

Distributed Data Streams and the Power of Geometry

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Work with: Haifa U, Technion, U Neuchatel, TU Dresden



Big Data is Big News (and Big Business...)

- Mobile computing, sensornets, social networks, ...
- Data-driven science
- How can we cost-effectively manage and analyze all this data...?



Big Data Challenges: The Four V's – and one D

- **Volume:** Scaling from Terabytes to Exa/Zettabytes
- **Velocity:** Processing massive amounts of *streaming data*
- **Variety:** Managing the complexity of multiple relational and non-relational data types and schemas
- **Veracity:** Handling inherent uncertainty and noise in the data
- **Distribution:** Dealing with massively distributed information
- ***Our focus:*** *Volume, Velocity, Distribution*



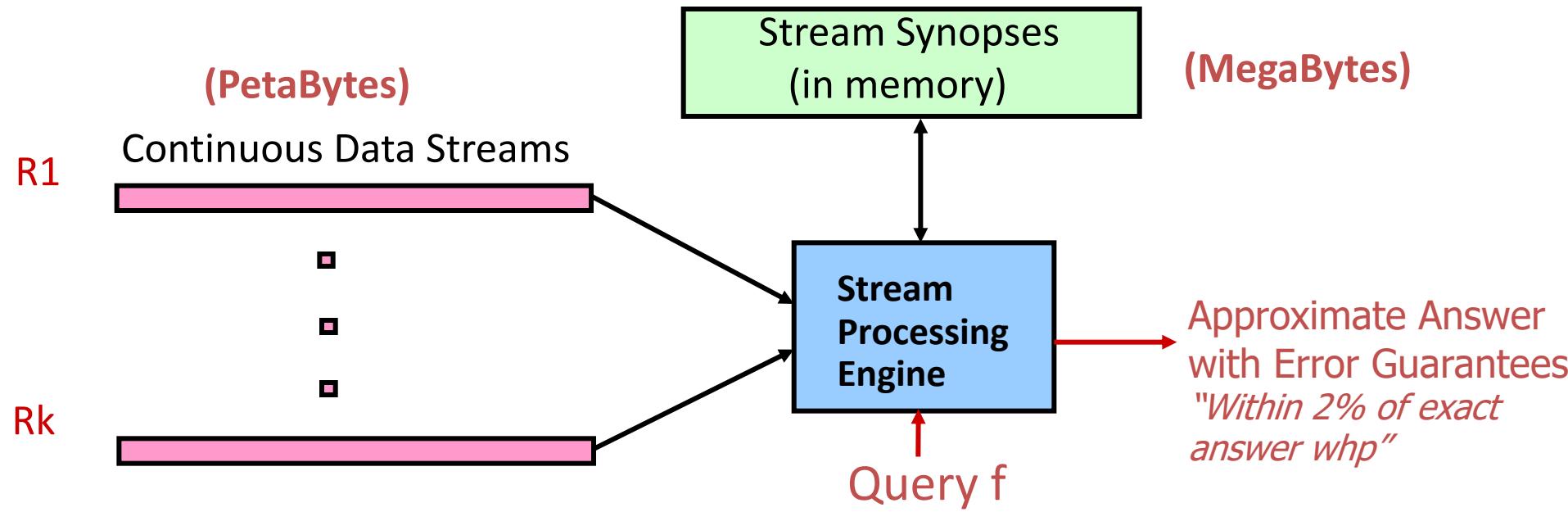
Velocity: *Continuous Stream Querying*

There are many scenarios where we need to **monitor/track events** over streaming data:

- Network health monitoring within a large ISP
- Collecting and monitoring environmental data with sensors
- Observing usage and abuse of large-scale data centers



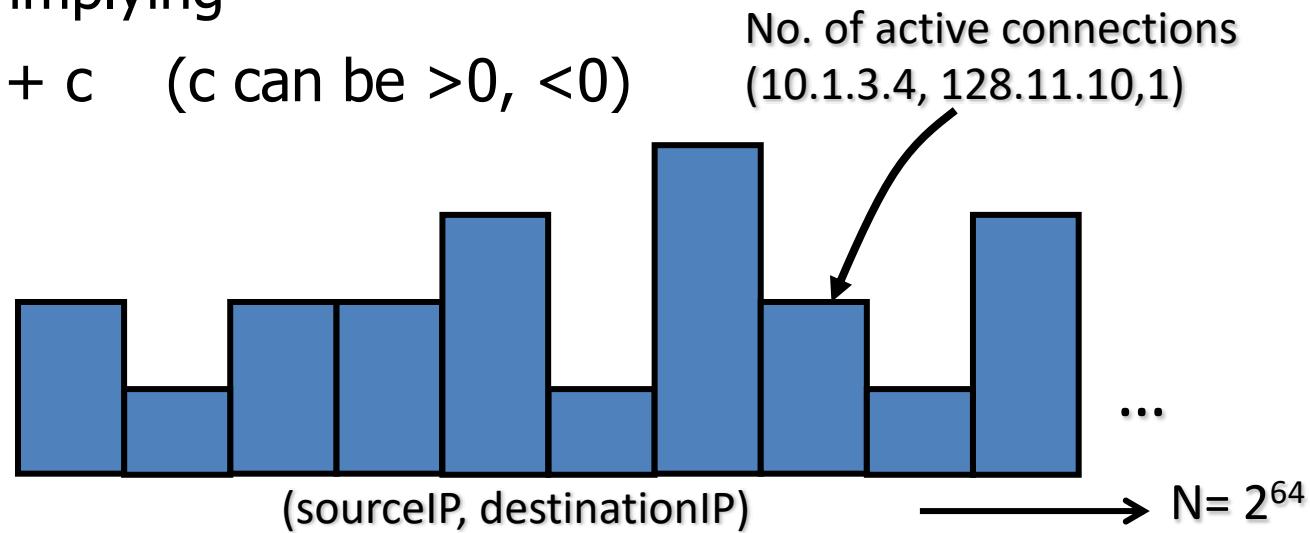
Stream Processing Model



- Approximate answers often suffice, e.g., trends, anomalies
- Stream synopses: *single-pass, small-space, small-time, ...*

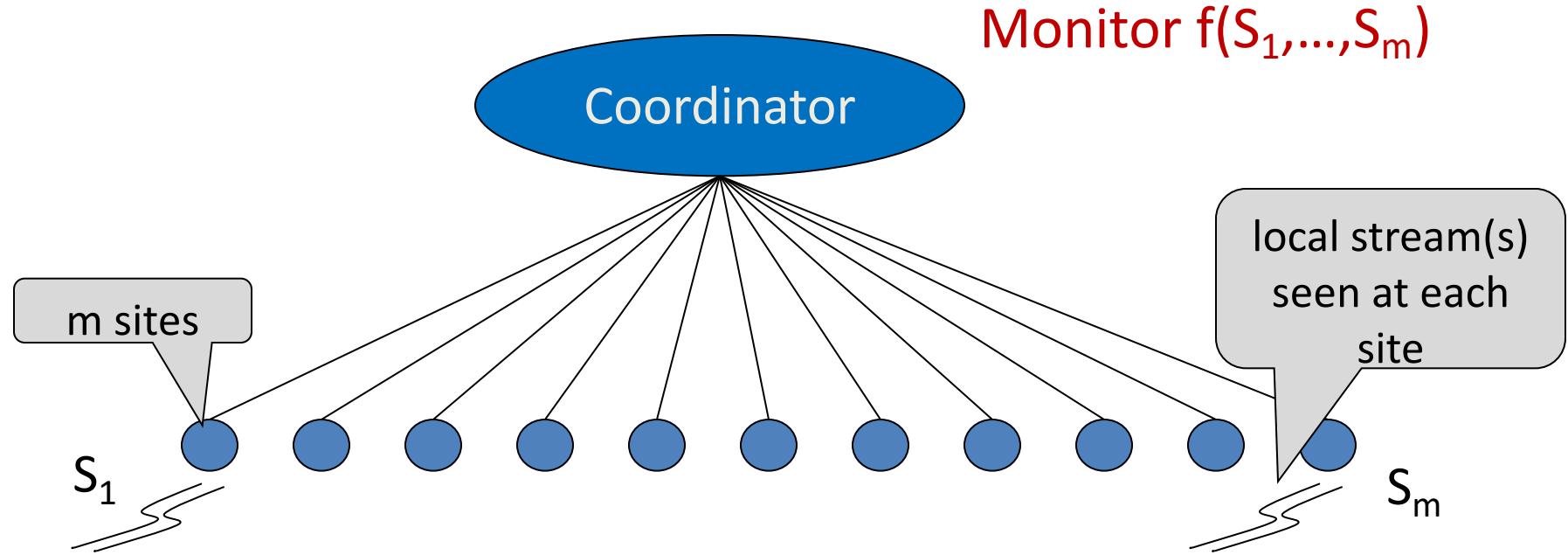
Model of a Relational Stream

- Relation “signal”: *Large* array $v_S[1\dots N]$ with values $v_S[i]$ initially zero
 - Frequency-distribution array of **S**
 - Multi-dimensional arrays as well (e.g., row-major)
- Relation implicitly rendered via a *stream of updates*
 - Update $\langle x, c \rangle$ implying
 - $v_S[x] := v_S[x] + c$ (c can be >0 , <0)



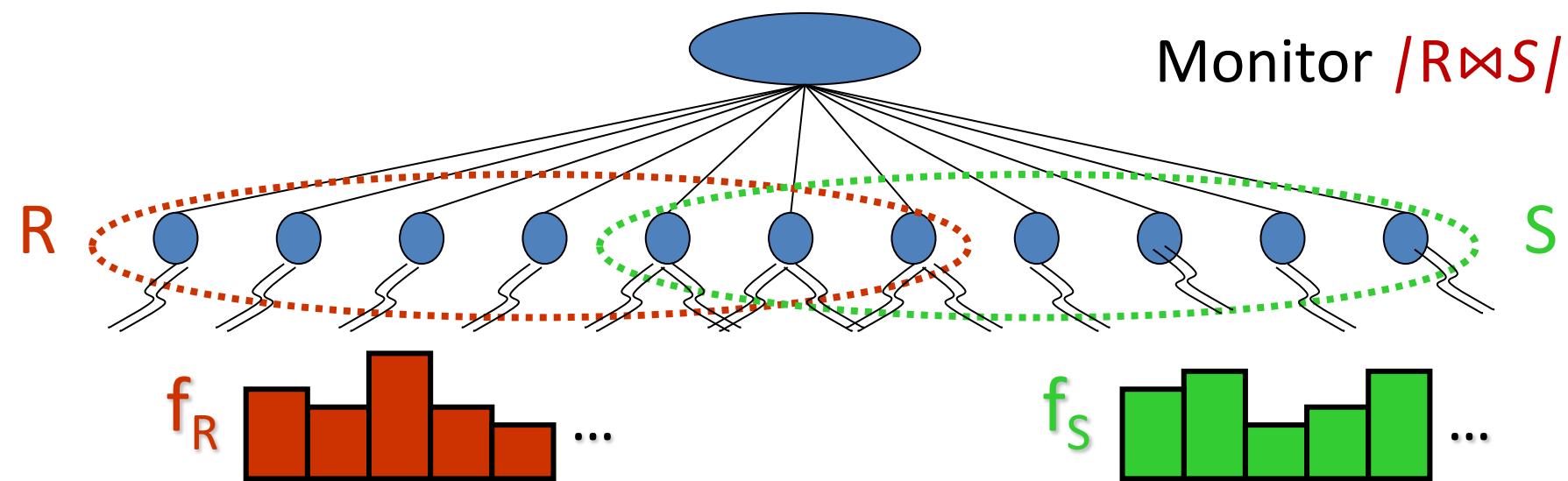
- *Goal:* Compute queries (functions) on such dynamic vectors in “small” space and time ($<< N$)

Velocity & Distribution: *Continuous Distributed Streaming*



- Other structures possible (e.g., hierarchical, P2P)
- Goal: *Continuously track* (global) query over streams at coordinator
 - Using small space, time, and **communication**
 - Example queries:
 - Join aggregates, Variance, Entropy, Information Gain, ...

