Online Outlier Detection in Sensor Data Using Non-Parametric Models

Themis Palpanas — *Univ of Trento*

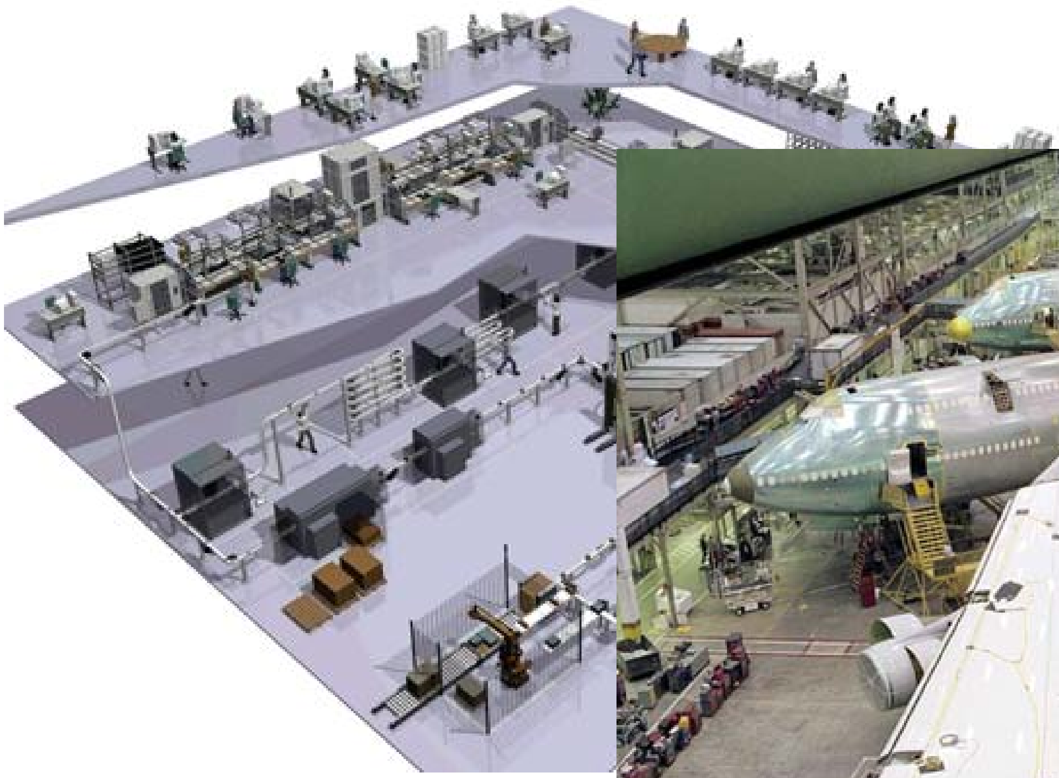
Sharmila Subramaniam
Dimitris Papadopoulos
Vana Kalogeraki
Dimitrios Gunopulos

Univ of California, Riverside

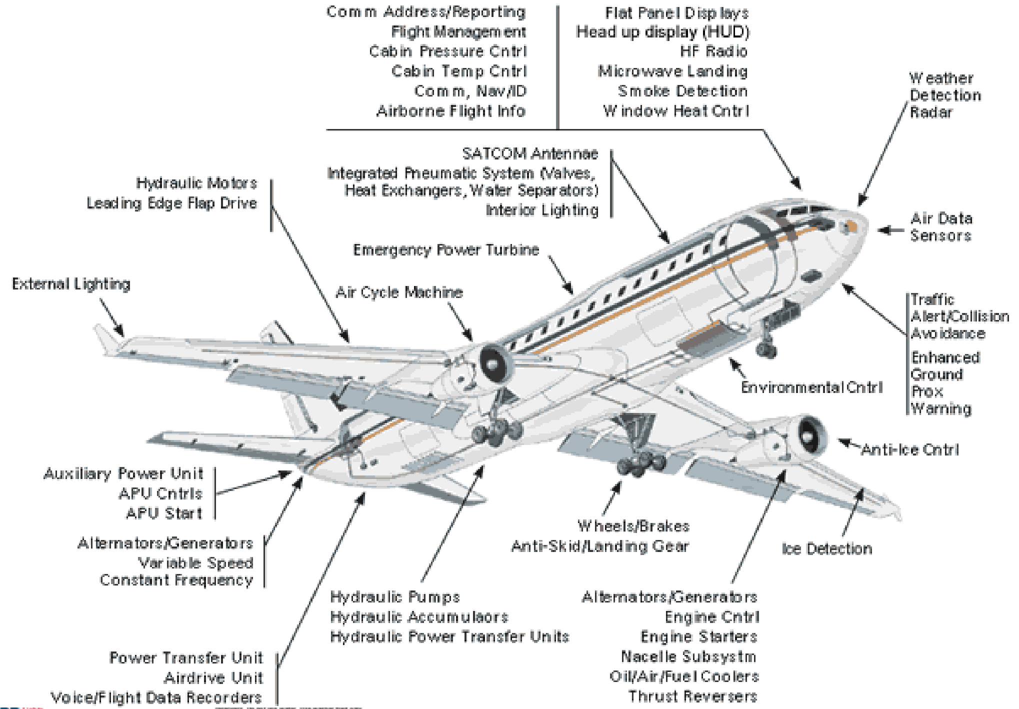
Introduction

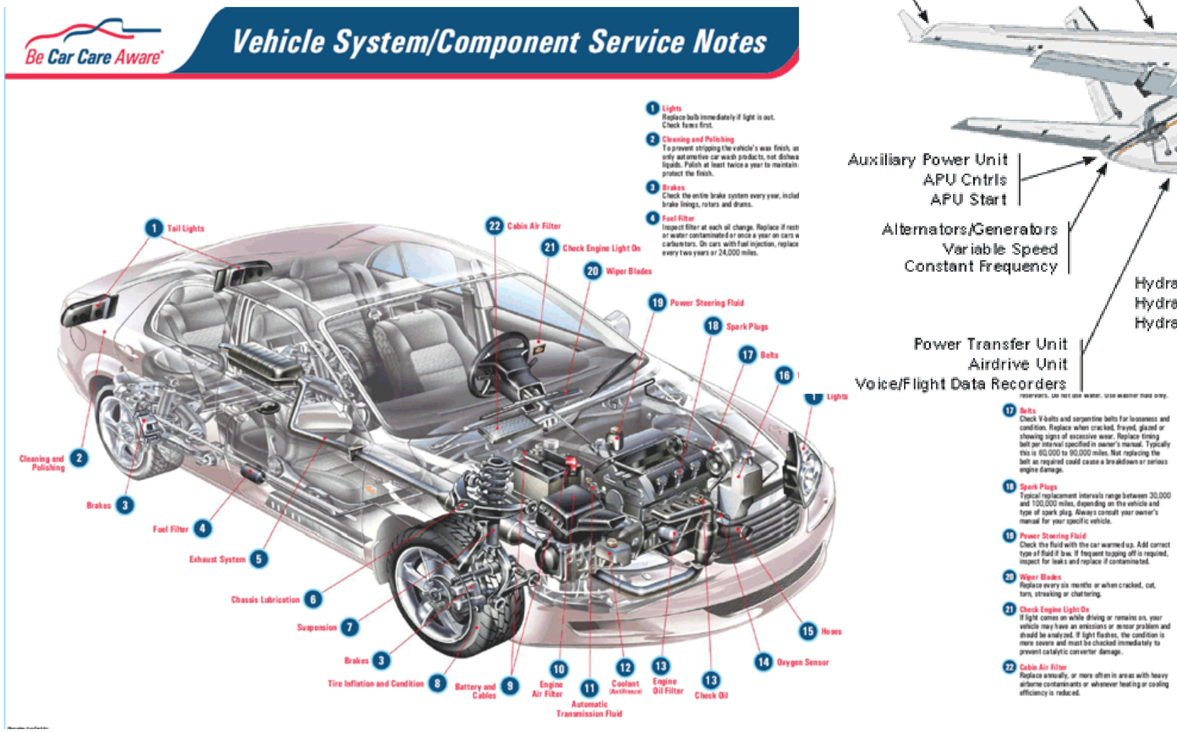
- several emerging applications across industries are event-driven
  - consume streaming data produced by a variety of data sources
  - process those data, reason about them, take corresponding actions
- streaming data management desiderata
  - process data in real time
  - be able to scale in number of sources, data rates
  - perform intelligent data analysis
- some applications are only interested in special events that constitute abnormal behavior
  - then, we can filter out of the streaming data the normal behavior
  - focus on the interesting (and infrequent) data values

