Scaling Geometric Monitoring Over Distributed Streams

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Data Stream Systems

(Brian Babcock et al. "Models and Issues in Data Stream Systems". In: *21st ACM SIGMOD-SIGACT-SIGART*. PODS '02. 2002)

- **Data streams**: Continuous, high volume, size unbound, violative, probably distributed
- *Pull paradigm*
- Centralizing and/or polling $\rightarrow$ prohibitive in terms of communication overhead
- Examples: telecommunication, sensor networks

The Geometric Monitoring Method

(Izchak Sharfman, Assaf Schuster, and Daniel Keren. "A Geometric Approach to Monitoring Threshold Functions over Distributed Data Streams". In: *2006 ACM SIGMOD ICMD*. SIGMOD '06. 2006)

- Threshold monitoring
- Nodes communicate when needed
  - Local constraints
  - Violation resolution (*false alarms*)
- Arbitrary function monitoring
- Tight accuracy bounds
- A promising framework for *distributed data stream monitoring*

Motivation

Problems:

- increasing node population
- data volume
- data dimensionality
- arbitrary functions
- **communication - accuracy tradeoff**

Need for:

- scalability warranties
- tight accuracy bounds
- incremental/real-time operation
- **Minimize communication while retaining accuracy bounds**

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Contributions

Expand the *geometric monitoring method*:

- heuristic method for violation resolution
- distance-based hierarchical node clustering (Daniel Keren, Guy Sagy, Amir Abboud, David Ben-David, et al. "Geometric Monitoring of Heterogeneous Streams." In: *IEEE TKDE* (2014))
- throughout method evaluation on synthetic and real-world datasets

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Geometric Threshold Monitoring

- Izchak Sharfman, Assaf Schuster, and Daniel Keren. "A Geometric Approach to Monitoring Threshold Functions over Distributed Data Streams". In: *2006 ACM SIGMOD ICMD*. SIGMOD '06. 2006
- **Threshold monitoring**: arbitrary function $f(\cdot)$, threshold T

$$f(\cdot) < T \text{ or } f(\cdot) > T$$

- **Idea**: decompose into local constraints at the nodes

System Architecture

Centralized Scenario

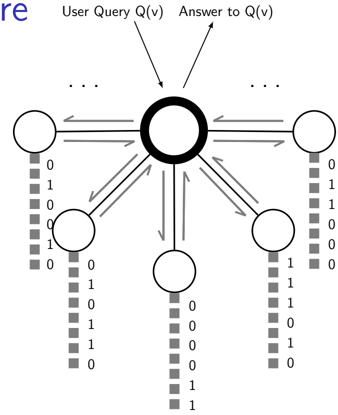


Figure: **Star-like network topology** example of the centralized scenario.The bold node represents the coordinator node. Dashed lines represent data streams and half arrows represent message exchanges.

Computational Model

Statistics vectors

- the *monitoring function* $f : \mathbb{R}^d \to \mathbb{R}$
- the *threshold* $T \in \mathbb{R}$
- the *monitoring node set* : $P = \{p_1, \ldots, p_n\}$
  with *weights* $w_1, \ldots, w_n$
- the *data streams* : $S = \{s_1, \ldots, s_n\}$
- the d-dimensional *local statistics vectors* : $\vec{v_1}(t), \ldots, \vec{v_n}(t)$
  represent each node's data stream at time t

Global statistics vector

$$\vec{v}(t) = \frac{\sum_{i=1}^{n} w_i \vec{v_i}(t)}{\sum_{i=1}^{n} w_i}$$

Computational Model

Estimate vector

Infrequent communication between nodes/nodes-coordinator:

Estimate vector

$$\vec{e}(t) = \frac{\sum_{i=1}^{n} w_i \vec{v_i}'}{\sum_{i=1}^{n} w_i}$$

- the last communicated *local statistics vector* of node p_i : $\vec{v_i}'$
- *Local statistics* divergence:$\Delta\vec{v_i}(t) = \vec{v_i}(t) - \vec{v_i}', i = 1, \ldots, n$