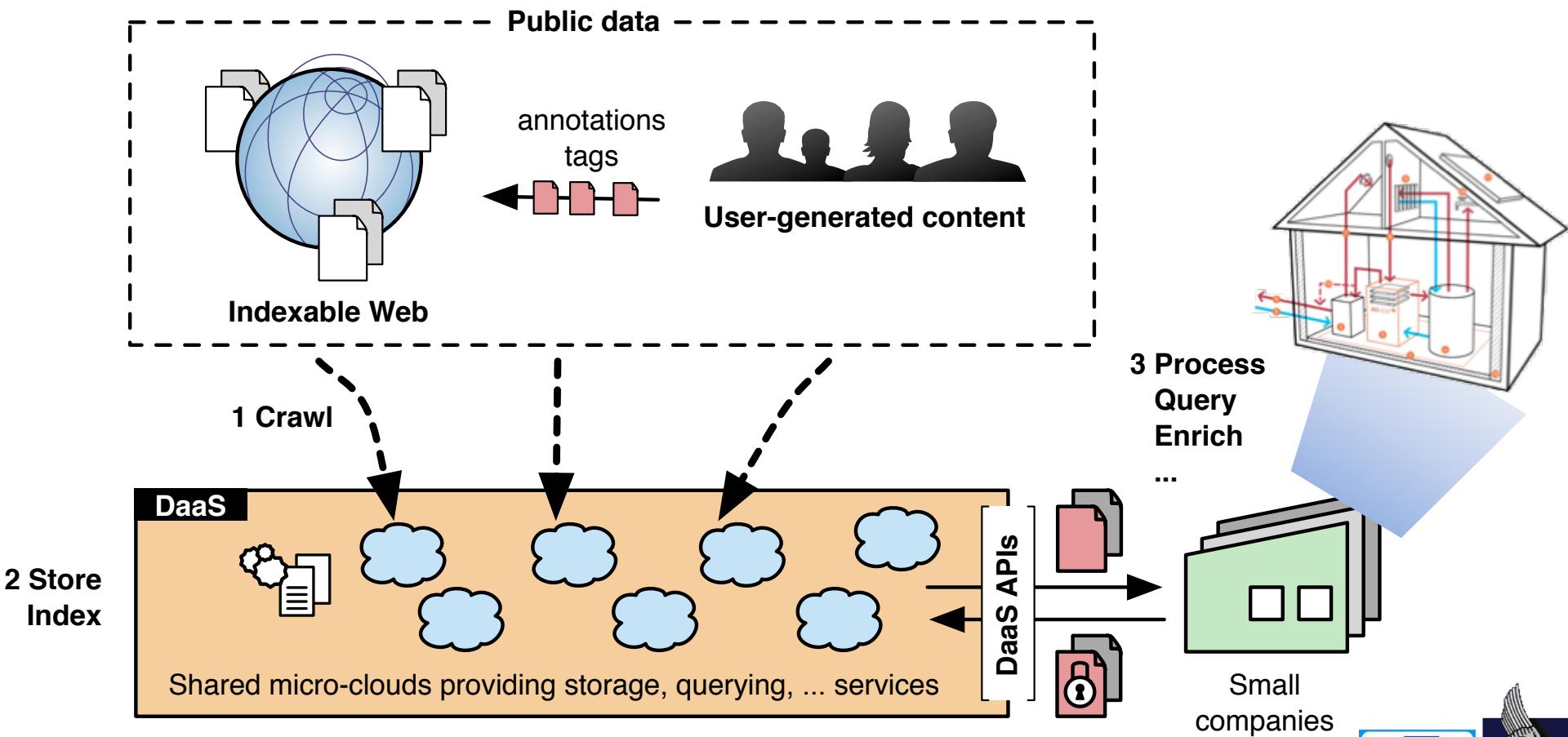
Tracking Complex Aggregate Queries



- *Class of queries:* Generalized inner products of streams
- $$|R \bowtie S| = f_R \cdot f_S = \sum_v f_R[v] f_S[v]$$
- Join/multi-join aggregates, range queries, heavy hitters, histograms, wavelets, ...

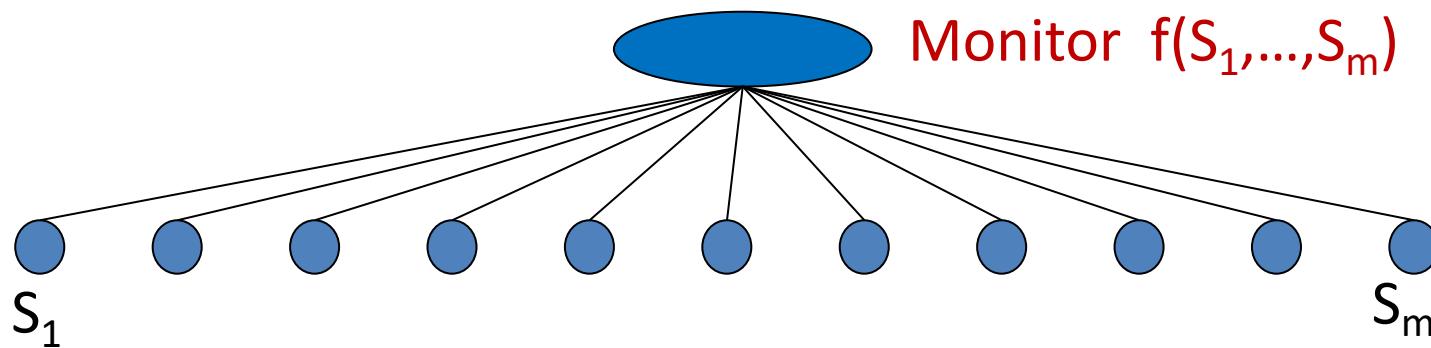


Example: LEADS Elastic µClouds Architecture *(<http://leads-project.eu>)*



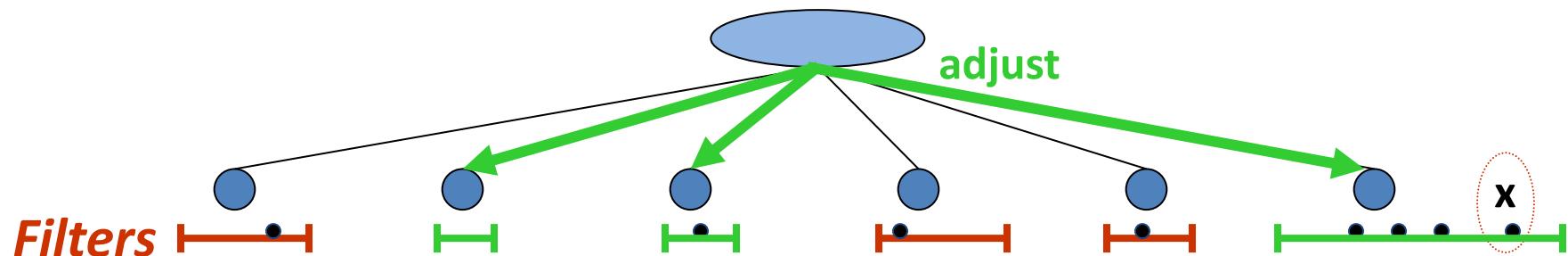
Continuous Distributed Streaming

- But... local site streams continuously change! New readings/data...
- Classes of monitoring problems
 - **Threshold Crossing:** Identify when $f(S) > \tau$
 - **Approximate Tracking:** $f(S)$ within **guaranteed accuracy bound θ**
 - Tradeoff *accuracy and communication / processing cost*
- Naïve solutions must *continuously* centralize all data
 - Enormous communication overhead!
- Instead, *in-situ* stream processing using *local constraints* !



Communication-Efficient Monitoring

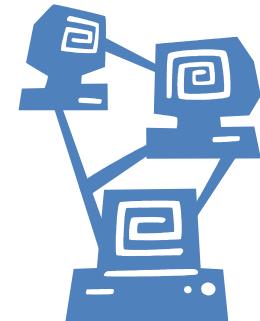
- **Key Idea:** "*Push-based*" *in-situ processing*
 - *Local filters* installed at sites process local streaming updates
 - Offer bounds on local-stream behavior (at coordinator)
 - "*Push*" information to coordinator only when filter is violated
 - "**Safe!**" Coordinator sets/adjusts local filters to guarantee accuracy



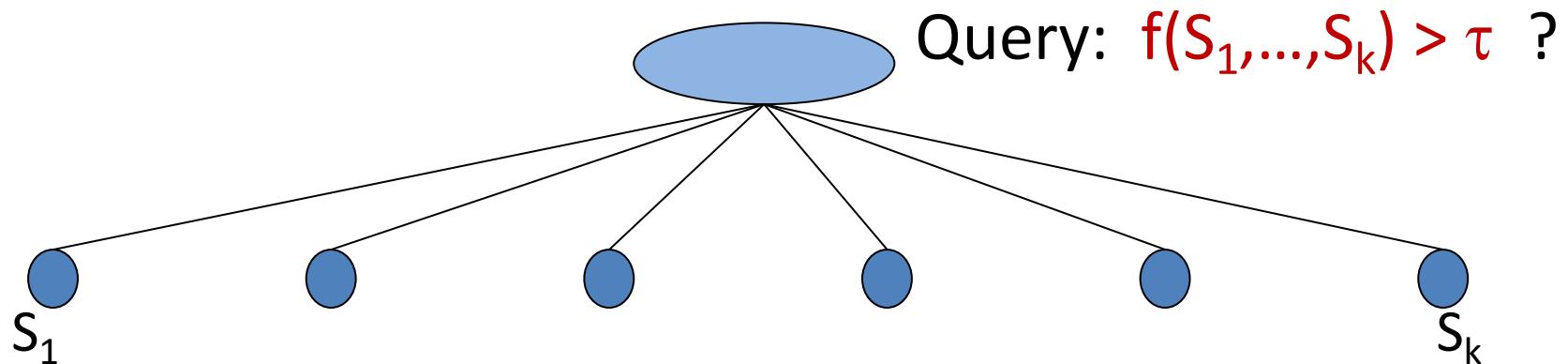
- Easy for linear functions! Exploit additivity...
- **Non-linear $f()$...??**

Outline

- Introduction: Continuous Distributed Streaming
- The Geometric Method (GM)
- GM + Sketches, GM + Prediction Models
- Towards Convex Safe Zones (SZs)
- Future Directions & Conclusions



Monitoring General, Non-linear Functions



Query: $f(S_1, \dots, S_k) > \tau ?$

- For general, non-linear $f()$, problem is a lot harder!
 - E.g., information gain over global data distribution
- Non-trivial to decompose the global threshold into “safe” local site constraints
 - E.g., consider $N = (N_1 + N_2)/2$ and $f(N) = 6N - N^2 > 1$
Tricky to break into thresholds for $f(N_1)$ and $f(N_2)$



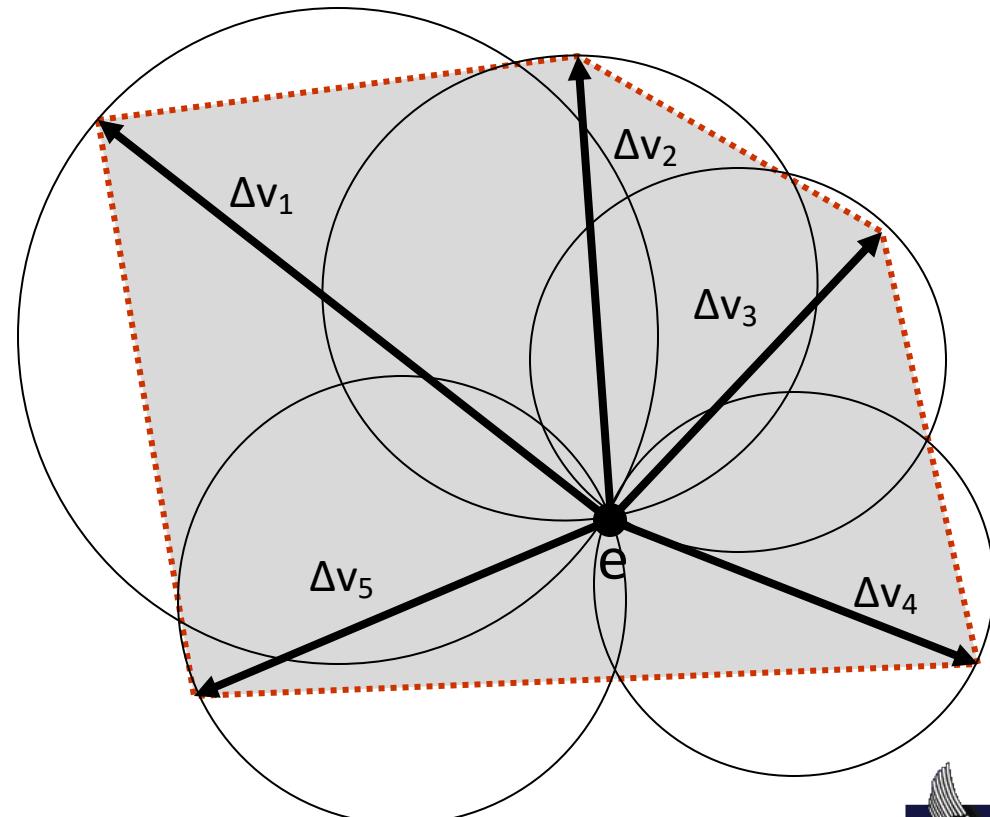
The Geometric Method

- A general purpose geometric approach [SIGMOD'06]
 - Monitor **function domain** rather than the range of values!
- Each site tracks a local statistics *vector* v_i (e.g., data distribution)
- Global condition is $f(v) > \tau$, where $v = \sum_i \lambda_i v_i$ ($\sum_i \lambda_i = 1$)
 - E.g., v = *average* of local statistics vectors
- All sites share estimate $e = \sum_i \lambda_i v'_i$ of v
 - based on latest update v'_i from site i
- Each site i tracks its drift from its most recent update $\Delta v_i = v_i - v'_i$