Applications:
Monitoring Production Control Systems



Applications:
Monitoring Vehicle Operation





Problem Overview

- detect abnormal behavior (identify outliers)
- important for
  - situation detection
  - focusing on the interesting events in the data
  - react only to the important readings
- focus of this study:
  - streaming data
  - sliding window model
  - distributed processing (in network of sensors)

Roadmap

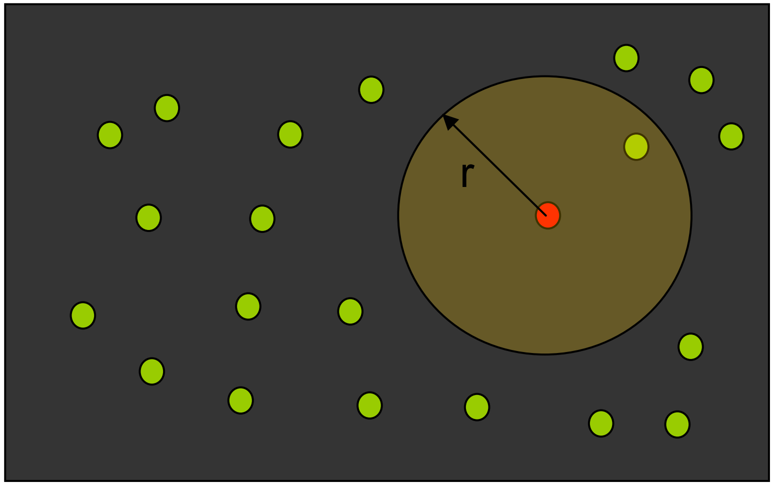
- Outliers
  - Distance-Based Outliers
  - Density-Based Outliers
- Input Data Distribution Estimation
  - Kernel Density Estimators
- Proposed Solution for Online, Distributed Outlier Detection
- Experimental Evaluation
- Related Work
- Conclusions

Abnormal Behavior

- deviations / outliers
  - a value that deviates significantly from the rest of the values in the dataset
  - several definitions
  - distance-based, density-based
- consider two definitions
  - *O(r, K)* (distance-based)
  - *MDEF* (density-based)
    - Multi-granularity Deviation Factor

O(r, K) Outliers

- outlier
  - a value that has few near neighbors
  - set of outliers $O = \{ p \in D \mid D_r, \forall q \in D_r : dist(p, q) < r \wedge |D_r| \leq K \}$
  - corresponds to statistical tests for outliers
    - for particular choices of *(r, K)*, gives the same result as statistical tests, for several probability distributions



Identifying *O(r, K)* Outliers

- problem
  - for every data point in the stream:
    - count the number of near neighbors
    - if these neighbors are too few, declare the data point an outlier
- issues
  - how can we count the number of neighbors?
  - how can we do these computations in a distributed fashion?
  - how can we do that fast, with an online algorithm?

MDEF Outliers

- outlier
  - a value whose near neighborhood is significantly less dense than its extended neighborhood

graph by S.Papadimitriou

MDEF Outliers

- outlier
  - a value whose near neighborhood is significantly less dense than its extended neighborhood

  - set of outliers $O = \{ p \in D \mid MDEF(p, r, a) > k_{\sigma} \sigma_{MDEF}(p, r, a) \}$
    - *MDEF* at radius *r* for point *p* is relative deviation of its local neighborhood density from the average local neighborhood density in its *r*-neighborhood

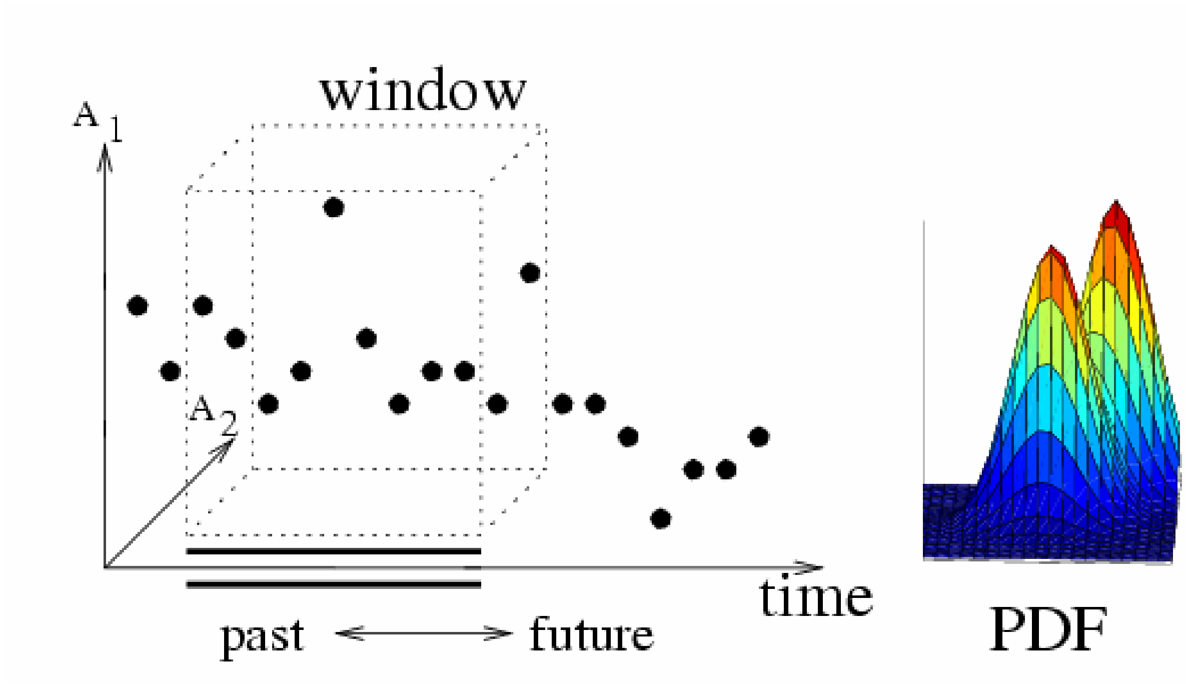
      $MDEF(p, r, \alpha) = 1 - n(p, \alpha r) / n'(p, \alpha, r)$
    - in uniformly distributed dataset (almost) all points have *MDEF* equal to 0
    - essentially parameter free: α and k_{σ} predetermined constants with robust behavior across different datasets