Centralized drift vector

$$\vec{u_i}(t) = \vec{e}(t) + \Delta\vec{v_i}(t) + \frac{\vec{\delta_i}}{w_i}$$

Computational Model

Balancing Process

Centralized scenario

Purpose: resolve possible false alarms

Balancing vector

$$\vec{b} = \frac{\sum_{p_i \in P'} w_i \vec{u_i}(t)}{\sum_{p_i \in P'} w_i}$$

- the *balancing set* P': a subset of nodes
- the *slack vector* at the nodes $\vec{\delta_i} = \vec{\delta_i}' + \Delta\vec{\delta_i}$, $\sum_{p_i \in P'} \Delta\vec{\delta_i} = \vec{0}$:

$$\Delta\vec{\delta_i} = w_i \vec{b} - w_i \vec{u_i}(t) \ \forall \ p_i \in P'$$

, readjusts the *drift vectors*.

Geometric Interpretation

Convexity Property & Local Constraints

Convexity Property

$$\vec{v}(t) = \frac{\sum_{i=1}^{n} w_i \vec{u_i}(t)}{\sum_{i=1}^{n} w_i}$$

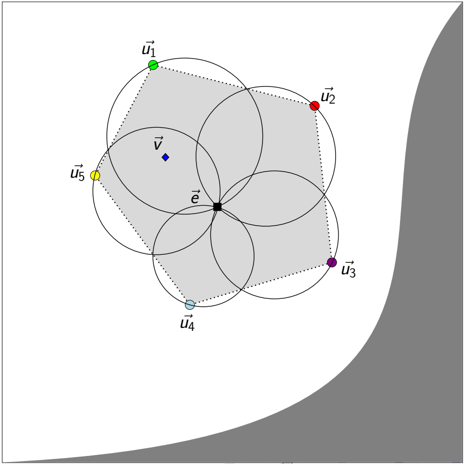


Figure: Example of a convex hull (light gray) defined by the drift vectors $\vec{u_i}, i = 1, 2, 3, 4, 5$ and bounded by spheres.

Related Work

- *Safe Zones*: optimal local constraints fitted to nodes' data distributions (Daniel Keren, Guy Sagy, Amir Abboud, David Ben-David, et al. "Safe-Zones for Monitoring Distributed Streams". In: *First International Workshop on Big Dynamic Distributed Data, Riva del Garda, Italy, 2013*)
- Ellipsoidal bounding regions, decouplement of estimate vector from bounding ball construction (D. Keren et al. "Shape Sensitive Geometric Monitoring". In: *IEEE TKDE* (2012))
- Simple shapes as local constraints, hierarchical clustering of nodes for participation to the balancing operation (Daniel Keren, Guy Sagy, Amir Abboud, David Ben-David, et al. "Geometric Monitoring of Heterogeneous Streams." In: *IEEE TKDE* (2014))
- Prediction models based on velocity and acceleration (Nikos Giatrakos et al. "Prediction-based Geometric Monitoring over Distributed Data Streams". In: *2012 ACM SIGMOD ICMD*. SIGMOD '12. 2012)

Multi-objective Optimization

- **Multiple**, possibly **conflicting** objectives to be *simultaneously* optimized
- *Pareto optimality*(*non-dominated solutions*): optimal solutions where none of the objective functions can be optimized without the simultaneous degradation of other objective functions' values.
- Let vector of m objectives $F(x) = [F_1(x), F_2(x), \ldots, F_m(x)]$:

$$
\begin{aligned}
&\min_{x \in \mathbb{R}^n} F(x) \\
&\text{s.t. } l \leq x \leq u \\
&\qquad G_i = 0, i = 1, \ldots, k_e \\
&\qquad G_j \leq 0, j = k_e + 1, \ldots, k
\end{aligned}
$$

- Finding *Pareto optimal* solutions is generally **NP-hard**.

SQP

- The *Lagrangian function*: $\mathcal{L}(x,\lambda) = F(x) + \sum_{i=1}^{k} \lambda_i G_i(x)$
- *Quadratic programming subproblems*:

$$\min_{d \in \mathbb{R}^n} \frac{1}{2} d^T H_t d + \nabla F(x_t)^T d$$
$$\nabla G_i(x_t)^T d + G_i(x_t) = 0, i = 1, \ldots, k_e$$
$$\nabla G_i(x_t)^T d + G_i(x_t) \leq 0, i = k_e + 1, \ldots k$$

,where:

H_t: Hessian of the Lagrangian function at iteration t

d: search direction

The Savitzky-Golay Low-Pass Smoothing Filter

- Convolution based **smoothing**, **velocity** and **acceleration** estimation
- *Moving window averaging* paradigm: $g_i = \sum_{n=-n_L}^{n_R} c_n f_{i+n}$
- *Least-squares fit* of polynomial:

$$y_i(x) = a_0 + a_1 \frac{x - x_i}{\Delta x} + a_2 (\frac{x - x_i}{\Delta x})^2 + \cdots + a_M (\frac{x - x_i}{\Delta x})^M$$

,over window $n_L + n_R + 1$:

$$\sum_{j=i-n_L}^{i+n_R} (y_i(x_j) - f_j)^2 = \min$$

- Set g_i to the value of the fitted point x_i.

Velocity and Acceleration Estimation via SG Filtering

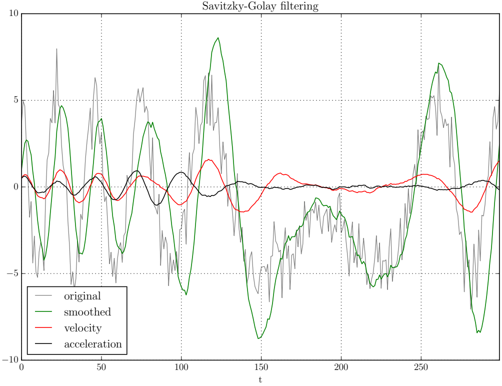
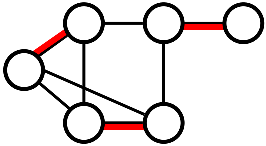


Figure: Savitzky-Golay filtering of a signal with added Gaussian noise. The smoothing window is 50 points, centered at the far right.

Maximum Weight Matching



Let $G = (V, E)$ a graph:

- *maximum weight matching* $M \subseteq E$: a subset of edges where
  - no two edges share a common vertex
  - largest possible number of edges
  - maximizes the sum of weights

Maximum Weight Matching

The Primal-Dual Method

Constraints in Primal $\Longleftrightarrow$ Variables in Dual
Constraints in Dual $\Longleftrightarrow$ Variables in Primal

The primal:

$$\begin{aligned} \max \quad & \sum_{(u,v)\in E} x_{u,v} w_{u,v} \\ \text{s.t.} \quad & x_{u,v} \geq 0 && ,(u,v)\in E \\ & \sum_{u\in e : e\in E} x_e \leq 1 && ,u \in V \end{aligned}$$

The dual:

$$\begin{aligned} \min \quad & \sum_{u\in V} y_u \\ \text{s.t.} \quad & y_u \geq 0 && ,u\in V \\ & y_u + y_v \geq w_{u,v} && ,(u,v) \in E \end{aligned}$$

Problem Formulation

Reduce the communication burden of the *Geometric Monitoring* method by:

- Optimally position *drift vectors* during the *balancing process*
- Appropriate node selection for inclusion in the *balancing set*

,in order to **increase scalability** in terms of:

- node popullation
- stream dimensionality.

The Geometric Monitoring Framework

Assumptions

- Coordinator-based scenario
- Instantaneous, loss-less, reliable communication
- Iterative operation based on time-steps
- System pause during violation resolution
- Coordinator node does not monitor a stream

The Distance-based Hierarchical Clustering

The Idea

Node selection for *violation resolution*:

- Elevate *randomness* of the initial *geometric monitoring* method (Izchak Sharfman, Assaf Schuster, and Daniel Keren. "A Geometric Approach to Monitoring Threshold Functions over Distributed Data Streams". In: *2006 ACM SIGMOD ICMD*. SIGMOD '06. 2006)
- Hierarchical node clustering scheme (Daniel Keren, Guy Sagy, Amir Abboud, David Ben-David, et al. "Geometric Monitoring of Heterogeneous Streams." In: *IEEE TKDE* (2014))
- Decouple matching from the data distribution at the nodes (Daniel Keren, Guy Sagy, Amir Abboud, David Ben-David, et al. "Geometric Monitoring of Heterogeneous Streams." In: *IEEE TKDE* (2014))
- Accurately follow *global statistics vector*
- Node "cancel each other out" during the *balancing process*