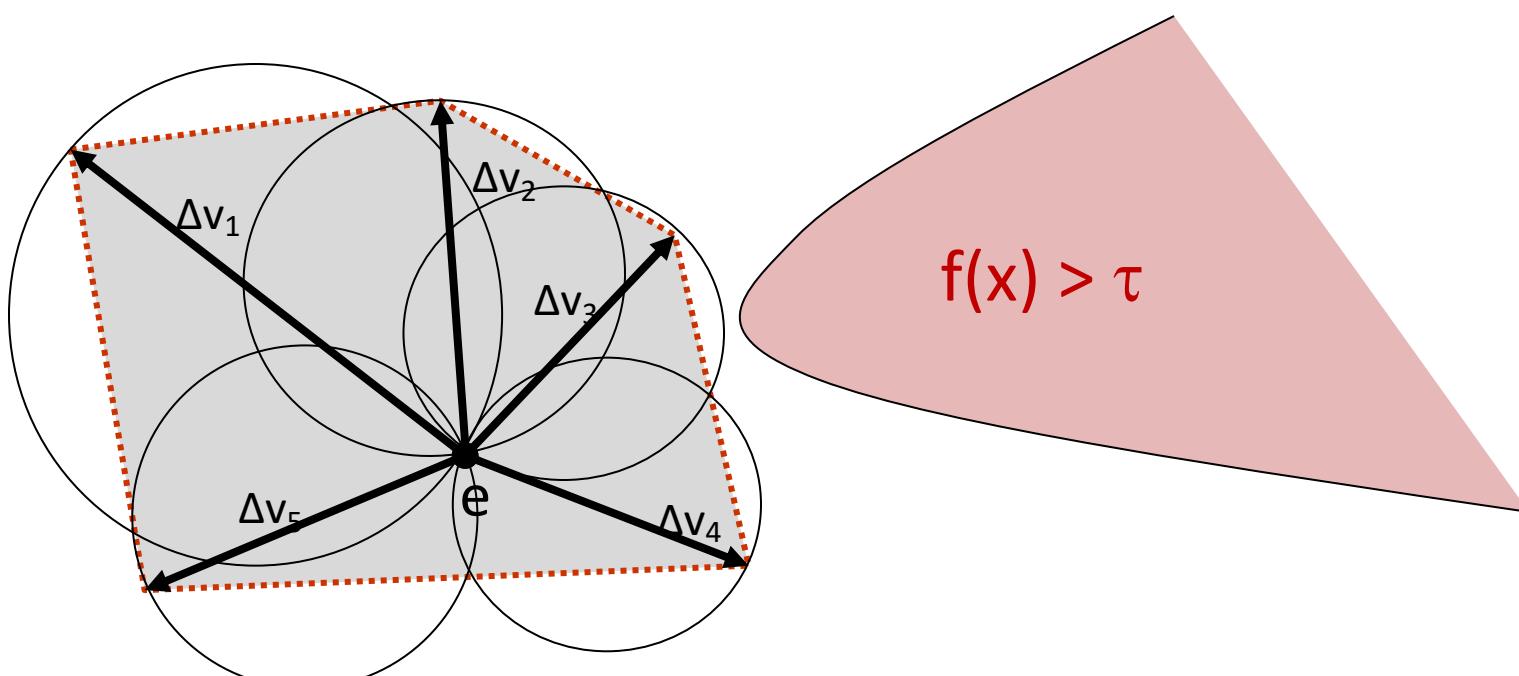
Covering the Convex Hull

- Key observation: $v = \sum_i \lambda_i \cdot (e + \Delta v_i)$
(a convex combination of “translated” local drifts)
- v lies in the convex hull of the $(e + \Delta v_i)$ vectors
- Convex hull is completely covered by spheres with radii $\|\Delta v_i/2\|_2$ centered at $e + \Delta v_i/2$
- Each such sphere can be constructed independently

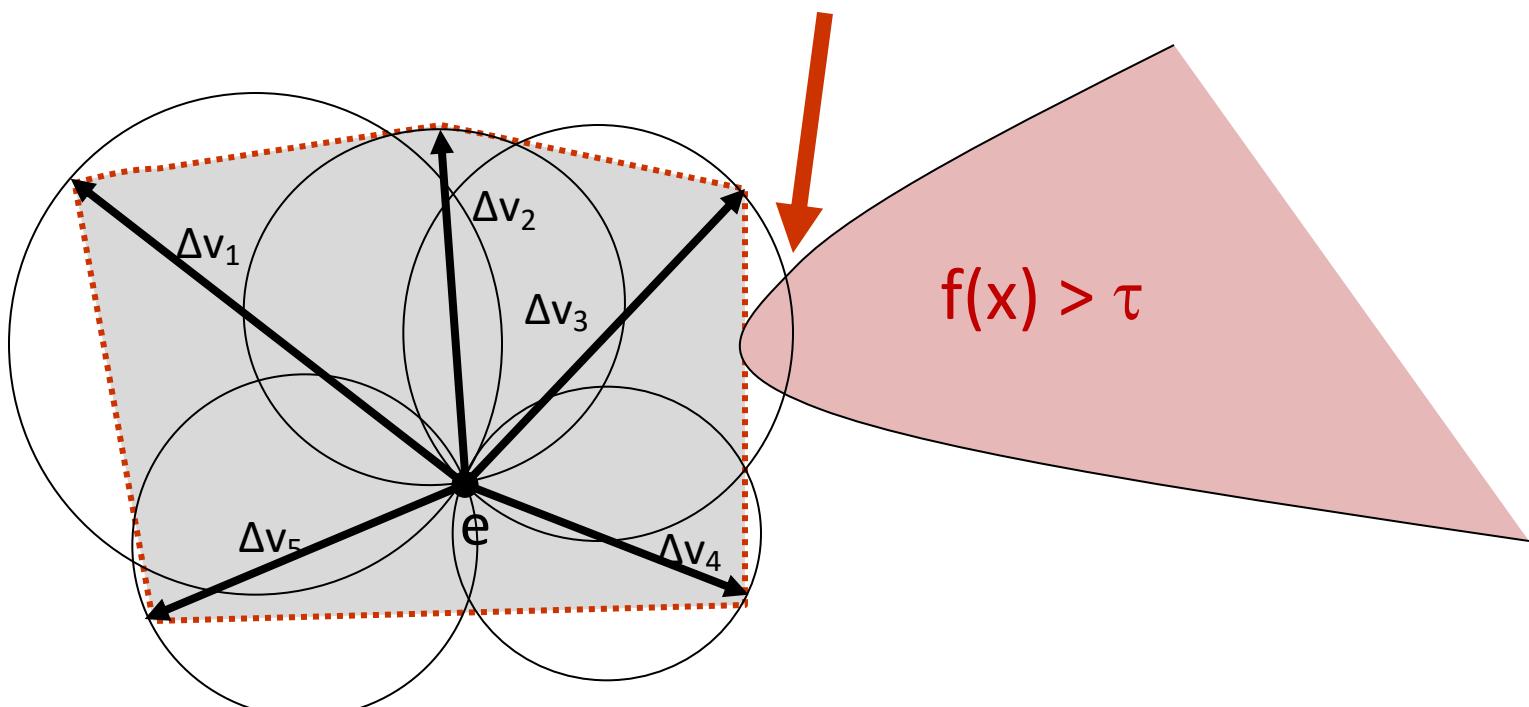


Monochromatic Regions

- **Monochromatic Region:** For all points x in the region $f(x)$ is on the same side of the threshold ($f(x) > \tau$ or $f(x) \leq \tau$)
- Each site independently checks its sphere is monochromatic
 - Find max and min for $f()$ in local sphere region (may be costly)
 - Send updated value of v_i if not monochrome

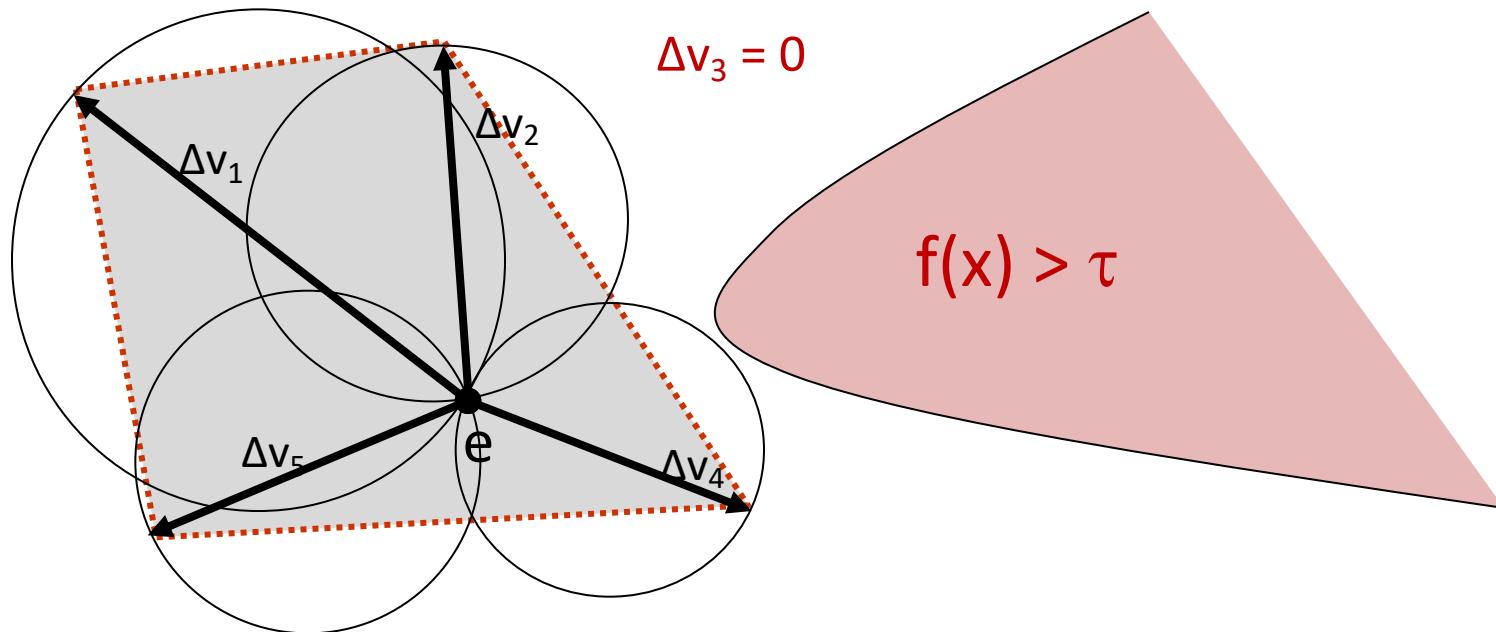


Restoring Monochromicity



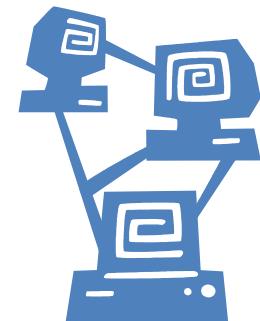
Restoring Monochromicity

- After update, $||\Delta v_i||_2 = 0 \Rightarrow$ Sphere at i is monochromatic
 - Global estimate e is updated, may cause more site updates
- Coordinator case: Can allocate local slack vectors to sites for “localized” resolutions

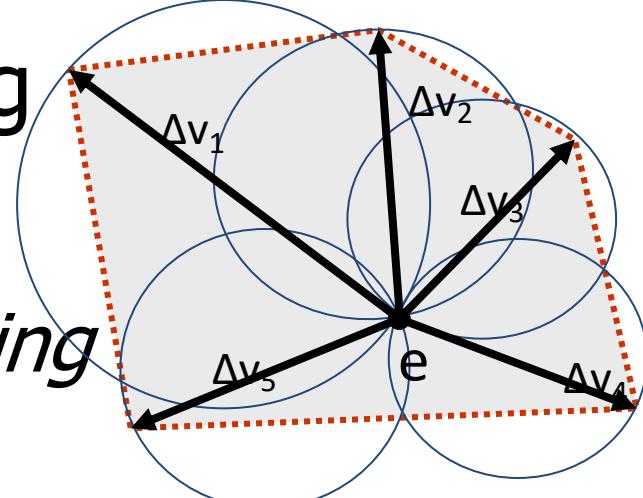


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Geometric Query Tracking using AMS Sketches [VLDB'13]

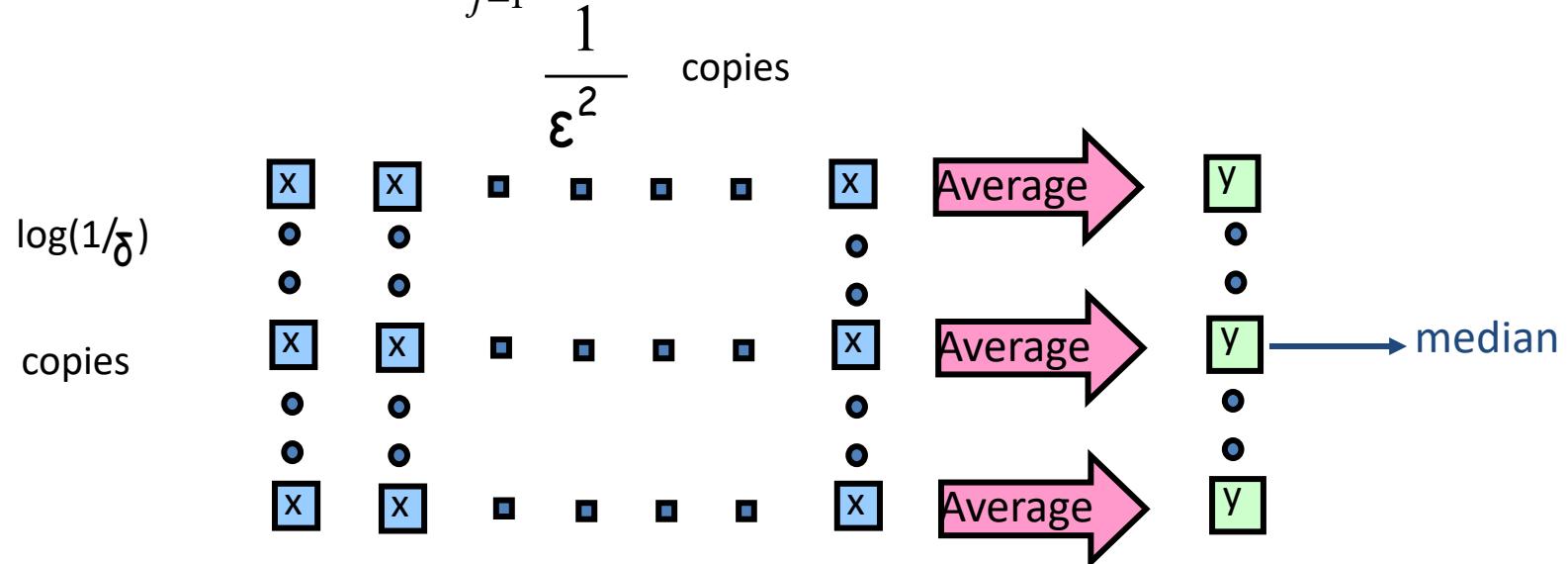


- *Continuous approximate monitoring*
 - Track value of a function to within specified accuracy bound θ
- Too much local info → *Local AMS sketch summaries*
 - Bounding regions for the *lower-dimensional sketching space*
 - Account for sketching error ε
- *Key Problems:* (1) Minimize data exchange volume (2) Deal with highly-nonlinear AMS estimator

Monitored Function...?