Identifying *MDEF* Outliers

- problem
  - for every data point in the stream:
    - count the number of near neighbors
    - average the number of near neighbors for all the points in the extended neighborhood
    - sum of number of neighbors for a grid decomposition of the data space
- issues
  - how can we compute all these counts for the number of neighbors?
  - how can we do these computations in a distributed fashion?
  - how can we do that fast, with an online algorithm?

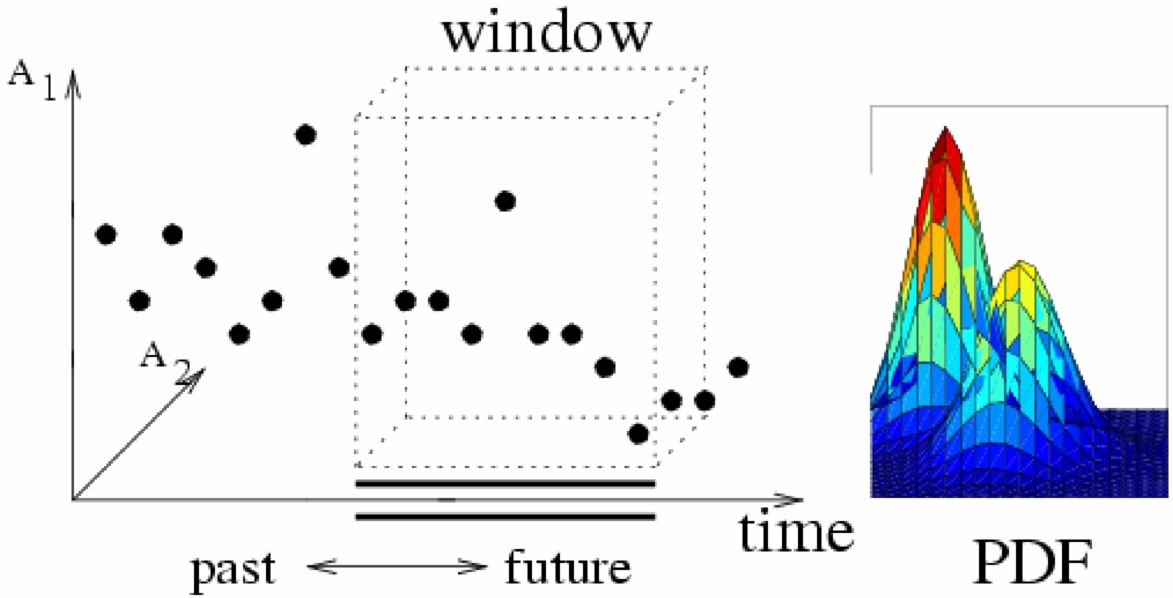
Input Data Distribution Estimation

- time t_1



Input Data Distribution Estimation

- time $t_2 > t_1$



Our Approach

- kernel density estimation
  - model estimation technique

- benefits
  - effectively approximates an unknown data distribution
  - non-parametric
  - efficiently computed in streaming environment
  - adjusts to changes in the input
  - can operate in a distributed fashion

Kernel Estimation

- kernel estimator
  - generalized form of random sampling

- works as follows
  - sample the data
  - assign a weight to each sample
  - distribute the weight of each sample in its neighborhood
    - according to a *kernel function*

Kernel Function

- Epanechnikov kernel function
  - generalized form of random sampling

    $k(x) = 3/4B\ (1 - (x/B)^2)$, if $|x/B| < 1$, 0 otherwise

    B is the kernel function bandwidth

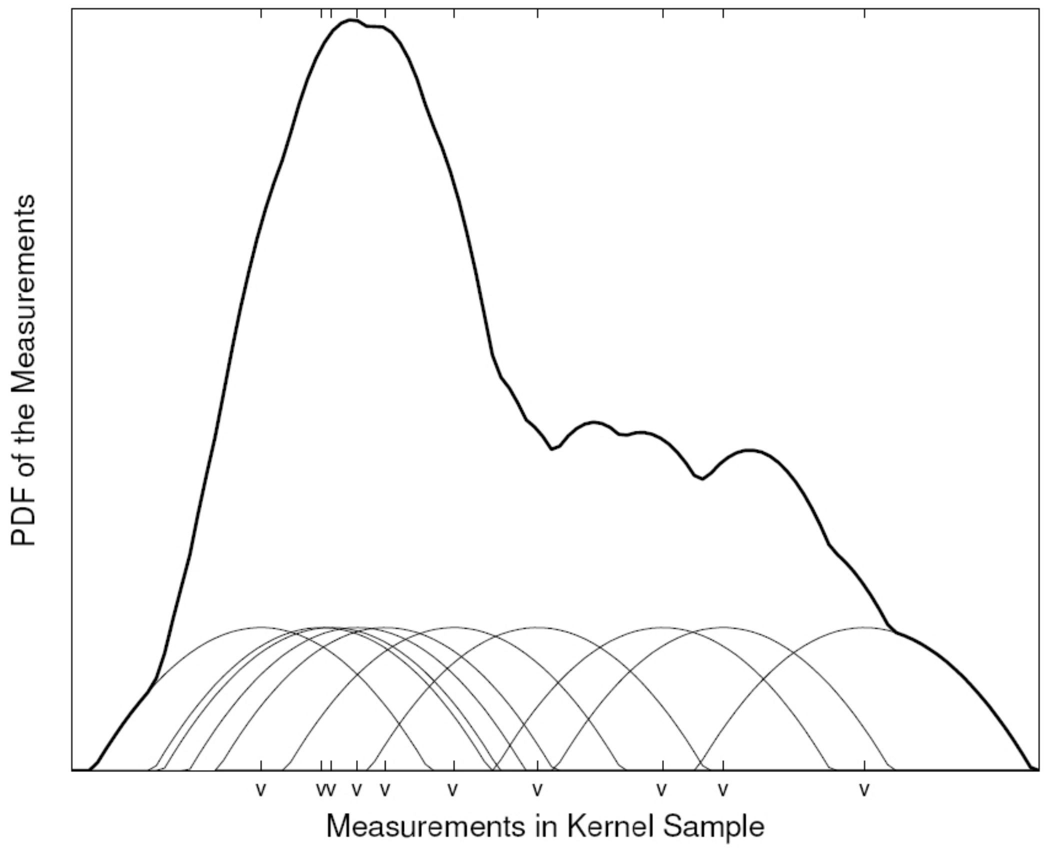
    $B = 5^{1/2}\sigma|R|^{-1/5}$ (Scott's rule)

