Scaling Geometric Monitoring Over Distributed Streams

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Data Stream Systems

- **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

- 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
- throughout method evaluation on synthetic and real-world datasets

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Geometric Threshold Monitoring

- **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

Decentralized Scenario

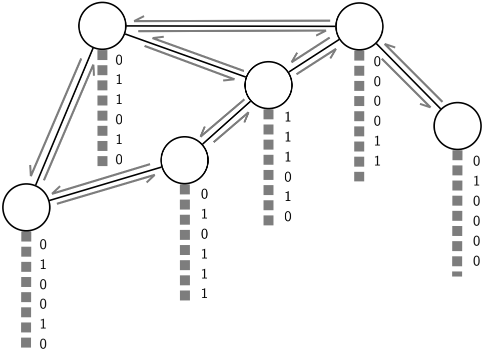


Figure: **Mesh-like network topology** example of the decentralized scenario. Dashed lines represent data streams and half arrows represent message exchanges.

System Architecture

Centralized Scenario

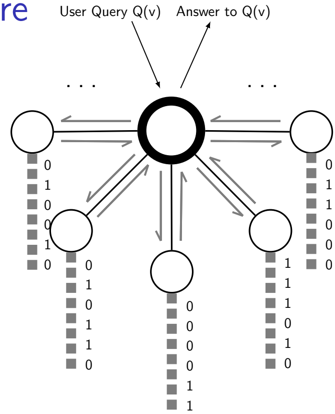


Figure: **Star-like network topology** example of the centralized scenario.The bold node represents the coordinator node. Dashed lines represent data streams and half arrows represent message exchanges.

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

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

Computational Model

Estimate vector

Infrequent communication between nodes/nodes-coordinator:

Estimate vector

$$\vec{e}(t) = \frac{\sum_{i=1}^{n} w_i \vec{v_i}'}{\sum_{i=1}^{n} w_i} \quad (2)$$

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

Decentralized drift vector

$$\vec{u_i}(t) = \vec{e}(t) + \Delta\vec{v_i}(t) \quad (3)$$

Centralized drift vector

$$\vec{u_i}(t) = \vec{e}(t) + \Delta\vec{v_i}(t) + \frac{\vec{\delta_i}}{w_i} \quad (4)$$

Computational Model

Balancing Process

Centralized scenario

Purpose: resolve possible false alarms

Balancing vector

$$\vec{b} = \frac{\sum_{p_i \in P'} w_i \vec{u_i}(t)}{\sum_{p_i \in P'} w_i} \quad (5)$$

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

$$\Delta\vec{\delta_i} = w_i \vec{b} - w_i \vec{u_i}(t) \ \forall \ p_i \in P' \quad (6)$$

, readjusts the *drift vectors* (4).

Geometric Interpretation

Convexity Property

Convexity Property

$$\vec{v}(t) = \frac{\sum_{i=1}^{n} w_i \vec{u_i}(t)}{\sum_{i=1}^{n} w_i} \tag{7}$$

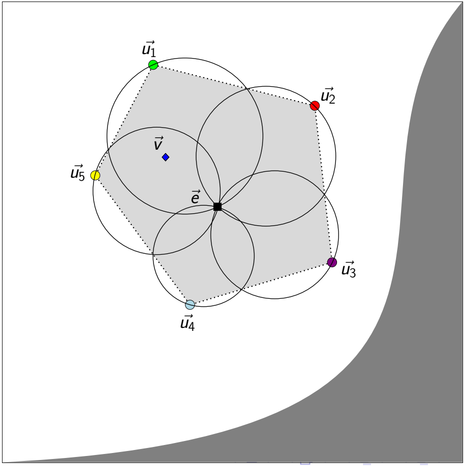
Theorem (Sharfman et al. [3])

Let $\vec{x}, \vec{y_1}, \ldots, \vec{y_n} \in \mathbb{R}^d$ be a set of vectors in $\mathbb{R}^d$. Let $Conv(\vec{x}, \vec{y_1}, \ldots, \vec{y_n})$ be the convex hull of $\vec{x}, \vec{y_1}, \ldots, \vec{y_n}$. Let $B(\vec{x}, \vec{y_i})$ be a ball centered at $\frac{\vec{x}+\vec{y_i}}{2}$ and with radius of $\|\frac{\vec{x}+\vec{y_i}}{2}\|_2$ i.e., $B(\vec{x}, \vec{y_i}) = \{\vec{z} \mid \|\vec{z} - \frac{\vec{x}+\vec{y_i}}{2}\|_2 \leq \|\frac{\vec{x}+\vec{y_i}}{2}\|_2\}$, then $Conv(vecx, \vec{y_1}, \ldots, \vec{y_n}) \subset B(\vec{x}, \vec{y_i})$.

Geometric Interpretation

Convexity Property

Figure: Example of a convex hull (light gray) defined by the drift vectors $\vec{u_i}, i = 1, 2, 3, 4, 5$. The hull is bounded by the spheres created from the estimate vector $\vec{e}$ and the drift vectors $\vec{u_i}, i = 1, 2, 3, 4, 5$. The global statistics vector $\vec{v}$ is guaranteed to be contained in the convex hull of the drift vectors.



Geometric Interpretation

Local Constraints

Protocol

Decentralized Algorithm

Protocol

Centralized Algorithm

Multi-objective Optimization

Non-linear Constraint Optimization

Primal Descent

Feasible Directions

SQP

The Savitzky-Golay Filter

Maximum Weight Matching

The Primal-Dual Method

Related Work

Problem Formulation

The Geometric Monitoring Framework

The Distance-based Hierarchical Clustering

The Idea

The Distance-based Hierarchical Clustering

The Weight Function

The Distance-based Hierarchical Clustering

The Algorithm

The Heuristic Balancing

The Idea

The Heuristic Balancing

The Optimizing Function

The Heuristic Balancing

The Function Formulation

The Heuristic Balancing

The Algorithm

An Nested Optimization Problem

Velocity and Acceleration Estimation via SG Filtering

Implementation Challenges

Synthetic Data

Real-world Data

Notation

RAND, DIST, DISTR Comparison

GM, HM Comparison

GM, HDM Comparison

Synthetic Data Monitoring

GM, HDM Comparison

Air Pollution Monitoring

Summary & Concluding Remarks

Future Work

The end
Questions?