The Distance-based Hierarchical Clustering

The Weight Function

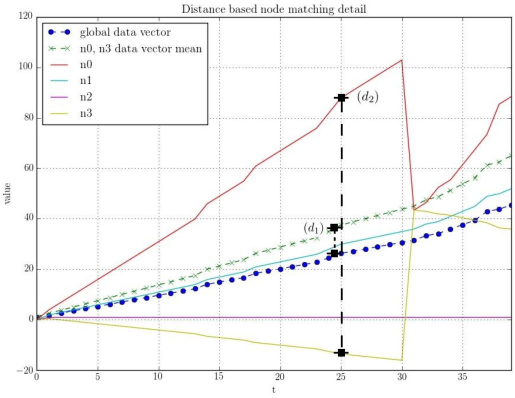
Weight function

$$w_{i,j} = \sum_{t=t_0}^{t_{end}} [(f(\vec{v}_{global}(t)) - f(\frac{\vec{v_i}(t) + \vec{v_j}(t)}{2})) + (|\vec{v_i}(t) - \vec{v_j}(t)|)]$$

The Distance-based Hierarchical Clustering

Example

Figure: Distance based node matching operating on 4 nodes ($\{n_0, n_1, n_2, n_3\}$). Distance d_1 : the distance of the data vector mean of the paired nodes n_0 and n_3 from the global mean (*global data vector*), distance d_2 : denotes the in-between distance of data vectors $\vec{v_0}(t)$ and $\vec{v_3}(t)$ of the node pair. Both distances are taking part in the edge weighting process.



The Heuristic Balancing

The Idea

In prior work:

- identical handling of nodes during the balancing process
- ignore stream idiosyncrasies and monitoring function peculiarities

The *heuristic balancing* method:

- optimally position *drift vectors in space*
- take into account stream behaviour (*velocity* and *acceleration*)

The Heuristic Balancing

The Optimizing Function

Weight function

$$\max\min \frac{(T - x_i) - accel_i(t_{lv}) * t^2}{vel_i(t_{lv})}, \forall n_i \in P'$$

where:

t : the variable to optimize

T : monitoring threshold

x_i : the maximum value of the monitoring function $f(\cdot)$ over the bounding ball $B(\vec{e}(t_{lv}), \vec{u_i}(t_{lv}))$

$vel_i(t_{lv})$: the estimated velocity of the maximum value of the monitoring function $f(\cdot)$

$accel_i(t_{lv})$: the estimated acceleration of the maximum value of the monitoring function $f(\cdot)$

t_{lv} : time of Local Violation occurrence

P' : the balancing set

The Heuristic Balancing

Example

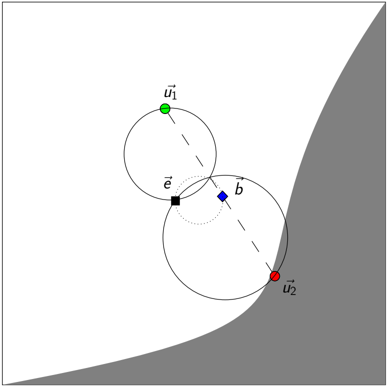


Figure: The classic balancing method.

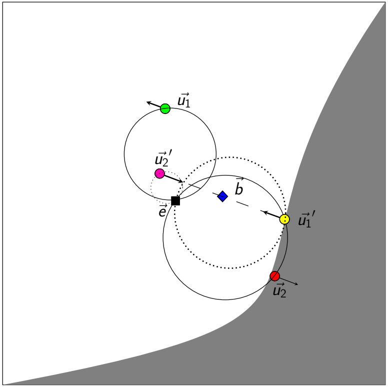


Figure: The heuristic balancing method.

Acronyms for Implemented Methods

GM: the initial geometric monitoring method (Izchak Sharfman, Assaf Schuster, and Daniel Keren. "A Geometric Approach to Monitoring Threshold Functions over Distributed Data Streams". In: *2006 ACM SIGMOD ICMD*. SIGMOD '06. 2006)

HM: the proposed heuristic balancing process

DIST: the proposed distance-based hierarchical node clustering

DISTR: the distribution-based hierarchical node clustering (Daniel Keren, Guy Sagy, Amir Abboud, David Ben-David, et al. "Geometric Monitoring of Heterogeneous Streams." In: *IEEE TKDE* (2014))