    σ standard deviation of points in the dataset

    $|R|$ sample size

  - easy to integrate
  - extends naturally to multiple dimensions

Kernel Density Estimation: Example



Kernel Density Estimation

- kernel estimation in a streaming environment (assume sliding window model)
  - compute and maintain online
    - random sample of data
    - standard deviation of data

- random sample
  - chain-sample algorithm produces uniform random sample
- standard deviation
  - concise histogram technique

- both algorithms adapt to shifting input distributions
- both algorithms can operate in a distributed fashion
  - models can be combined

Online Outlier Detection: Distance-Based Outliers

- *O(r, K)* outliers
  - count the number of points within a circle of radius *r*

- solution based on kernel density estimation

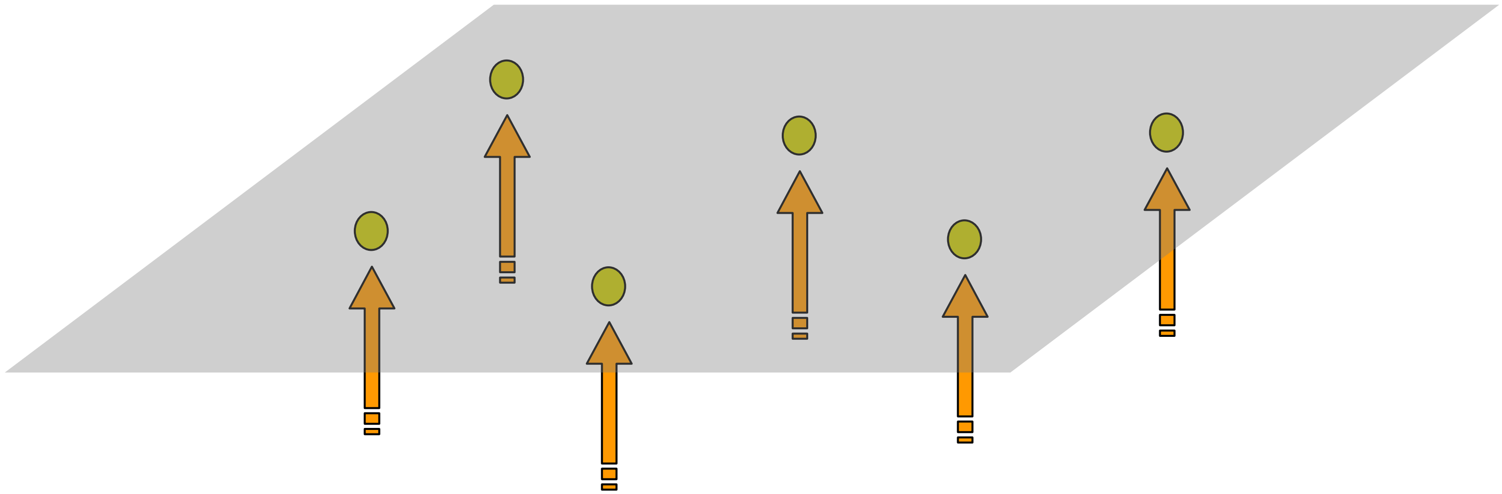
$$N(p,r) = \int_{[p-r,p+r]} \left(\frac{1}{|T|} \sum_{p_i \in D} \frac{3}{4B} \left(1 - \left(\frac{x - p_i}{B} \right) \right) \right) dx$$

  - estimates the number of neighboring points

- space and time efficient for each sensor

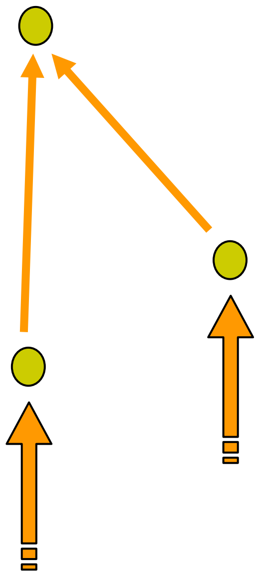
(space: $O(d(|R|+1/\varepsilon^2 log|W|))$, time 1-d: $O(log|R|+|R'|)$, time m-d: $O(d|R|)$)

Online Outlier Detection: Distance-Based Outliers



Detection of Region Outliers

- identify outliers wrt multiple data streams
- parent has to build a model for the combined data distribution of its children
- possible solution: each sensor in hierarchy has to compute its own sample
- expensive solution!
  - even if sampling only happens at leaf level



Distributed Computation of Estimators

- kernel estimator model composition
  - combine random sample and kernel bandwidth of children nodes
    - new random sample is union, possibly followed by downsampling
    - kernel bandwidth estimation based on: $V_{12}=V_1+V_2+N_1N_2/N_{12}(\mu_1-\mu_2)^2$
  - single model describing the behavior of all children nodes

- adapting to shifting data distributions
  - children propagate estimator updates to parent nodes according to:
    - changes in input distribution
      - have to monitor changes, adapt update rate accordingly

        monitor first moments of distribution, or apply specialized techniques
    - probability that depends on number of children and sample sizes
      - update probability $f=|R_p|/c|R|$