AMS Estimator function for Self-Join

$$f(\text{sk}(v)) = \text{median}_{i=1..n} \left\{ \frac{1}{m} \sum_{j=1}^m \text{sk}(v)[i, j]^2 \right\} = \text{median}_{i=1..n} \left\{ \frac{1}{m} \| \text{sk}(v)[i] \|^2 \right\}$$



- Theorem(AMS96): Sketching approximates $\| v \|^2_2$ to within an error of $\pm \epsilon \| v \|^2_2$ with probability $\geq 1 - \delta$ using $O(\frac{1}{\epsilon^2} \log(1/\delta))$ counters

Geometric Query Monitoring using AMS Sketches

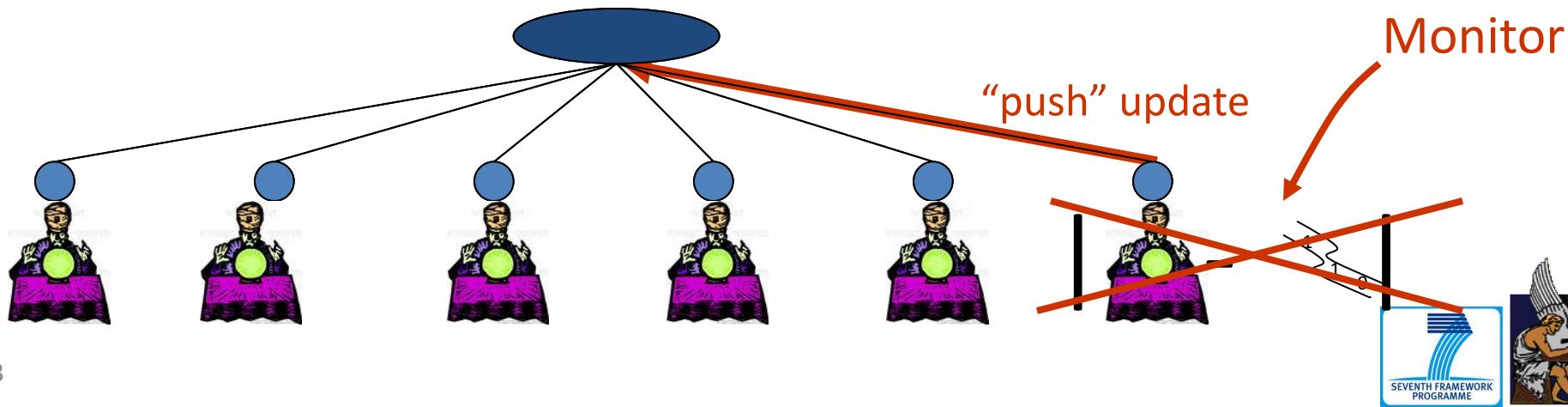
[VLDB'13]

- Efficiently deciding ball monochromaticity for median
 - Fast greedy algorithm for determining the distance to the inadmissible region
- (*Non-trivial!*) extension to *general join aggregates*
- Minimizing volume of data exchanges
 - Sketches can still get pretty large!
 - Can reduce to monitoring in $O(\log(1/\delta))$ dimensions



Exploiting Shared Prediction Models

- Naïve "*static*" prediction: Local stream assumed "unchanged" since last update
 - No update from site ⇒ last update ("predicted" value) is unchanged ⇒ global estimate vector unchanged
- *Dynamic prediction models* of site behavior
 - Built locally at sites and *shared* with coordinator
 - Model complex stream patterns, reduce number of updates
 - But... more complex to maintain and communicate



Adopting Local Prediction Models

[VLDB'05, TODS'08]

Model	Predicted v_i^p	
Linear Growth	$v_i^p(t) = \frac{t}{t_s} v_i(t_s)$	
Velocity/ Acceleration	$v_i^p(t) = v_i(t_s) + (t - t_s) \text{vel}_i + (t - t_s)^2 \text{acc}_i$	
Static	Equivalent to the basic framework	$v_i^p(t) = v_i(t_s)$

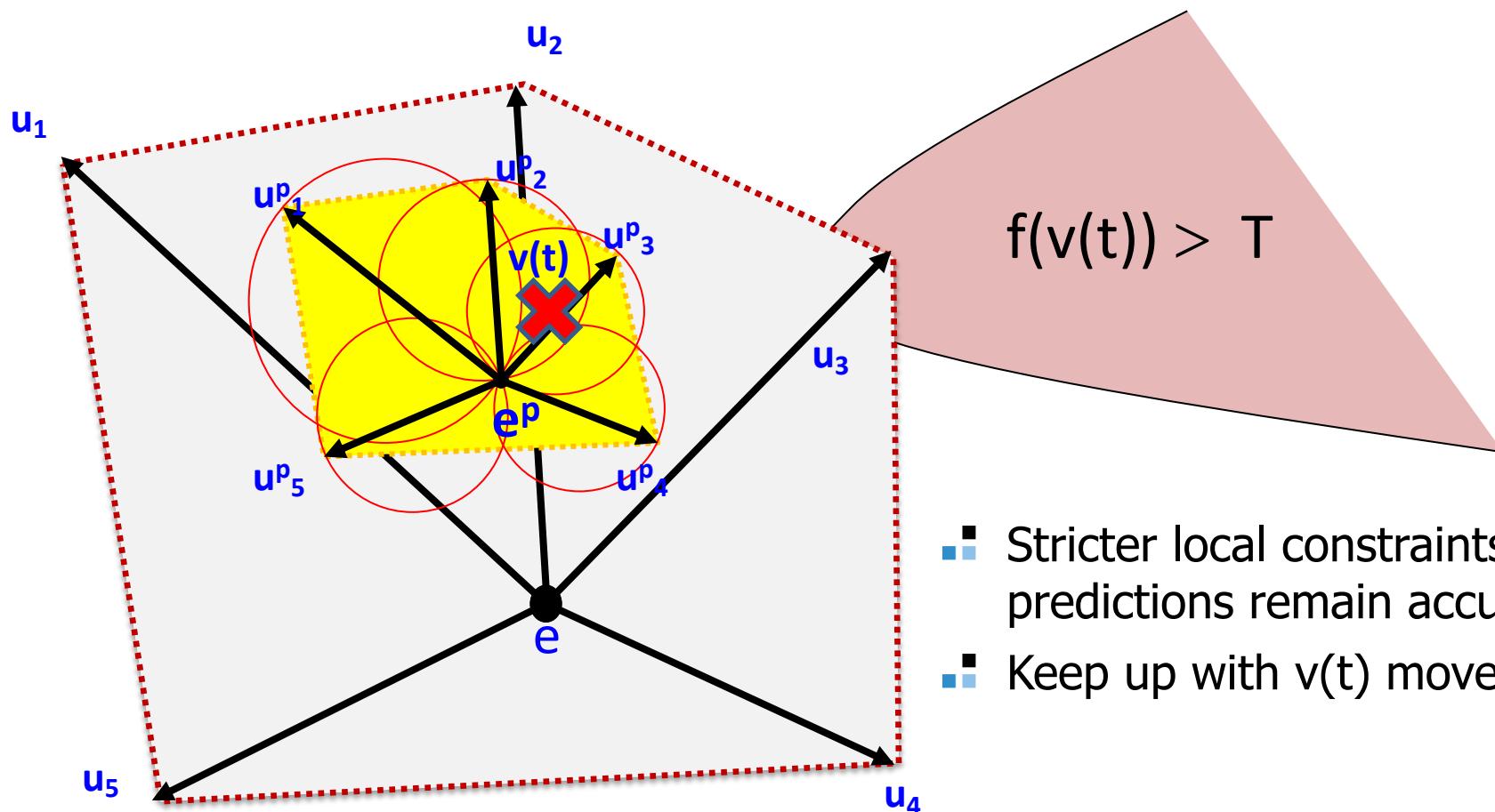
Predicted Global Vector:

$$e^p(t) = \sum \lambda_i v_i^p(t)$$



Prediction-based Geometric Monitoring

[SIGMOD'12, TODS'14]

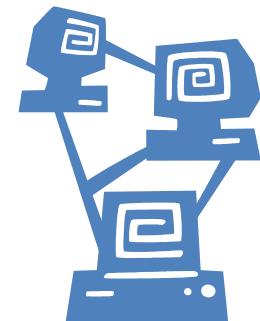


- Stricter local constraints if local predictions remain accurate
- Keep up with $v(t)$ movement



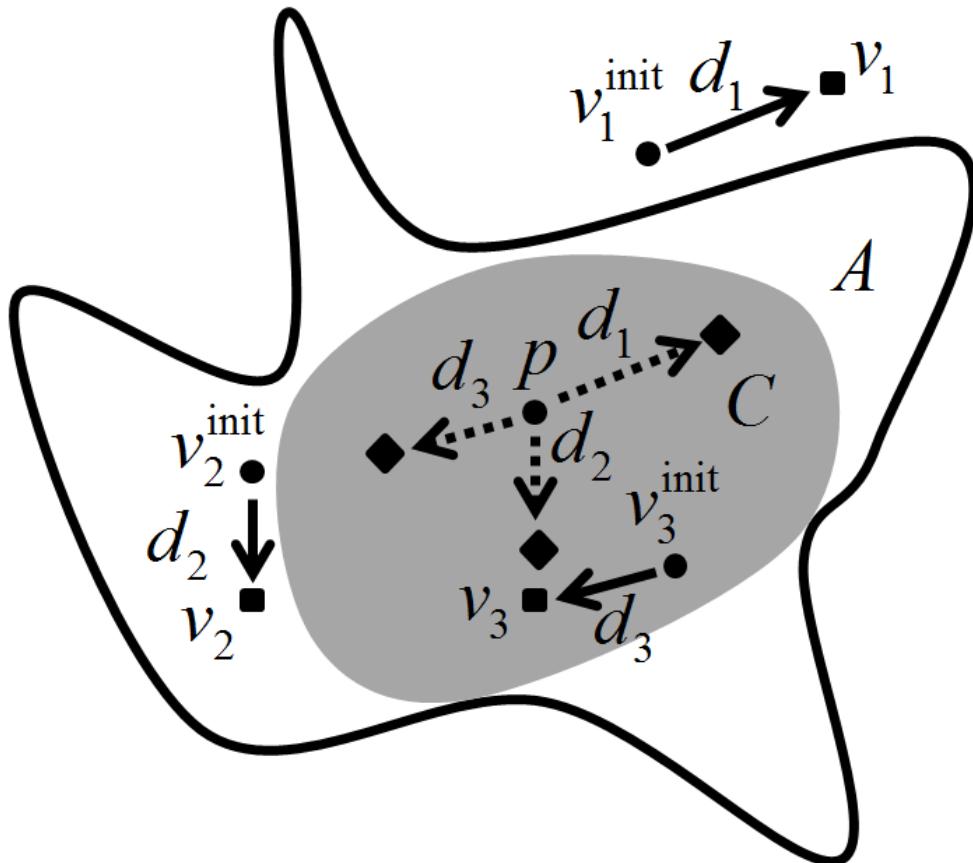
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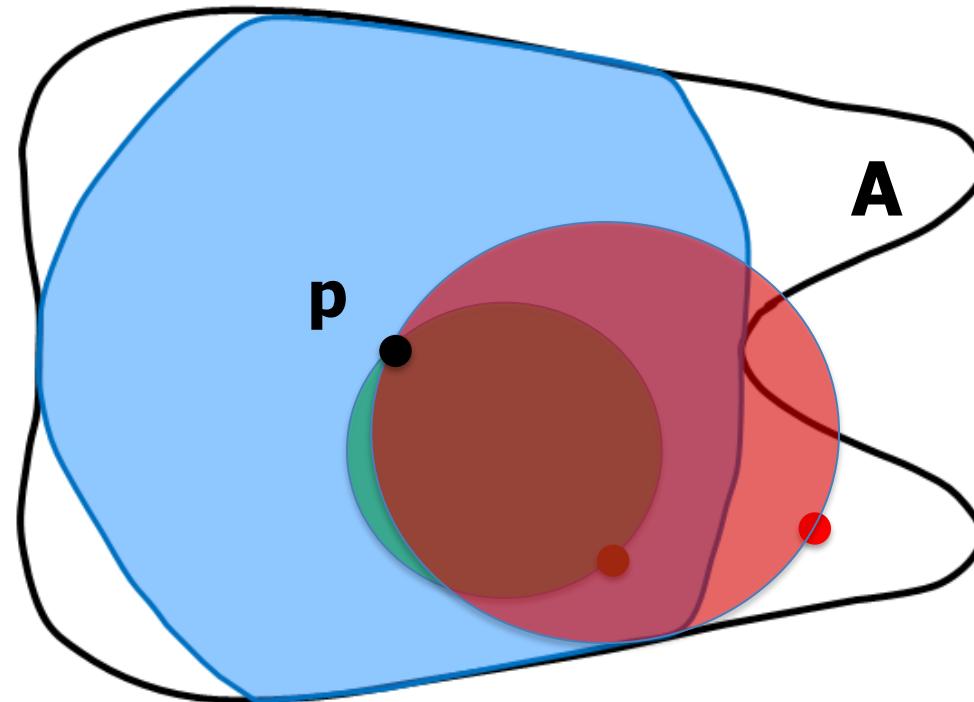