Synthetic Data

- $v_i(t_{k+1}) = v_i(t_k) + (1 - \lambda)u_k + \lambda u_{k+1}$
- 1-dimensional
- Velocities sampled from user-specified Gaussian distribution
- λ smoothing parameter
- Additive Gaussian noise
- 3 sets of datasets: *LIN*, *INT*, *NOISE*
- First 20% of data streams used as training data, when needed

Synthetic Data

Examples

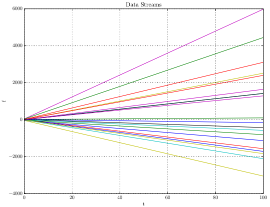


Figure: *LIN* local statistics streams of 20 nodes

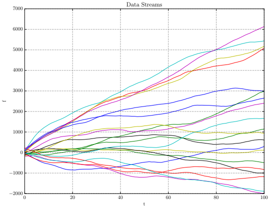


Figure: *INT* local statistics streams of 20 nodes

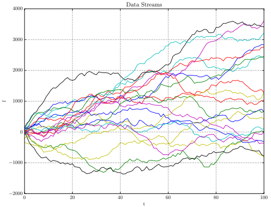


Figure: *NOISE* local statistics streams of 20 nodes

Real-world Data

- "European Environmental Agency - AQ e-Reporting" database
  (*European Environmental Agency - AQ e-Reporting.*)
- Hourly measurements of NO_2 and NO, in micro-grams per cubic meter, averaged over a window of five days for a whole year.
- Nodes correspond to randomly selected air quality measurement stations across Austria.
- First month of measurements used as training data, when needed.

Real-world Data

Examples

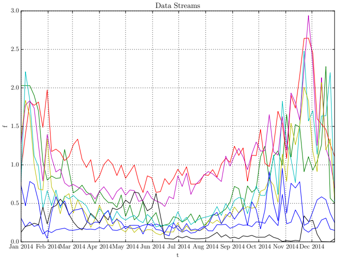


Figure: Streams of 8 nodes monitoring the ratio NO/NO_2.

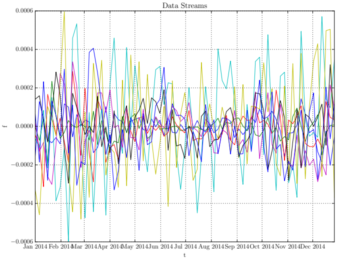


Figure: Streams of 8 nodes monitoring the variance of NO_2 air pollutant.

GM, DIST, DISTR Comparison

LIN dataset

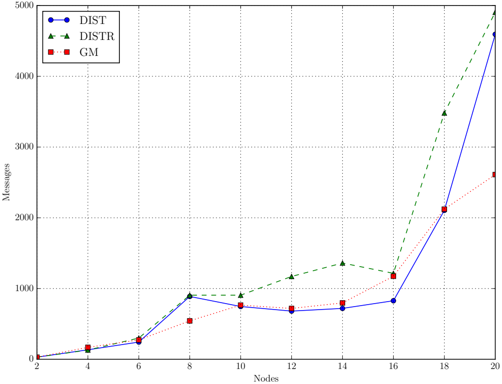


Figure: Communication costs of methods GM, DISTR and DIST for the *LIN* dataset.

GM, DIST, DISTR Comparison

INT dataset

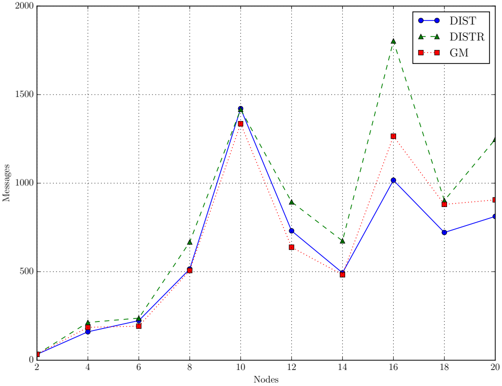


Figure: Communication costs of methods GM, DISTR and DIST for the *INT* dataset.