Online Distributed Outlier Detection: Distance-Based Outliers

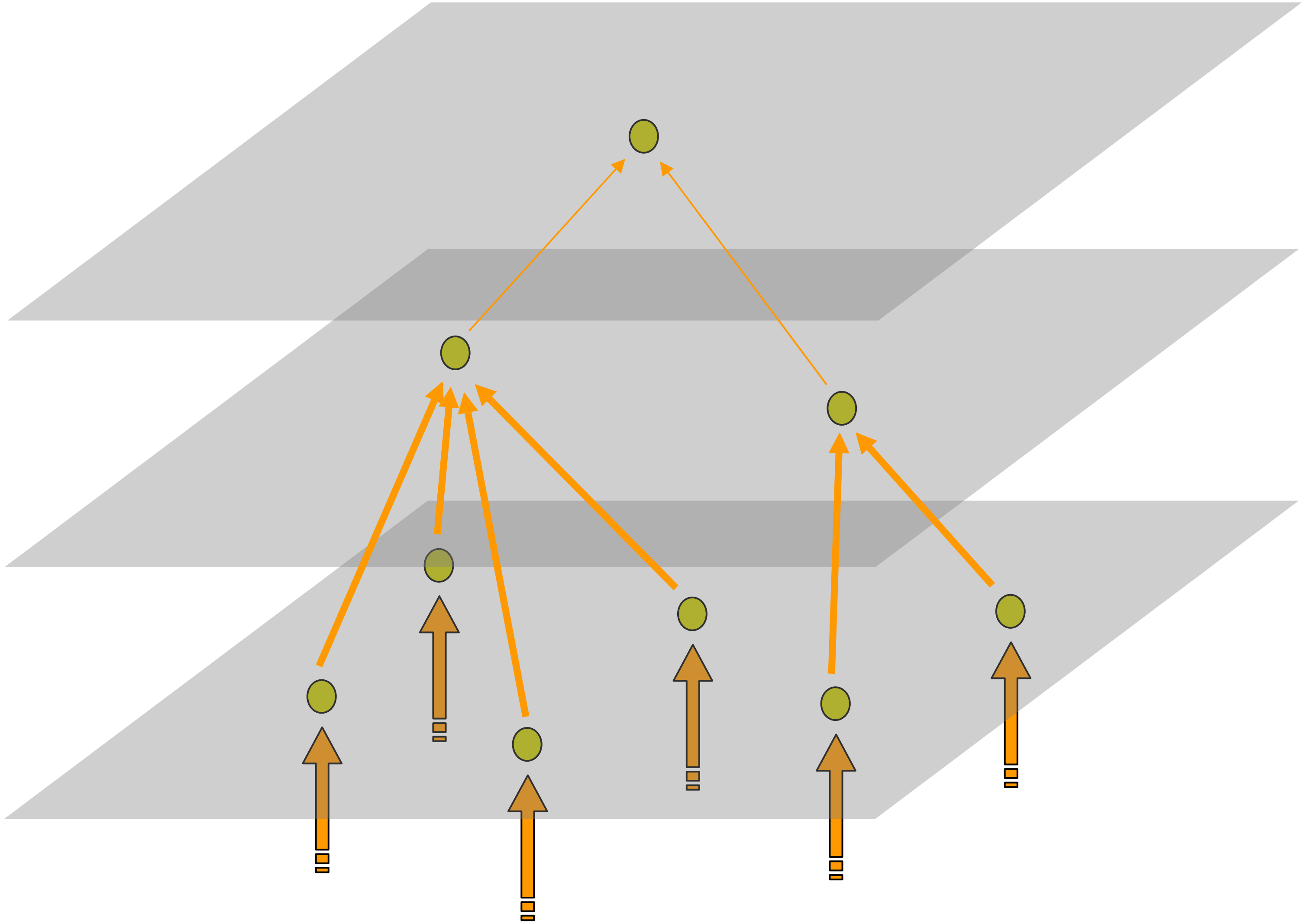
- theorem

  Assume nodes $n_1, \ldots, n_l$ children of node n_p. Assume data streams $S_1, \ldots, S_l$ referring to the l children nodes, and corresponding sliding windows $W_1, \ldots, W_l$. The sliding window of node n_p is defined as $W_p=U_{i=1}^{l}W_i$. Let, at some point in time, $O_1, \ldots, O_l$ be the sets of distance based outliers corresponding to each one of the l sliding windows. Then, for the set O_p of outliers in W_p it holds that O_p subset of $U_{i=1}^{l}O_i$.

- if a value is an outlier in the combination of two or more streams, then it is an outlier in at least one of those streams

- as we combine streams we can ignore all points that are not outliers

Online Distributed Outlier Detection: Distance-Based Outliers



Online Distributed Outlier Detection: Density-Based Outliers

- *MDEF* outliers
  - count the number of near neighbors
  - compare to the average count across the extended neighborhood
    - an outlier at the parent node may not be an outlier at any child node!
  - leaf level nodes report outliers wrt to the values they observe, or wrt to the values of the entire region they belong in
- when combining streams, the children nodes have to know the global distribution
  - parents have to communicate their models to the children
- we apply the following scheme:
  - children update parent models about their changes with probability *f*
  - when the global model changes, the changes are propagated to all the leaf nodes
    - may reduce communication by propagating only if change is significant (by computing the distance of the models)

Experimental Evaluation

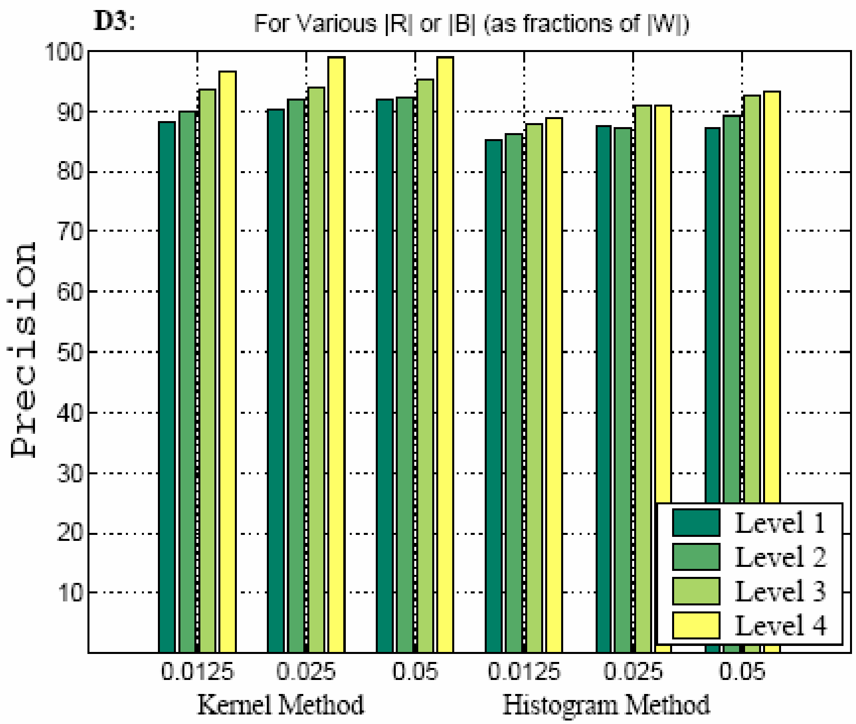
- technique implemented on top of TAG sensor network simulator
  - 5,000 lines of java code

