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Joint work with P. Indyk and A. McGregor.

Data Streams

- We are given a sequence of input
 x₁,...,x_i,...,x_m and have to compute some function f
- Computation proceeds in passes
- Space is restricted
- Any x_i not explicitly remembered: inaccessible in the same pass

Example

- Sitting next to the wireless router delay suffered by every packet
- Interested in the distribution of the delay
 - Pkt 1, 0.2 ms..
 - Pkt 2, 0.3
 - .
 - Pkt ?, 0.2 \Rightarrow 2 pkts at 0.2 ...



- Stream is specified by Updates.
- Every stream item is a <i (=delay),+1>
- Assume we normalize somehow. No deletions (this talk).
- o Of course we cannot store an explicit vector ... $i \in [n]$
- Space in o(n) & input is given is a piece meal fashion.

Data Streams (this talk) ...

• Understanding the impact of the order of the input on computation.

• A view of 2 well known problems

- (dis) Similarity of streams
 -> 1996
- Order statistic
 -> 1978

Distances between 2 streams

- Channel 9 similar to channel 1?
 Distributions X & Y
- "I believe the distribution is the same as last Thursday"
- (1+ ε) approximation; i.e., (1+ ε) D(X,Y)
- Alon, Matias & Szegedy
- Johnson Lindenstrauss
- Feigenbaum, Kannan, Strauss & Vishwanathan ℓ_1 but in an "aggregate model" \Rightarrow ... (i,# of packets) ...
- Indyk ℓ_k for 0<k≤ 2 ...
- o Tight results for $k \ge 3$ have since been achieved...

Random Projections

- o [Johnson, Lindenstrauss] 1984
- Given a matrix A whose elements are iid Gaussian, and any vector x, with high prob.

$$\left\|x\right\|_{2} \le \left\|Ax\right\|_{2} \le (1+\varepsilon)\left\|x\right\|_{2}$$

if $x \in \mathbb{R}^n$ then $A \in \mathbb{R}^{n \times O(\log n)}$ $\Rightarrow Ax \in \mathbb{R}^{O(\log n)}$.

Dimensionality reduction, nearest nbr searches.



What it achieves

• Computes Norm when elements arrive out of order.

Note: A proof that such a pseudorandom generator exists is Necessary – and is not always easy.



• Philosophical ...

Which other distances are approximable? What property?

(likely) That is it. The only approximable distances are likely to be norms, i.e., function of $\{x_i-y_i\}$.

Stable distributions appear as the key idea in context thing ...



• Philosophical ...

Example ... $D^2 = \Sigma_i (\sqrt{x_i} - \sqrt{y_i})^2$

(squared) Hellinger distance





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(squared) Hellinger distance

"Aggregate" Model (FKSV) easy ... Hard in update models.

 $\sum_i \sqrt{|\textbf{x}_i\textbf{-}\textbf{y}_i|}$ is easy (1/2 stable distribution)



• Philosophical ...

Example ... $D^2 = \Sigma_i (\sqrt{x_i} - \sqrt{y_i})^2$

(squared) Hellinger distance

Small space embedding (into ℓ_2) easy Hard for streaming



• Philosophical.

- Pragmatic ...
 - What measures of distances are meaningful for distributions ?
 - Hypothesis testing:
 - f-divergences or Ali-Silvey-Cziszar divergences
 - Mathematical programming:
 - Bregman divergences
 - Model "Risk" etc.,



- Philosophical.
- Pragmatic.
 - f-divergences:
 - Pick a j from x and consider the expected likelihood $D_f(x,y)=E_{x,j} f(y_j/x_j)$ provided f(1)=0,f convex...

? • KL(x,y) =
$$\sum_j x_j \log (x_j/y_j) \Rightarrow f(u)$$
=- log u

- ? Hellinger^2 = $\Sigma_j (\sqrt{x_j} \sqrt{y_j})^2 = \sum_j x_j (1 \sqrt{(y_j/x_j)})^2$ or $f(u) = (1 \sqrt{u})^2$.
- $\bigcirc \circ \ell_1 = \sum_j |\mathbf{x}_j \mathbf{y}_j| = \sum_j \mathbf{x}_j |\mathbf{1} (\mathbf{y}_j/\mathbf{x}_j)| \text{ or } \mathbf{f}(\mathbf{u}) = |\mathbf{1} \mathbf{u}|$
 - Also arises from loss functions in learning ...



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A Kaleidoscope of questions

- Philosophical.
- Pragmatic.
 - The only f-divergence which can be (1+ ϵ) approximated over update streams is ℓ_1
 - Bregman divergences..
 - Potential field F
 - Convex F

 $\mathsf{B}_{\mathsf{F}}(\mathbf{p},\mathbf{q}) \!=\! \mathsf{F}(\mathbf{p}) - \mathsf{F}(\mathbf{q}) - (\nabla \mathsf{F}(\mathbf{q})) \circ (\mathbf{p} \!-\! \mathbf{q})$

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• Philosophical.