From Bounding Spheres to Safe Zones (SZs)

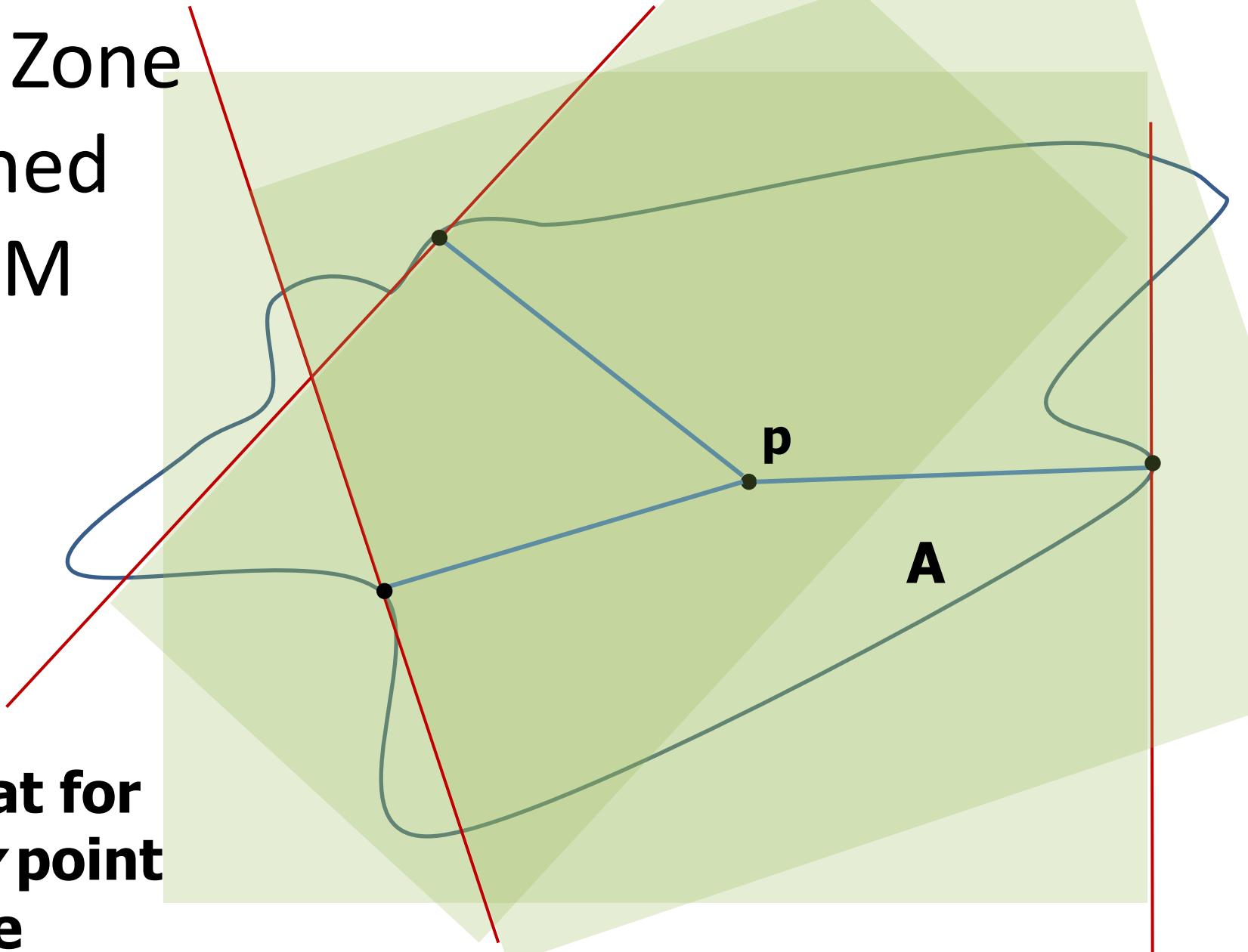
- **Safe Zone:** Any convex subset of the Admissible Region
 - As long as translated drifts stay within SZ, we are “safe”
 - By convexity
- Aim for large SZs, far from the boundary



Safe Zone defined by GM



Safe Zone
defined
by GM

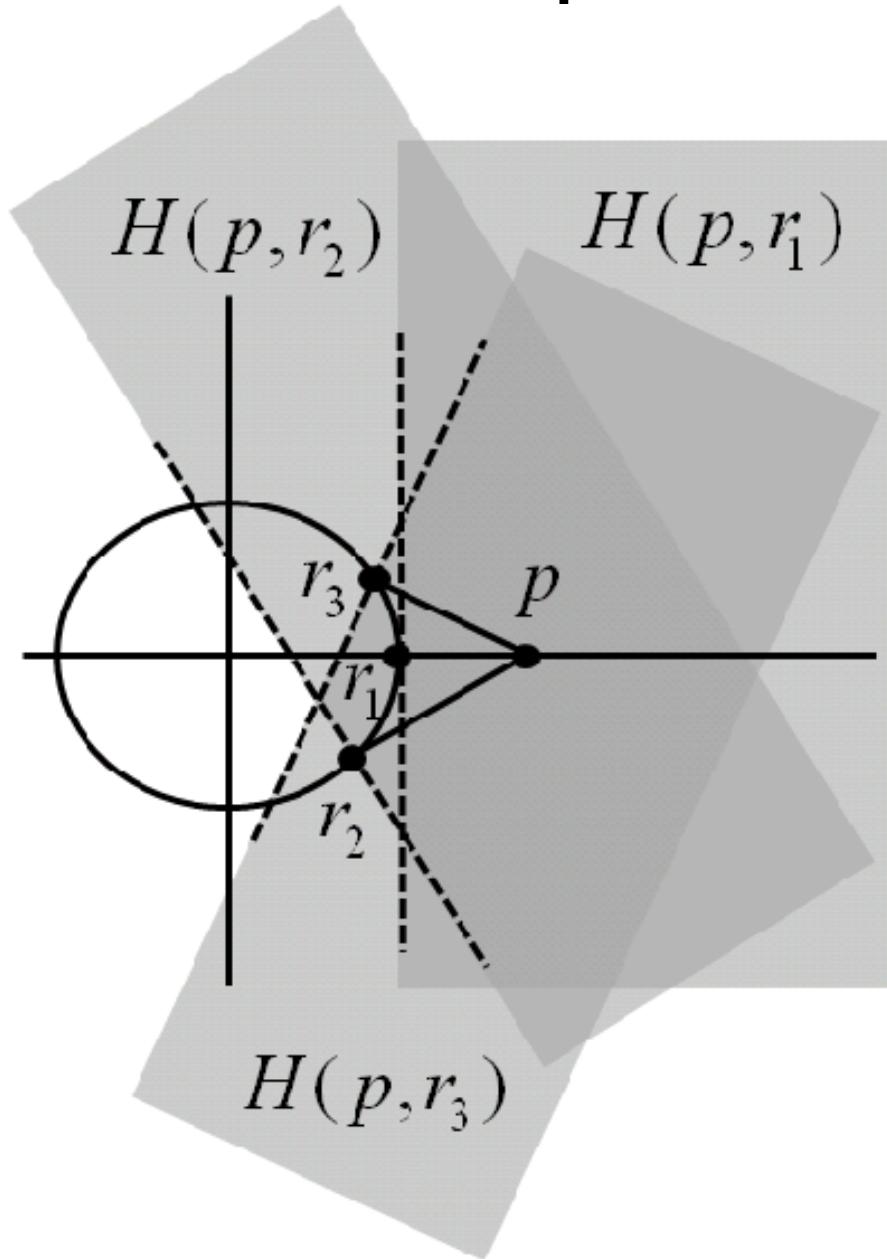


Repeat for
every point
on the
boundary



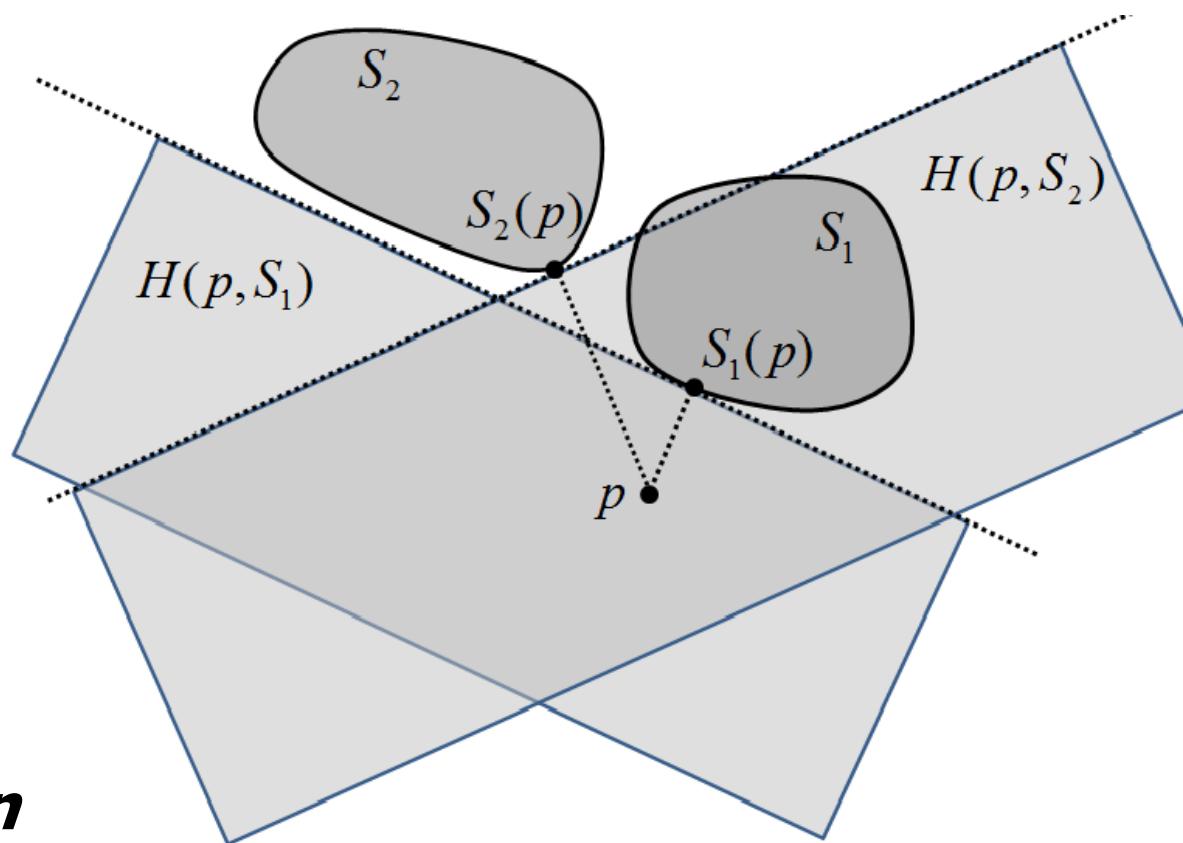
GM Safe Zones can be Far from Optimal!

- For instance, when inadmissible region is convex
- Taking the intersection of all half-spaces is overly restrictive
- In this case, half-space $H(p,r_1)$ is clearly the optimal SZ!



SZs through Convex Decompositions [VLDB'15]

- Inadmissible region is (can be covered by) a union of convex sets
- Just intersect half-spaces that separate p from each set
 - Avoid *redundancy!*



■ **Provably better than GM!**

■ Application in sketches and median monitoring

$S_1(p), S_2(p)$: "support vectors"

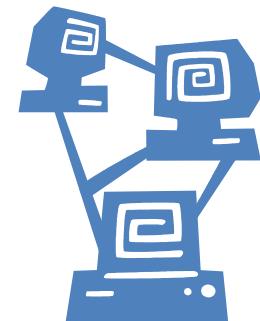
A “Cookbook” for Distributed Stream Monitoring?