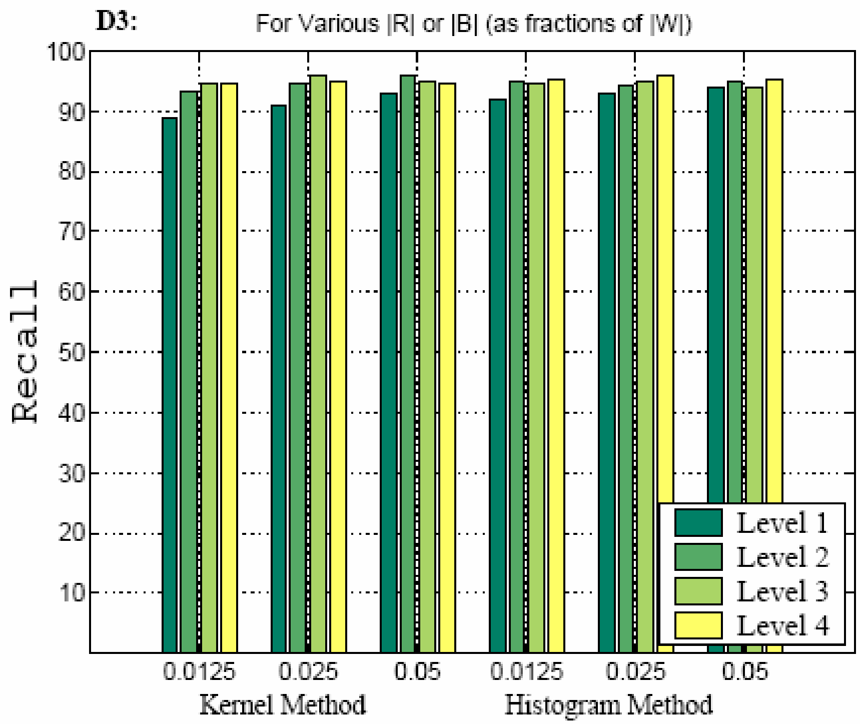
- synthetic datasets
  - mixtures of Gaussians
  - 35,000 observations
  - values normalized to [0,1]
- real datasets
  - sensor readings from Pacific Northwest region (35,000 observations)
  - engine operation measurements (50,000 observations)

- measured precision and recall (compared to offline algorithm)

Experimental Results: Accuracy – *O(r, K)* Outliers

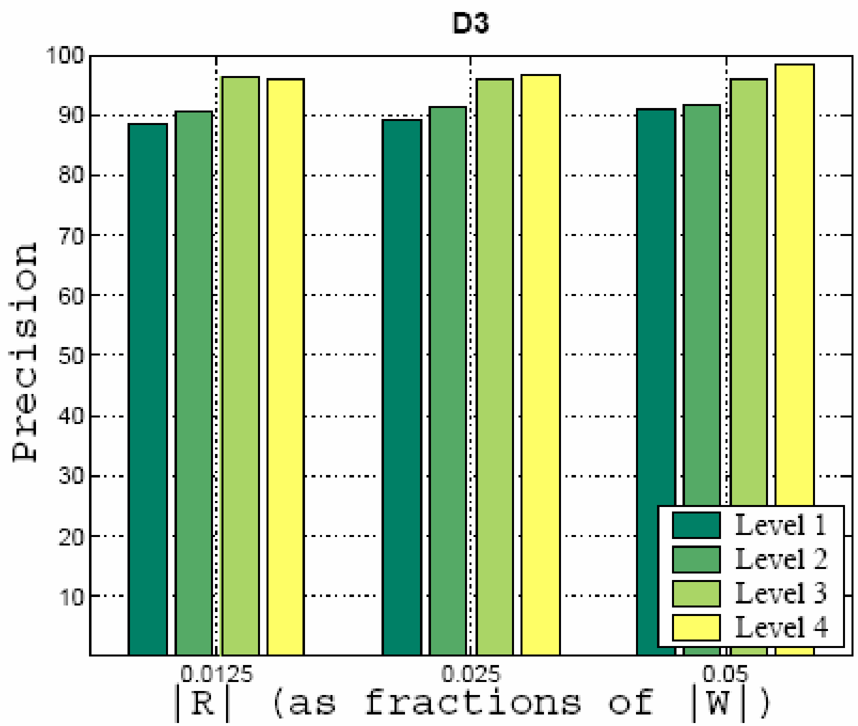
- varying the sample size (available memory), 1-d synthetic data

