paper

Other Dominances



- Natural questions: are other notions of dominance on multiple streams tractable?
- Take Min-Dominance:

 $MinDom(S) = \Sigma_{i} \min_{j} \{a[i,j]\}$

- Let X₁, X₂ be subsets of {1...n/2}. Set a[i,j]=1 ⇔ i ∈ X_i
- Then MinDom(S) = $|X_1 \cap X_2|$
- Requires Ω(n) space to approximate, even allowing probability, several passes etc.

Extensions



- Other reasonable definitions of dominances eg Median Dominance, Relative Dominance between two streams, also require linear space
- Are there other natural quantities which are computable over streams of multiple signals?
- What quantities are good indicators for actionable events?