- GM/bounding spheres is a generic, off-the-shelf technique
 - Any function, but can be far from optimal
- SZs: much better performance but must be designed for function/data at hand
 - Some initial progress on automated SZ construction (difficult optimization problem) **[TKDE'14]**
 - Work on generic mechanisms for composing SZs **[working paper]**



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Work in CD Streaming

- Much interest in these problems in TCS and DB areas
- Many functions of (global) data distribution studied:
 - Set expressions [Das,Ganguly,G,Rastogi'04]
 - Quantiles and heavy hitters [Cormode,G, Muthukrishnan, Rastogi'05]
 - Number of distinct elements [Cormode et al.,'06]
 - Spectral properties of data matrix [Huang,G, et al.'06]
 - Anomaly detection in networks [Huang ,G, et al.'07]
 - Samples [Cormode et al.'10]
 - Counts, frequencies, ranks [Yi et al.,'12]
- NII Shonan meeting on Large-Scale Distributed Computation
 - <http://www.nii.ac.jp/shonan/seminar011/>



Monitoring Systems

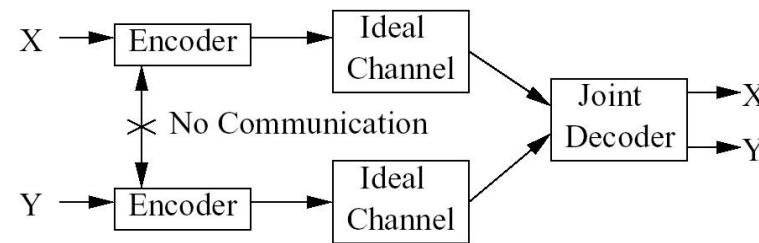
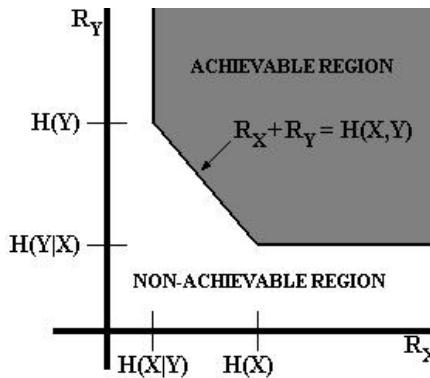
- Much theory developed, but less progress on deployment
- Some empirical study in the lab, with recorded data
- Still, applications abound: Online Games [Heffner, Malecha'09]
 - Need to monitor many varying stats and bound communication
 - Also, Distributed CEP systems (**FERARI project**)
- Several steps to follow:
 - Build lib
 - Evolve t
- Several qu
 - What fu
 - What ke



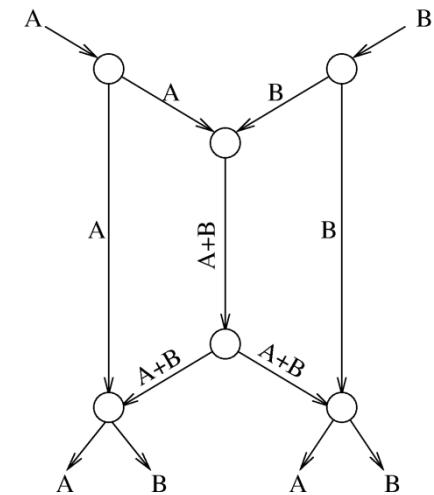
Theoretical Foundations

“Communication complexity” studies lower bounds of distributed **one-shot** computations

- Lower bounds for various problems, e.g., **count distinct** (via reduction to abstract problems)
- Need new theory for **continuous** computations
 - Link to distributed source coding or network coding?



Slepian-Wolf theorem [Slepian Wolf 1973]



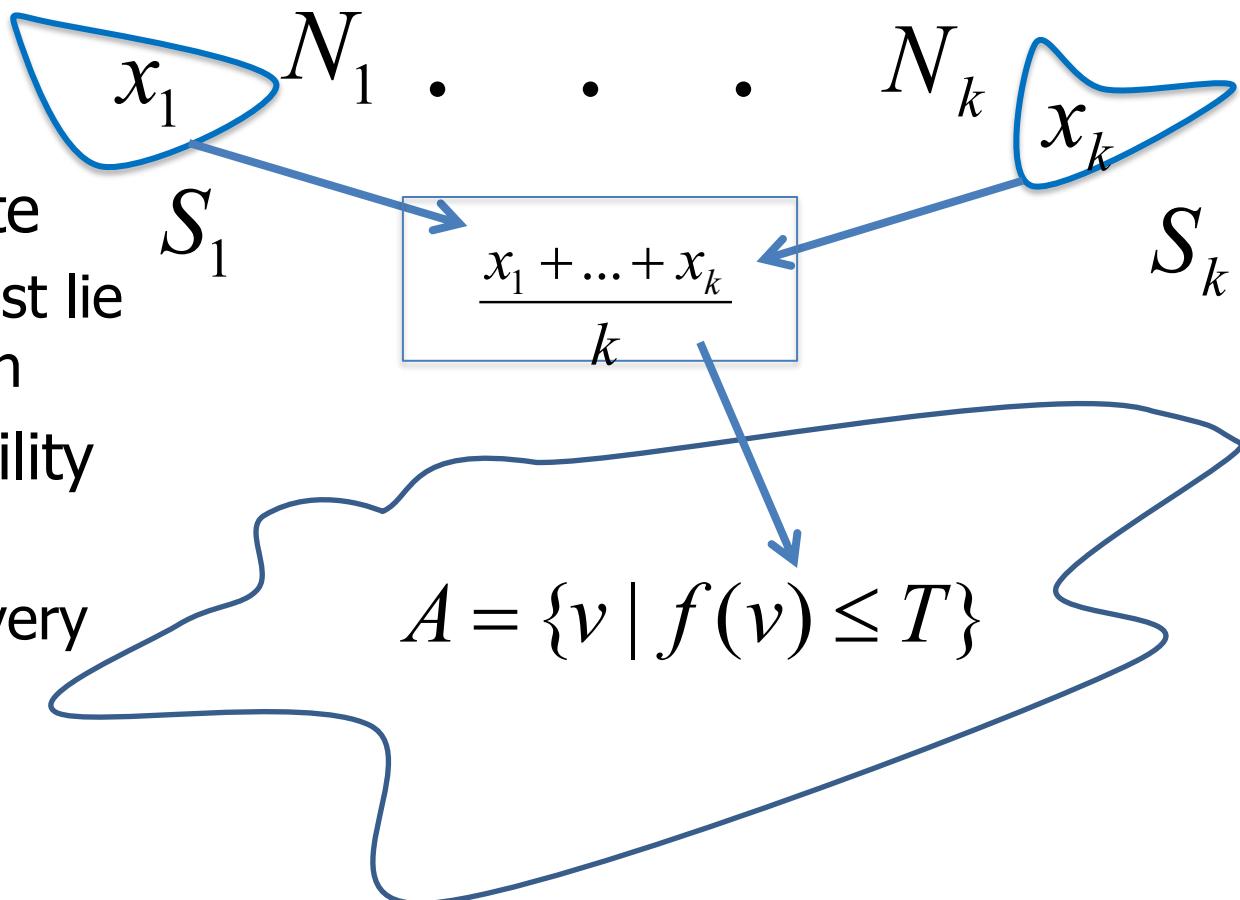
<http://www.networkcoding.info/>

https://buffy.eecs.berkeley.edu/PHP/resabs/resabs.php?f_year=2005&f_submit=chapgrp&f_chapter=1



The General SZ Problem

- *Different SZs, per site*
 - *Minkowski sum* must lie in admissible region
- Minimize the probability of local violations
 - **NP-hard** even in very simple cases!
- Heuristics for automated SZ construction
 - E.g., using hierarchical clustering of sites



Challenges, challenges, challenges...

- Distributed streaming versions of hard analytics functions (e.g., PageRank)?
- Geometric monitoring for Distributed CEP hierarchies?
 - Deal with uncertain events ("V" for Veracity)?
- Implementing GM ideas in scalable stream-processing engines (e.g., Storm)?
- CD machine learning to dynamically adapt to data/workload conditions?
 - Communication just one of our concerns
- Scalable analytics tools for streaming *time series*?



Conclusions

- Continuous querying of distributed streams is a natural model
 - Interesting space/time/communication tradeoffs
 - Captures several real-world applications
- **GM, SZs** : Generic geometric tools for monitoring complex queries
 - Sketches [VLDB'13], dynamic prediction models [SIGMOD'12, TODS'14], Skyline Monitoring [ICDE'14]
 - Novel insights through Convex Geometry [TKDE'14, VLDB'15]
- ***Much interesting algorithmic/systems work to be done!***



Thank you!



<http://www.softnet.tuc.gr/~minos/>

<http://lift-eu.org> , <http://leads-project.eu>

<http://ferari-project.eu> , <http://qualimaster.eu>

Current Big Data Projects @SoftNet



LARGE-SCALE ELASTIC ARCHITECTURE
FOR DATA AS A SERVICE

ICT STREP (2012-5)
<http://leads-project.eu>

FERARI

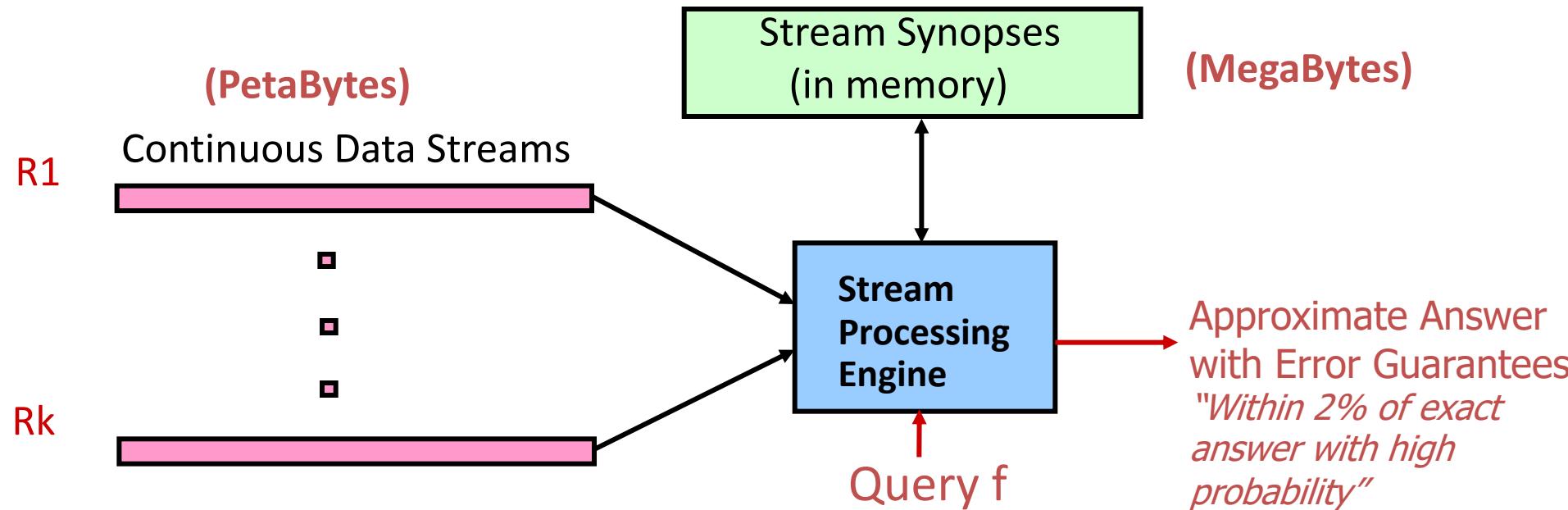
QualiMaster

Flexible Event Processing for Big Data Architectures
ICT STREP (2014-7)
<http://ferari-project.eu>

Configurable, Autonomously-Adaptive Real-time
Data Processing
ICT STREP (2014-7)
<http://qualimaster.eu>



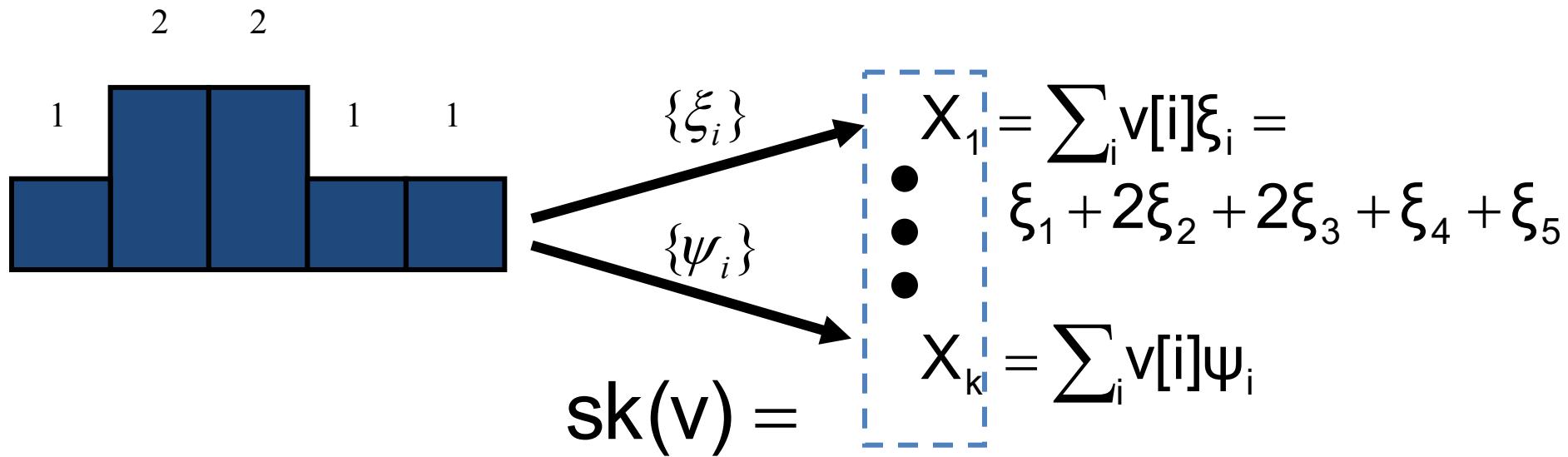
Stream Processing Model



- Approximate answers often suffice, e.g., trends, anomalies
- Requirements for stream synopses
 - *Single Pass*: Each record examined at most once, in arrival order
 - *Small Space*: Log or polylog in data stream size
 - *Small Time*: Per-record processing time must be low
 - Also: *Delete-proof, Composable*, ...