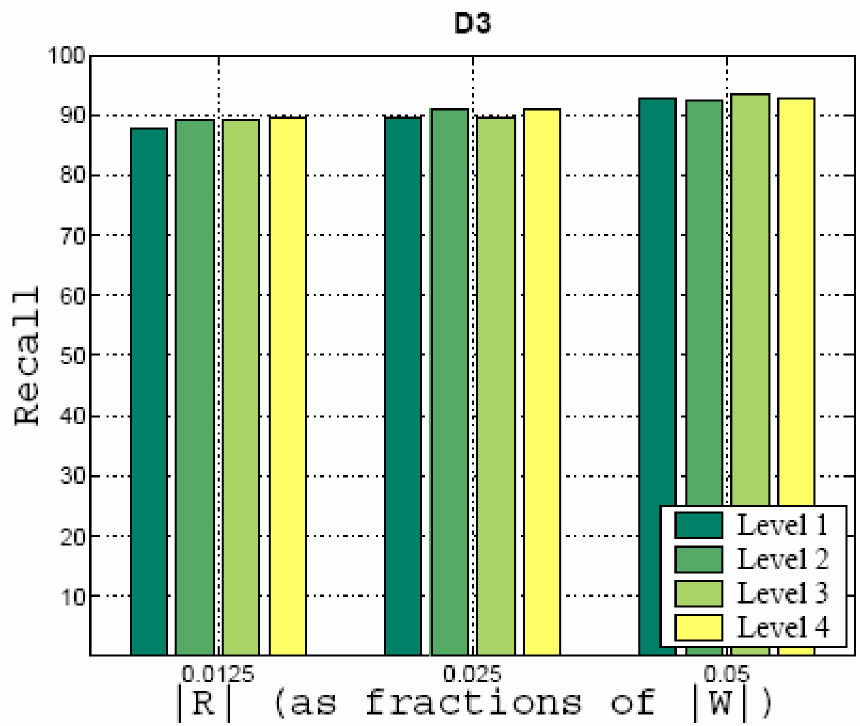




Experimental Results: Accuracy – *O(r, K)* Outliers

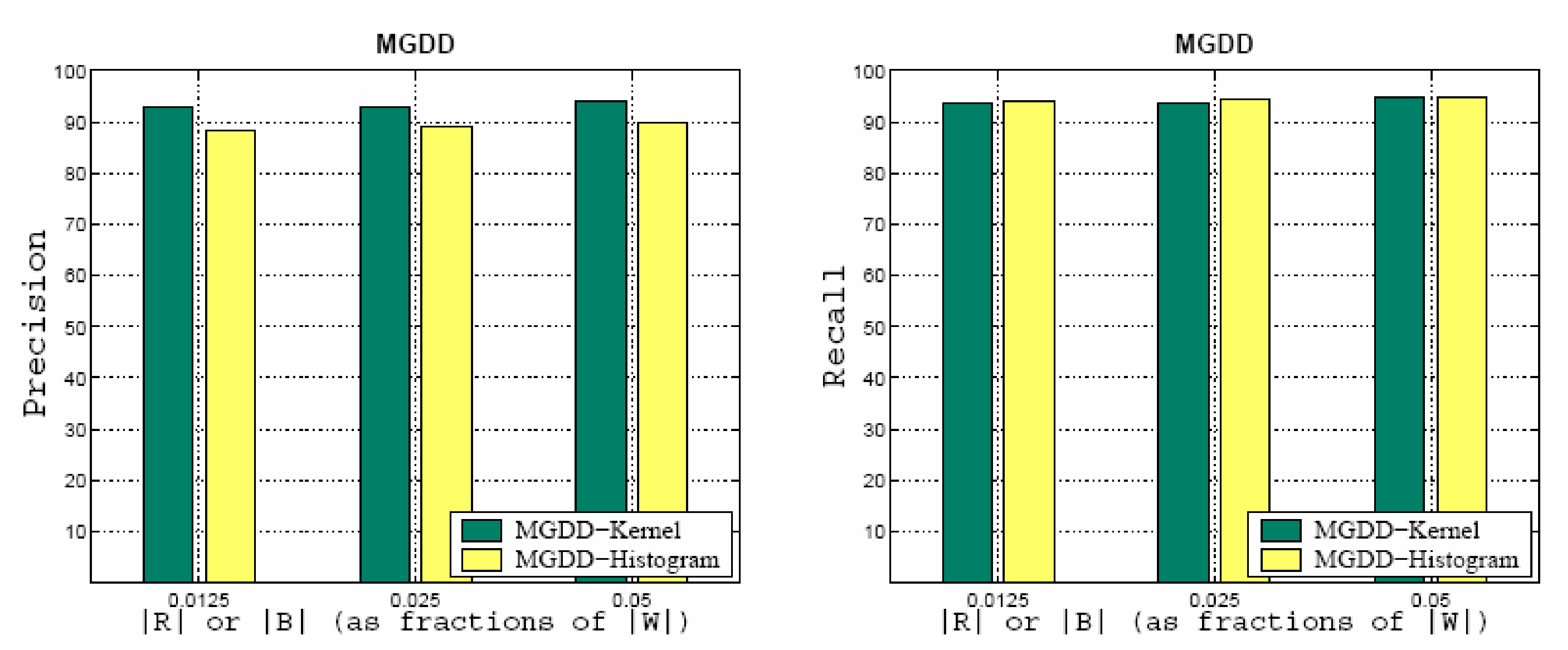
- varying the sample size, 2-d real data





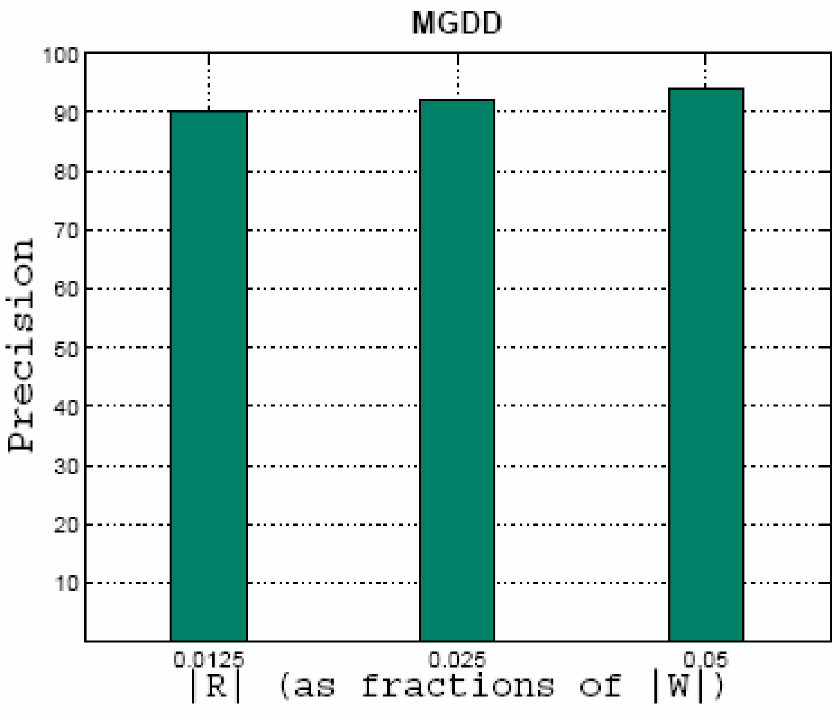
Experimental Results: Accuracy – *MDEF* Outliers

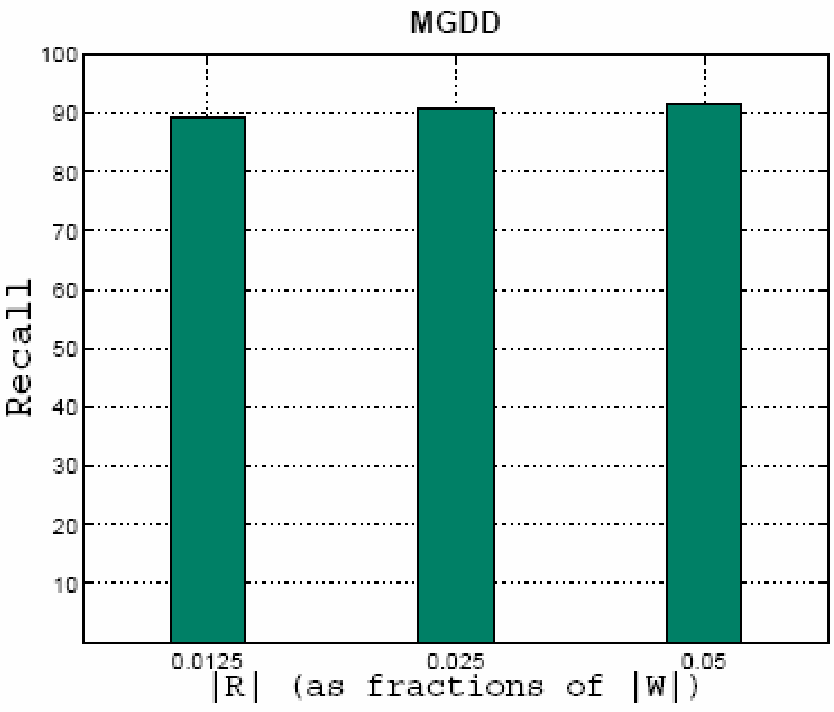
- varying the sample size (available memory), 1-d synthetic data



Experimental Results: Accuracy – *MDEF* Outliers

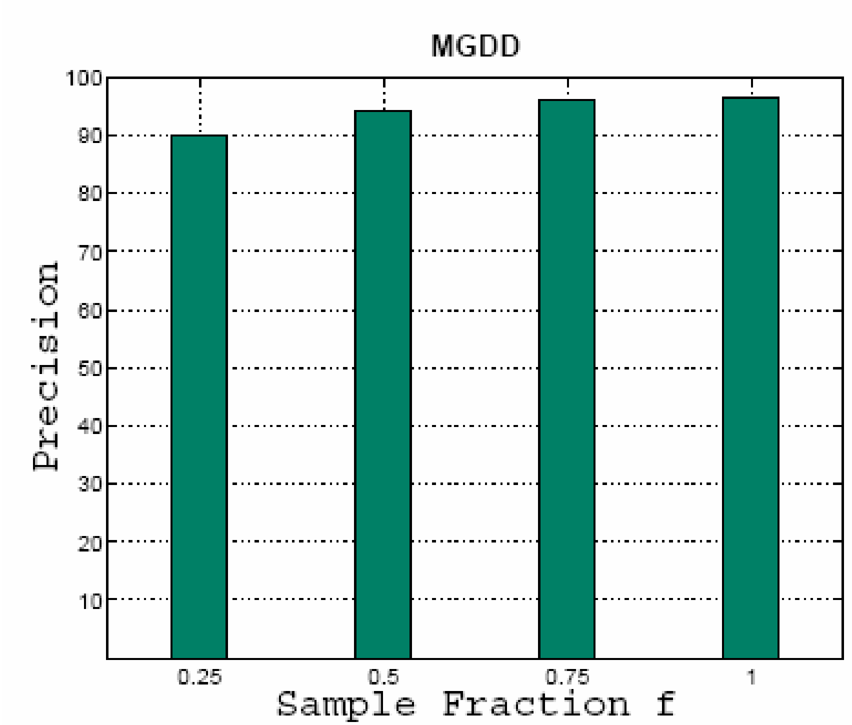
- varying the sample size, 2-d real data