GM, DIST, DISTR Comparison

NOISE dataset

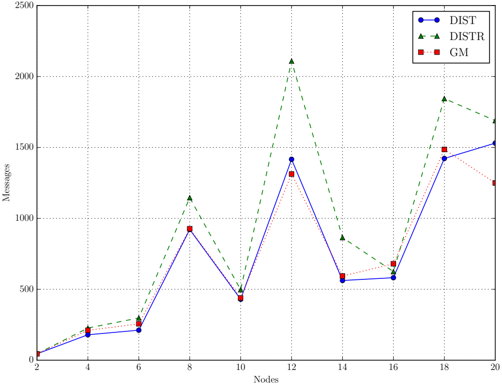


Figure: Communication costs of methods GM, DISTR and DIST for the *NOISE* dataset.

GM, DIST, DISTR Comparison

LIN dataset

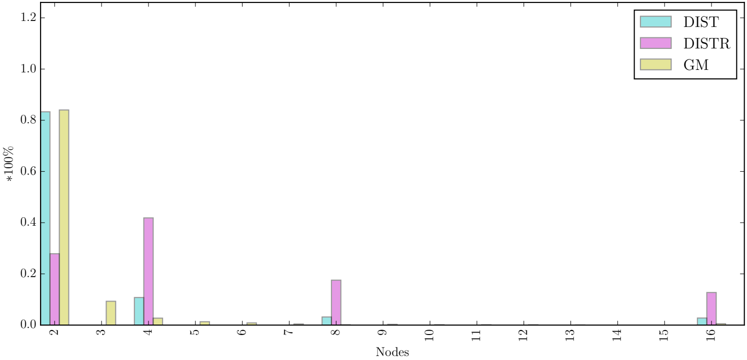


Figure: Number of nodes participating in violation resolutions as a fraction of total Local Violations, for the *LIN* dataset.

GM, DIST, DISTR Comparison

INT dataset

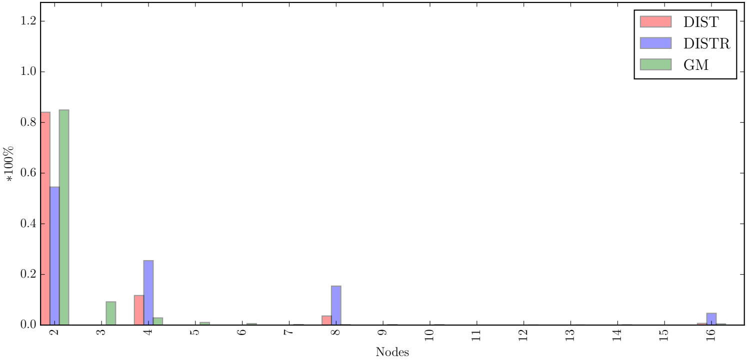


Figure: Number of nodes participating in violation resolutions as a fraction of total Local Violations, for the *INT* dataset.

GM, DIST, DISTR Comparison

NOISE dataset

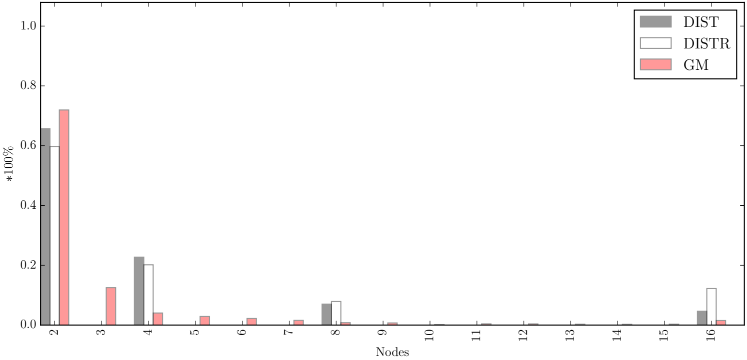


Figure: Number of nodes participating in violation resolutions as a fraction of total Local Violations, for the *NOISE* dataset.

GM, HM Comparison

Messages

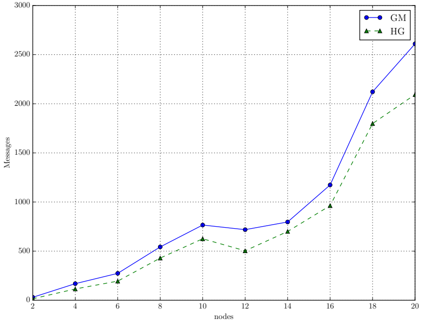


Figure: Communication cost of methods GM and HM for the *LIN* dataset.