AMS Sketches 101

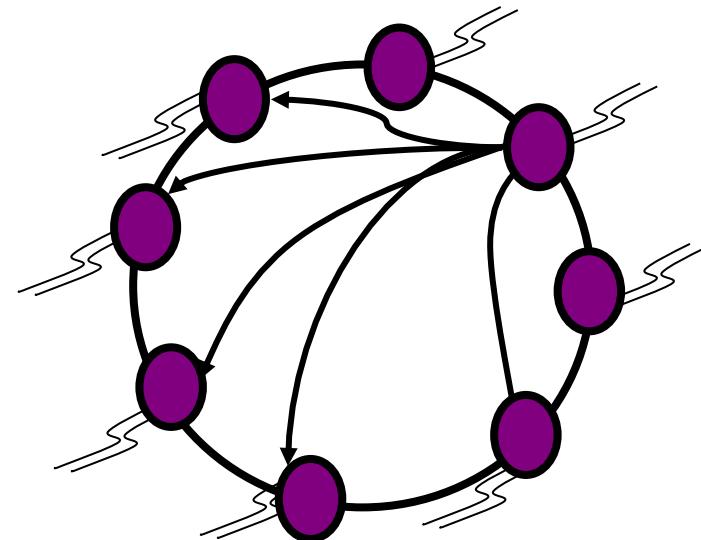


- Simple randomized linear projections of data distribution
 - Easily computed over stream using logarithmic space
 - *Linear*: Compose through simple vector addition



CD Monitoring in Scalable Network Architectures

- E.g., DHT-based P2P networks
- Single query point
 - “Unfolding” the network gives hierarchy
 - But, single point of failure (i.e., root)
- Decentralized monitoring
 - Everyone participates in computation, all get the result
 - Exploit epidemics? Latency might be problematic...



Exploring the Prediction Model Space

- The better we can capture and anticipate future stream direction, the less communication is needed
- So far, only look at predicting each stream alone
- Correlation/anti-correlation across streams should help?
 - But then, checking validity of model is expensive!
- Explore tradeoff-between power (expressiveness) of model and complexity (number of parameters)
 - Optimization via Minimum Description Length (MDL)?
[Rissanen 1978]



Thank you!



<http://www.lift-eu.org/>

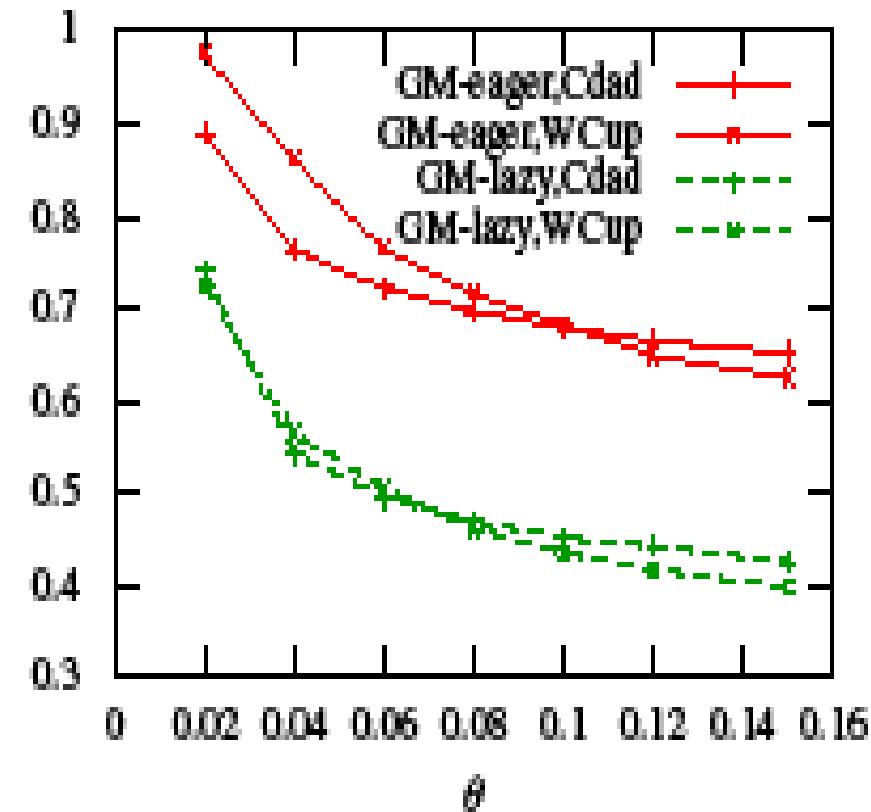
<http://www.softnet.tuc.gr/~minos/>



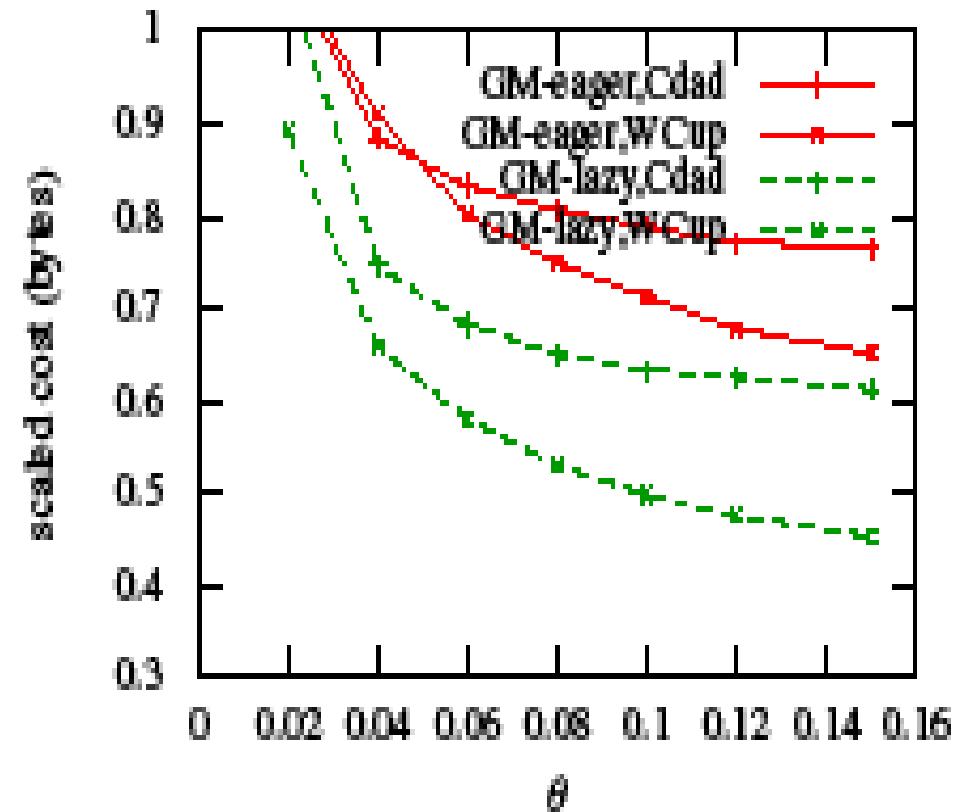
Geometric Query Monitoring using AMS Sketches

[GKS VLDB'13]

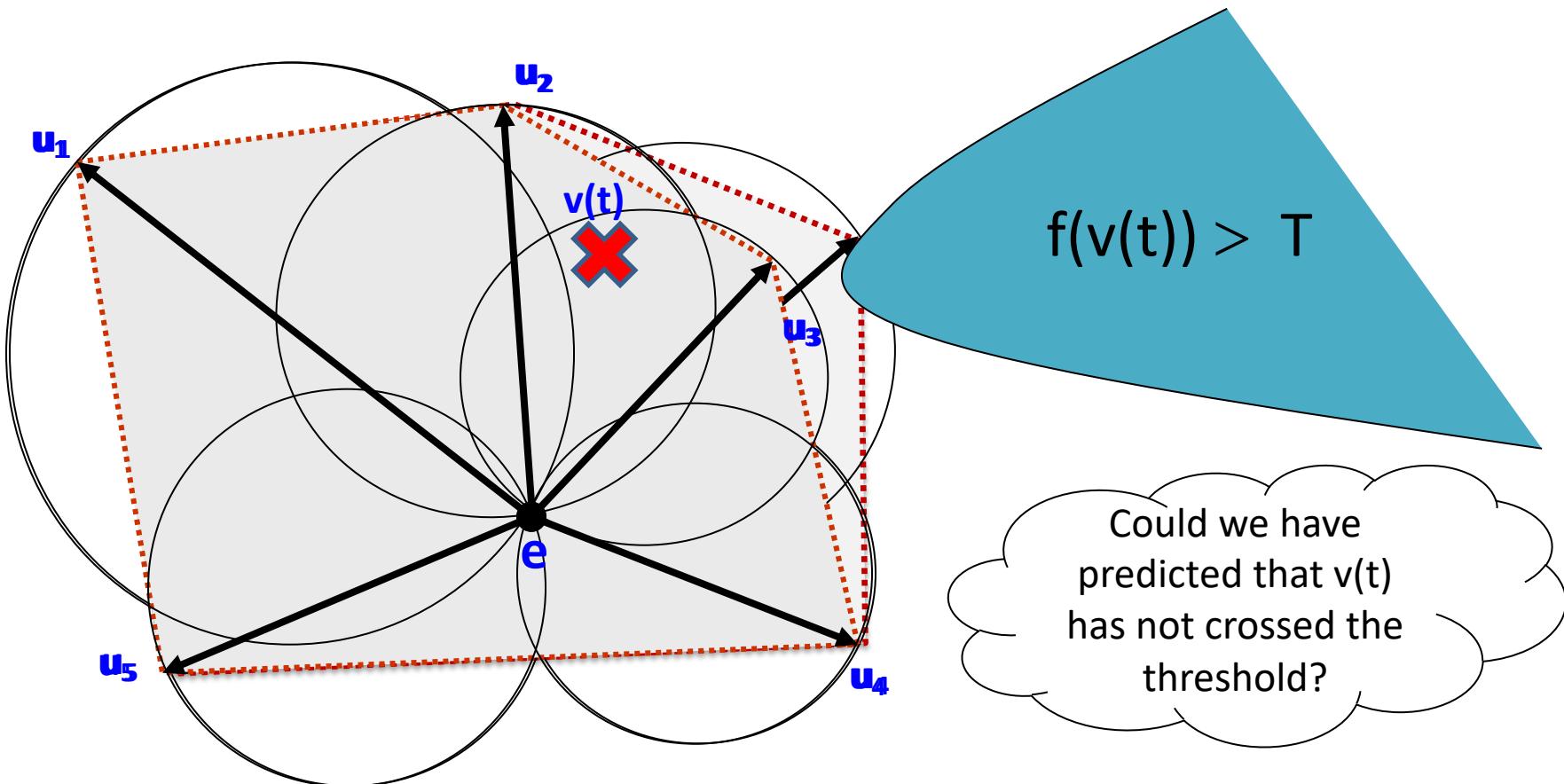
Full Join–Data comm. cost relative to CG method, $\epsilon = 0.01$