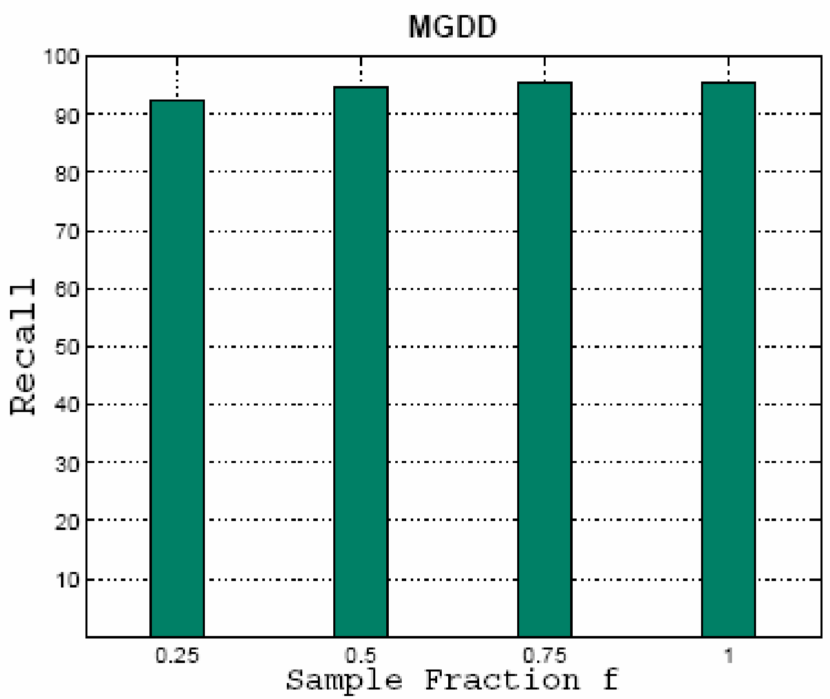




Experimental Results: Accuracy – *MDEF* Outliers

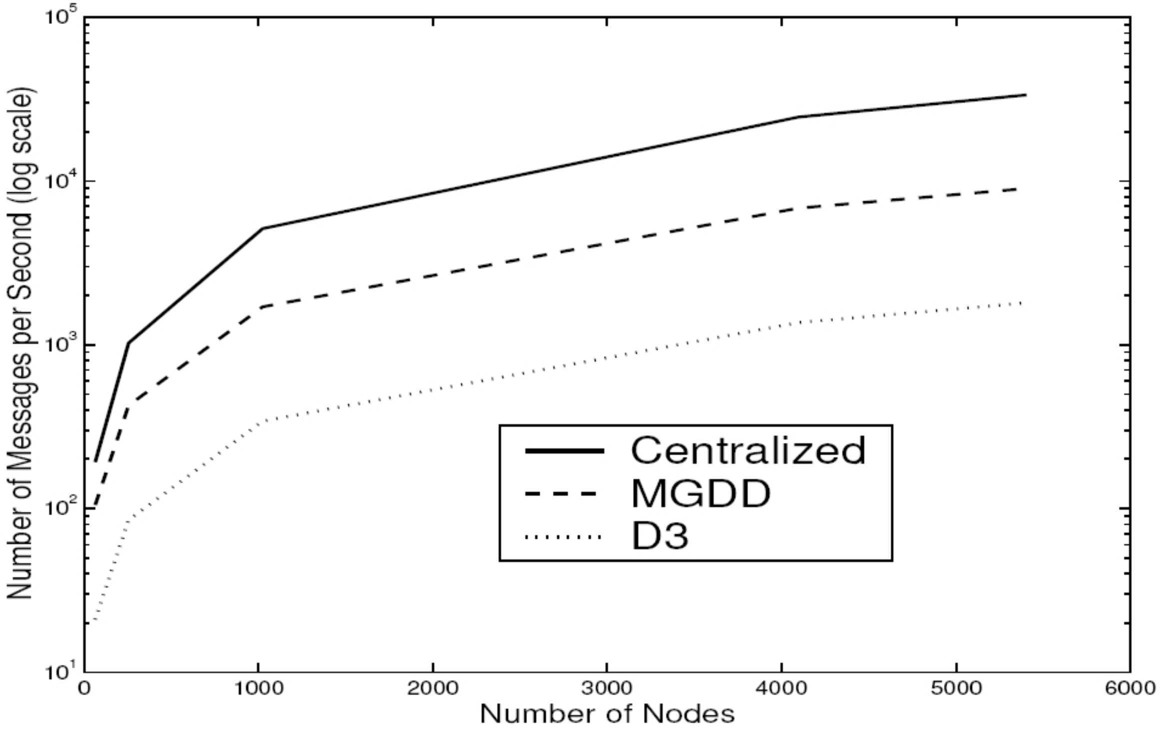
- varying the update probability *f*, 1-d synthetic data





Experimental Results: Communication Costs

- cost comparison of outlier detection algorithms
  - distance-based *D3*, density-based *MGDD*, centralized approach



Related Work

- statistical outliers
  - suppose knowledge of input distribution, offline
    [Barnet,Lewis'94]
- outliers in databases
  - offline algorithms
    [Arning et al'96][Knorr,Ng'98][Papadimitriou et al'03][Breunig et al'00]
    [Ramaswamy et al'00]
- outliers in time series
  - temporal ordering is key
    [Puttagunta,Kalpakis'02][Muthukrishnan et al'04][Yamanishi et al'04]
- sensor data processing systems
  - query processing
    [Madden et al'02][Yao,Gehrke'03][Bonfils,Bonnet'03]
  - approximate query answering
    [Deshpande et al'05][Guestrin et al'04][Cormode,Garofalakis'05][Olston et al'03][Jain et al'04]

Conclusions

- studied the problem of online outlier detection in sensor networks
- proposed general and flexible data distribution approximation framework
  - does not require a priori knowledge of the input data distribution
  - based on non-parametric model
- described technique for efficient distributed deviation detection
  - focus on the interesting, unexpected events
- validated the proposed approach experimentally

thank you!

Themis Palpanas
themis@dit.unitn.it