- Pragmatic.
 - Example:
 - $\circ F(x)=x^{2} \Rightarrow B(x,y)=x^{2}-y^{2}-2y(x-y)=(x-y)^{2} \Rightarrow \ell_{2}$
 - o F(x)=x lg x ⇒ B(x,y)=x lg x - y lg y - (1+lg y)(x-y) = x lg (y/x) -x + y ⇒ Gen. KL div

$$\mathsf{B}_{\mathsf{F}}(\mathbf{p},\mathbf{q}) = \mathsf{F}(\mathbf{p}) - \mathsf{F}(\mathbf{q}) - (\nabla \mathsf{F}(\mathbf{q})) \circ (\mathbf{p} \cdot \mathbf{q})$$



• Philosophical.

- Pragmatic.
 - Bregman div. :
 - $\circ \ell_2$ is sketchable/estimable in small space.
 - \circ What about the others? Sorry ...

How?

- Lemma (one part): ρ,c >0, distributions
 x,y
 - \bullet For all (in some range) M, δ
 - $\begin{array}{l} \text{if } \min \left\{ \begin{array}{l} \phi(\delta, 2\delta), \phi(2\delta, \delta) \end{array} \right\} \geq c \mathsf{M}^{\rho} \\ \left\{ \phi(\mathsf{M}\delta, (\mathsf{M}+1)\delta) \!+ \phi((\mathsf{M}+1)\delta, \mathsf{M}\delta) \end{array} \right\} \end{array}$

then $\exists \gamma > 0$ such that to get a n^{γ} approximation of $\sum_{i} \phi(x_{i}, y_{i})$ over [2n] we need $\Omega(n)$ space.



Consequence ...

 O If f', f" exist ...
 $\phi(M\delta, (M+1)\delta) = M\delta f(1+1/M)$ ≤ Mδ [f(1) + f'(1)/M + f"(ζ)/(2M²)]

Suppose f'(1) exists and \neq 0; then consider g(u)=f(u) - f'(1)(u-1).

Well known: the change has no effect ... Lemma applies ...

Exceptions?





Proof of the Lemma

- Reduction from Communication Complexity of set disjointness.
- $\circ~$ Alice and Bob have \approx n/4 numbers each from [n]. How many bits do they need to exchange to find a common number if such an element exists.
- \circ $\Theta(n/P)$ even with P rounds
- If an efficient streaming algorithm existed then they can communicate the "state" of the algorithm.
 - But dimensionality reduction may be possible...
 - Two copies: critical that you are allowed updates



Other results

- Bregman: F" vanishes or diverges polynomially at the nbd of 0 \Rightarrow Same conclusion. Note F"=constant for ℓ_2
- \circ If f(0) is bounded then any symmetric f-divergence can be approximated to \pm ϵ using $\sqrt{n} \log^{O(1)} n$ space
- \circ If one distribution is known \Rightarrow Polylog.

Takeaway ...

• Order of the input is important...

• Hellinger: easy in aggregated model can embed in small space

hard in update models

• It's the update which is the problem.



Changing gears...

 Analysis of streaming model is typically worst case.

O What if we consider average case?
O Average over what?
O The order. ⇒ Exchangeability ...

Order Statistic – Median finding

• Given a sequence of n numbers, find the median. Space is restricted.

Munro Paterson 1978

- For p passes n^{1/p} space suffices
- Mention that for random order log log n pass and polylog space appears feasible, but known techniques do not seem to work.
- Manku, Rajagopalan, Lindsay; Greenwald Khanna,
 - error $\pm \epsilon$ n using O((1/ ϵ) log n) space

Exact Median Finding

- \circ For p passes $n^{1/p}$ space suffices
 - This is best possible $\Rightarrow \Omega(\log n)$ passes.
- \circ error $\pm \, \epsilon$ n using O((1/ ϵ) log n) space
 - 1 pass adversarial order $\pm n^{\delta}$ error $\Rightarrow \Omega(n^{1-\delta})$ space
 - 1 pass random order $\pm n^{1/2+\epsilon}$ error in polylog space
 - Multipass extention not automatic ...

A new hope in thousand words



Time or Number of Samples

Value



- \circ Now we do not know the length of the stream anymore it is $\zeta N \pm {\it O}(\sqrt{N})$
- Ignore and repeat. The constant in O() increases but N is already ζN .



The takeaway ...

 Random order gives an exponential speedup in passes.

 Permuting your data might give you a faster algorithm. The question is of course to analyze the benefit.

The road ahead

- A promising idea
 - Assume random order
 - Prove your claim
 - Go back and "fix/simulate" the randomness
 - Clustering data streams
 - \circ G., Motwani, Mishra & O'callaghan n^{1/p} & 2^{O(p)}
 - Meyerson : Random order $\log^{O(1)}$ n & O(1)
 - Charikar, Panigrahy, O'callaghan: $\log^{O(1)} n \& O(1)$
 - More examples
- What about SVD ?
 - Assume any random order you see fit
 - Can you analyze passes/runtime/space better?



That's all Folks