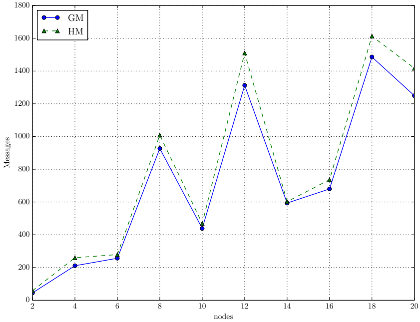


Figure: Communication cost of methods GM and HM for the *NOISE* dataset.

GM, HM Comparison

Drift vectors

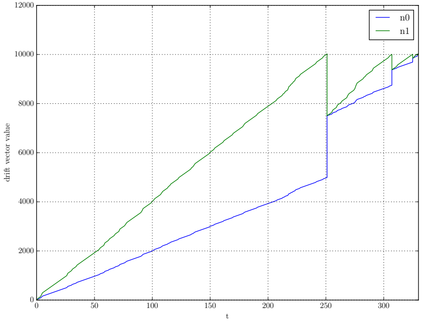


Figure: Drift vectors of 2 nodes, as formulated by the GM algorithm.

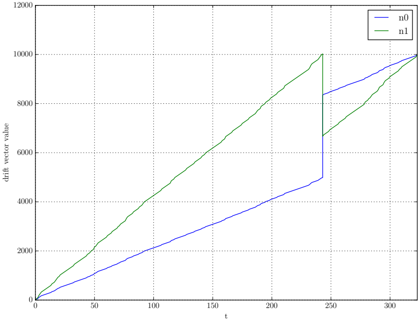


Figure: Drift vectors of 2 nodes, as formulated by the HM algorithm.

GM, HDM Comparison

LIN

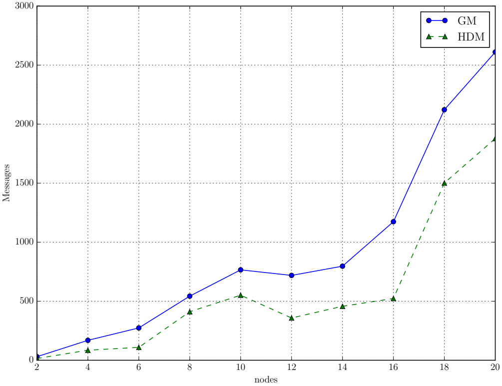


Figure: Communication cost of methods GM and HDM for the *LIN* dataset.

GM, HDM Comparison

INT

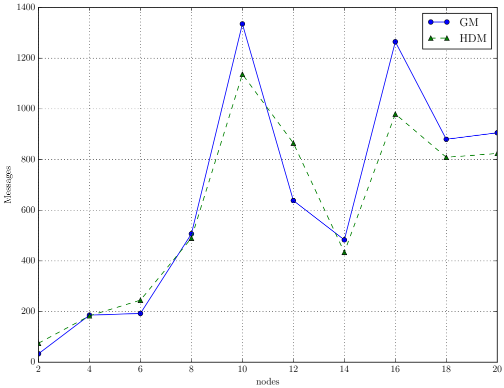


Figure: Communication cost of methods GM and HDM for the *INT* dataset.

GM, HDM Comparison

NOISE

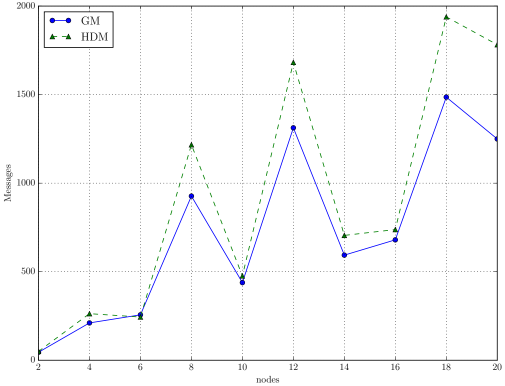


Figure: Communication cost of methods GM and HDM for the *NOISE* dataset.