Full Join–Total comm. cost relative to CG method, $\epsilon = 0.01$

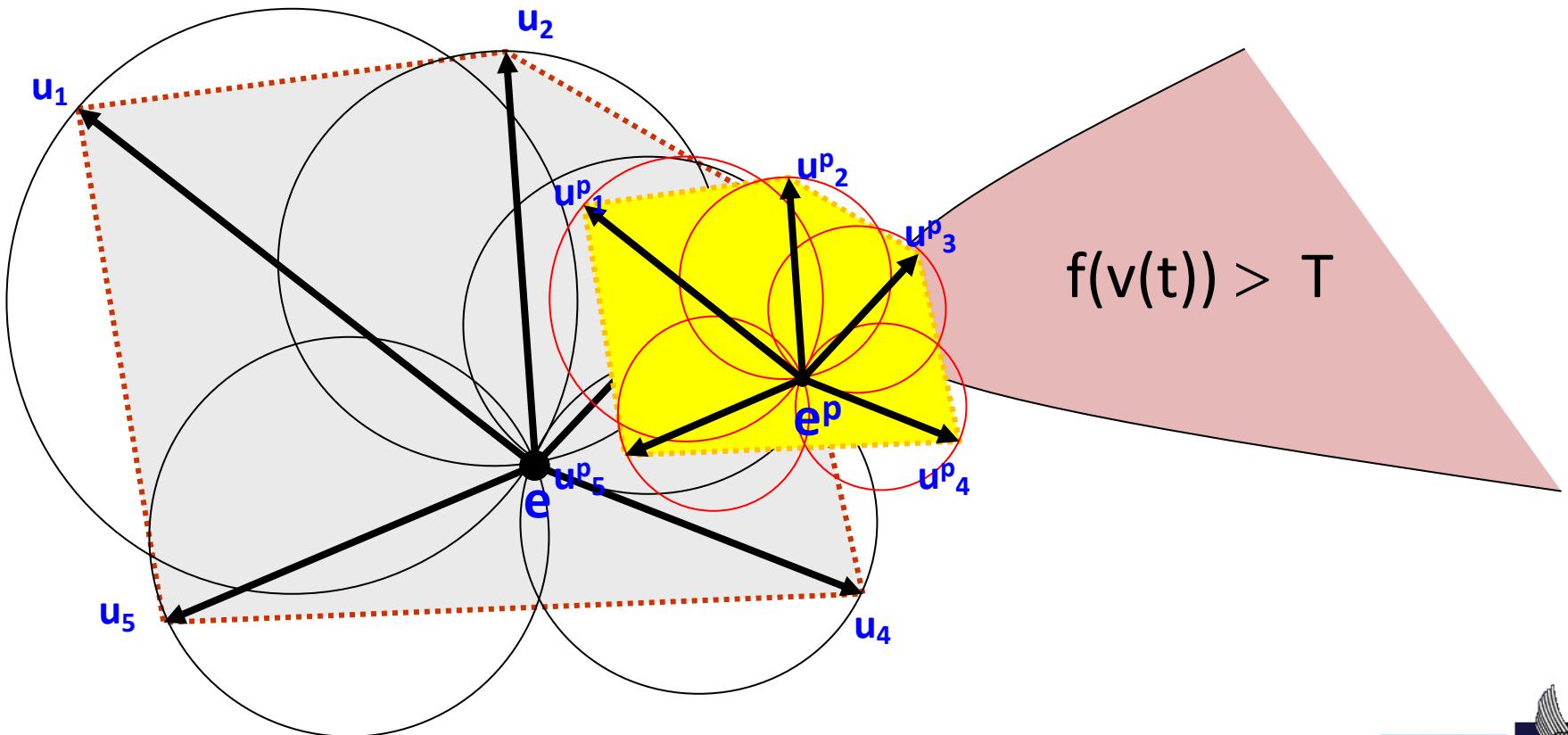


Prediction-based Geometric Threshold Monitoring [GDG SIGMOD'12, TODS'14]



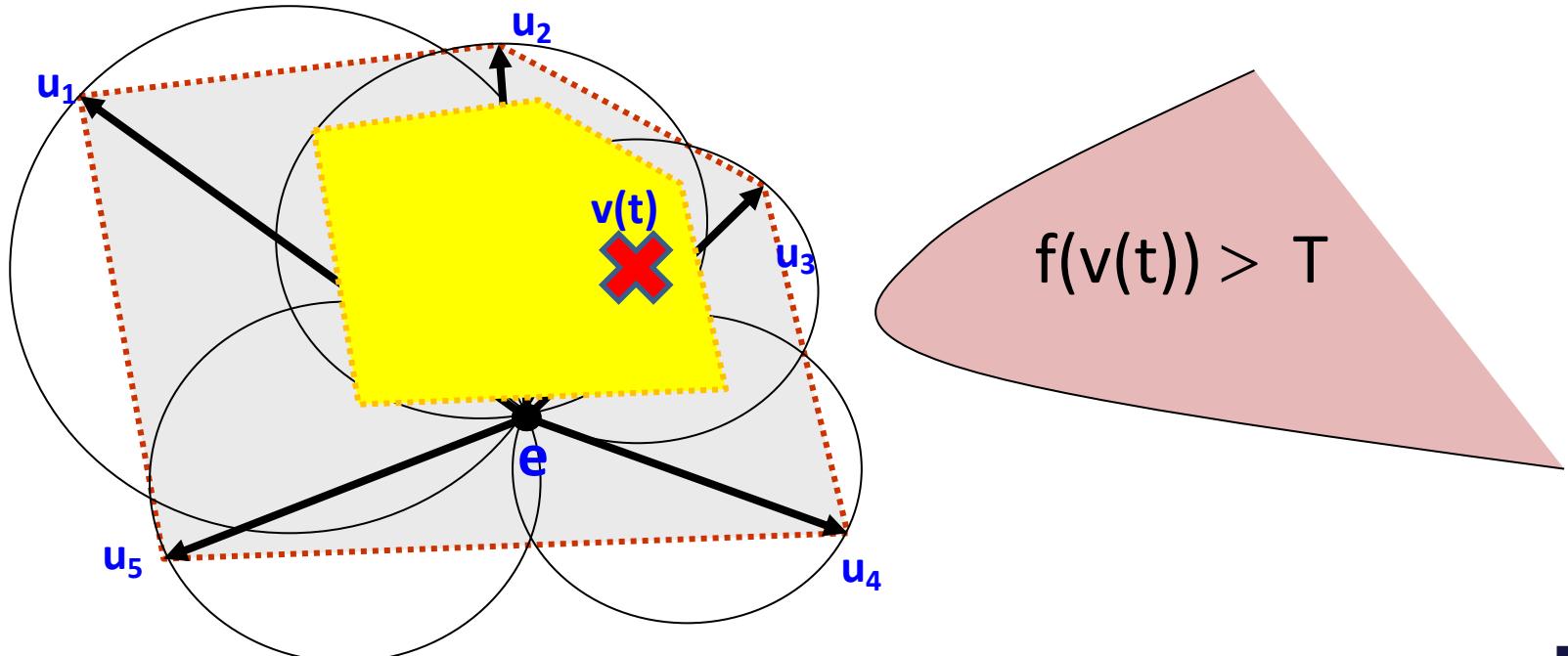
Issues

- Stricter local constraints do not guarantee less communication / lower false positives
- “Bad” scenarios may occur



Towards Strong Geometric Monitoring Models

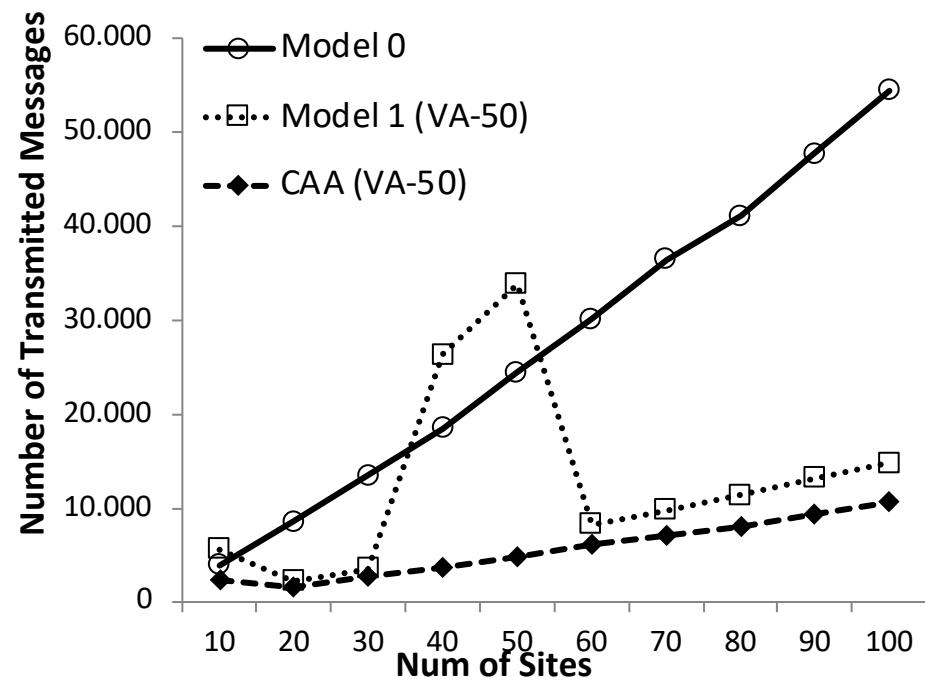
- **Containment of convex hulls:** hard to maintain/verify in distributed settings
- Designed several algorithms that try to approximately ensure containment with no/minimal information sharing
 - Based on combining static and prediction-based bounding regions



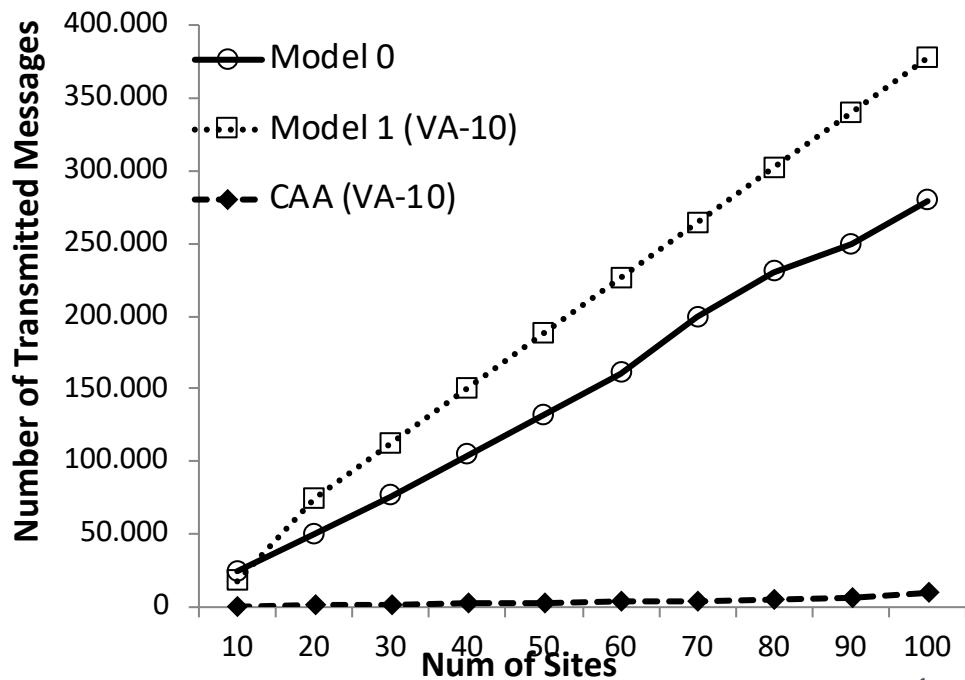
Some Experiments

- Sliding Window
 - Up to 600 times lower cost compared to the basic GM

Wind Peak - Signal to Noise Ratio Monitoring under sliding window of 200 tuples varying #sites for 0.5



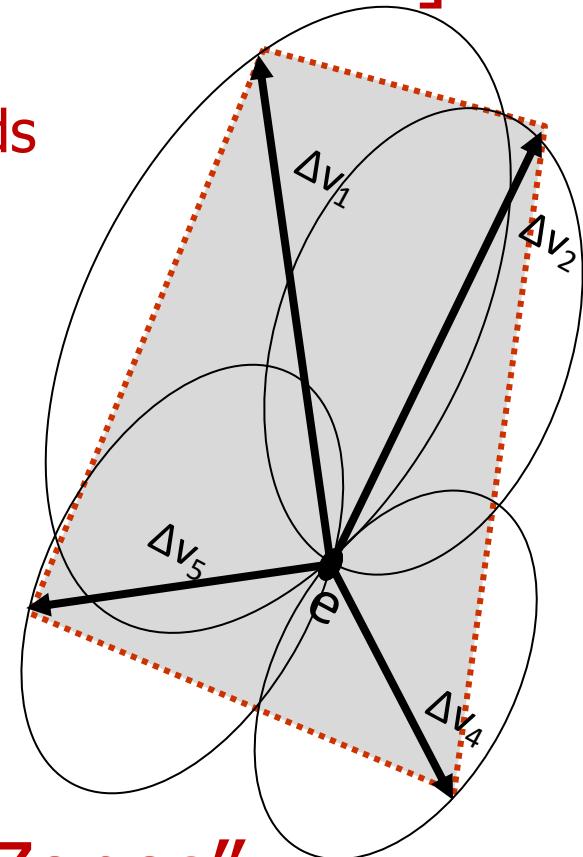
Solar Irradiance - Variance Monitoring under sliding window of 200 tuples varying #sites for 50000 threshold



Extensions: Transforms, Shifts, Safe Zones

- Subsequent developments [SKS TKDE'12]

- Same analysis of correctness holds when spheres are allowed to be **ellipsoids**
- Different **reference vectors** can be used to increase radius when close to threshold values
- Combining these observations allows additional cost savings



- More general theory of “Safe Zones”

- Convex subsets of the admissible region