GM, HDM Comparison

NOISE - window

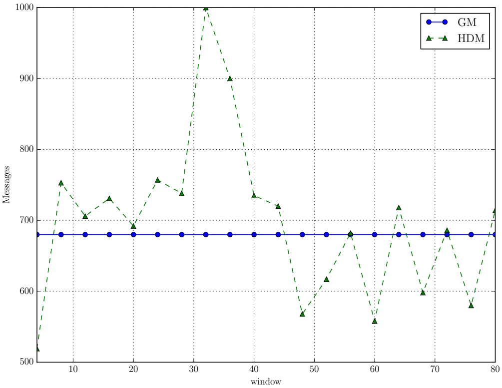


Figure: Communication cost of methods GM and HDM for the *NOISE* dataset. Approximation order is set to 1.

GM, HDM Comparison

NOISE - order

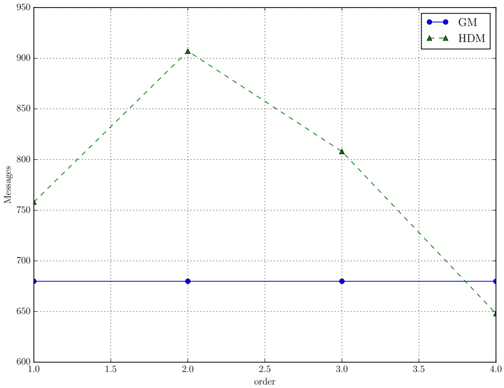


Figure: Communication cost of methods GM and HDM for the *NOISE* dataset. The Savitzky-Golay window size is set to 24.

GM, HDM Comparison

Dimensions - Quadratic Function

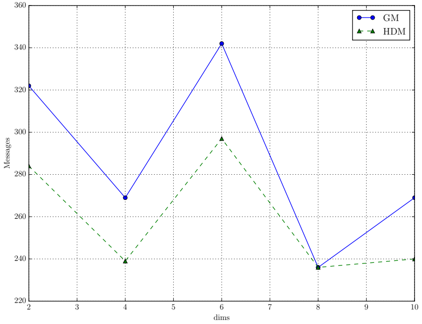


Figure: Communication cost of methods GM and HDM for the *LIN* dataset.

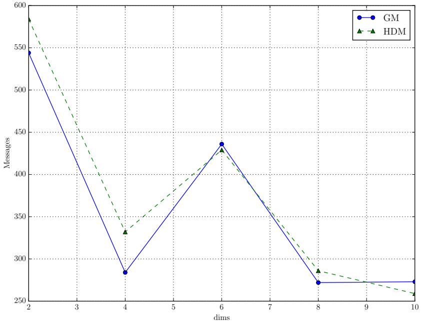


Figure: Communication cost of methods GM and HM for the *NOISE* dataset.

GM, HDM Comparison

Air Pollution Monitoring

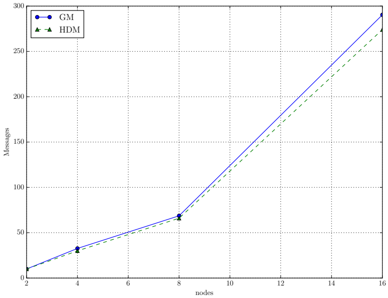


Figure: 4 to 16 nodes,variance monitoring of NO_2. The Savitzky-Golay window size is set to 6, the order is set to 2.

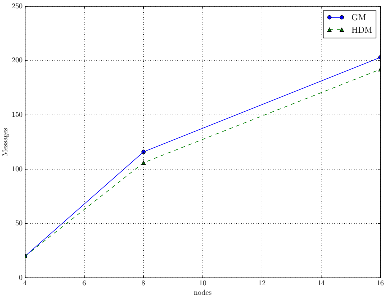


Figure: 4 to 16 nodes, when monitoring NO/NO_2. The Savitzky-Golay window size is set to 10, the order is set to 1.

Summary & Concluding Remarks

The *Geometric monitoring* method:

- An efficient framework for monitoring distributed data streams
- Scalability can be improved $\rightarrow$ reduce communication costs

Our contributions:

- Distance-based hierarchical node clustering
- Heuristic balancing method based on SQP and Savitzky-Golay Filtering
- Detailed evaluation of proposed methods

Comments:

+ Communication reduction of up to 60%
+ Methods fully compatible with the rest of the work
- Parameter tweaking for satisfactory results
- Multi-objective optimization can be computationally expensive

Future Work

- Multi-objective optimization solvers
- More elaborate optimizing fuctions
- Sophisticated prediction models (Gaussian processes)
- Parameter estimation techniques

Thank you

Questions?