VoI for Learning and Inference in Sensor Networks

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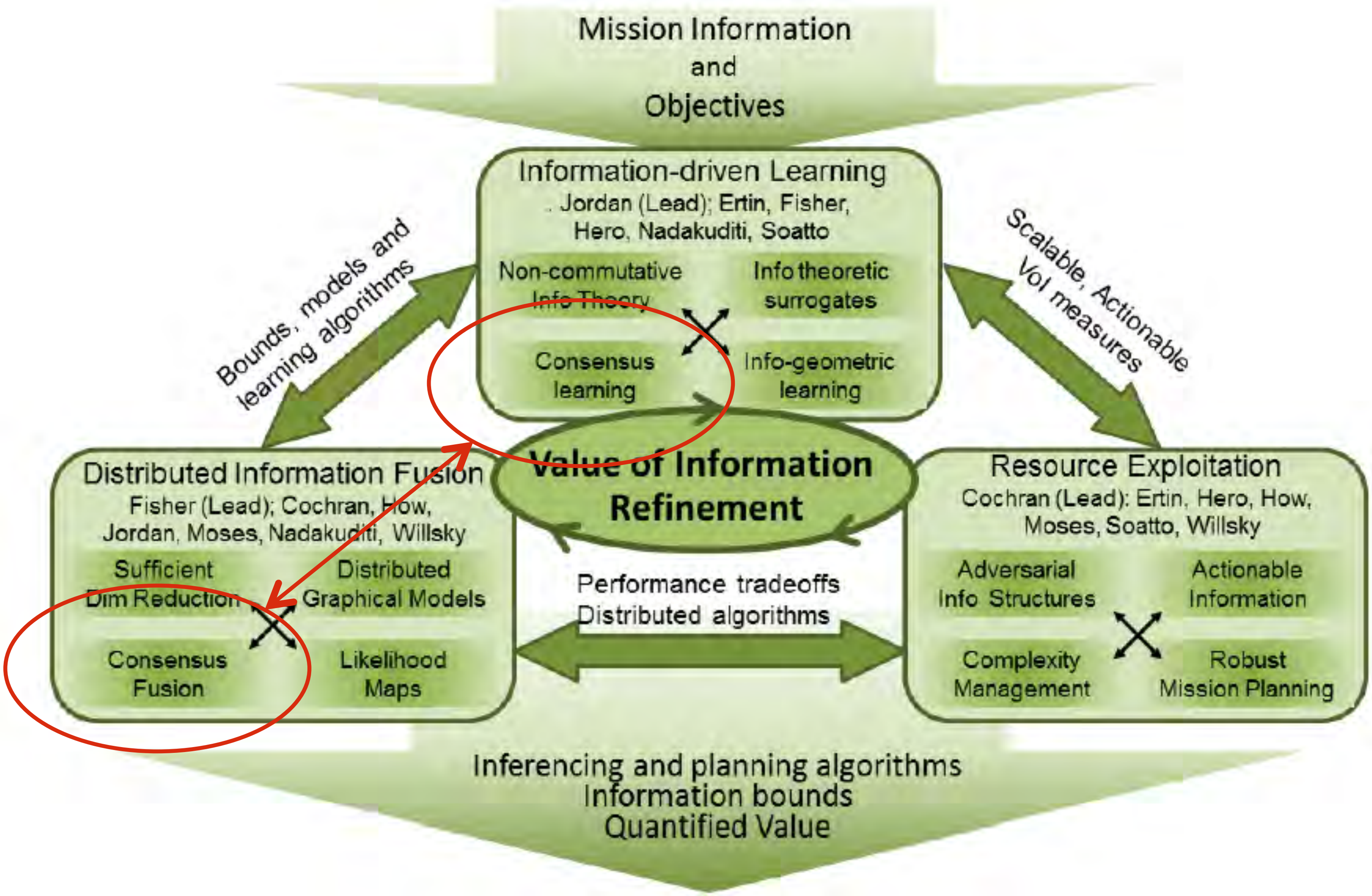

Mission Information
and
Objectives
Information-driven Learning
Jordan (Lead); Ertin, Fisher,
Hero, Nadakuditi, Soatto
Non-commutative
Info Theory
Info theoretic
surrogates
Consensus
learning
Info-geometric
learning
Bounds, models and
learning algorithms
Scalable, Actionable
VoI measures
Value of Information
Refinement
Distributed Information Fusion
Fisher (Lead); Cochran, How,
Jordan, Moses, Nadakuditi, Willsky
Sufficient
Dim Reduction
Distributed
Graphical Models
Consensus
Fusion
Likelihood
Maps
Performance tradeoffs
Distributed algorithms
Resource Exploitation
Cochran (Lead): Ertin, Hero, How,
Moses, Soatto, Willsky
Adversarial
Info Structures
Actionable
Information
Complexity
Management
Robust
Mission Planning
Inferencing and planning algorithms
Information bounds
Quantified Value

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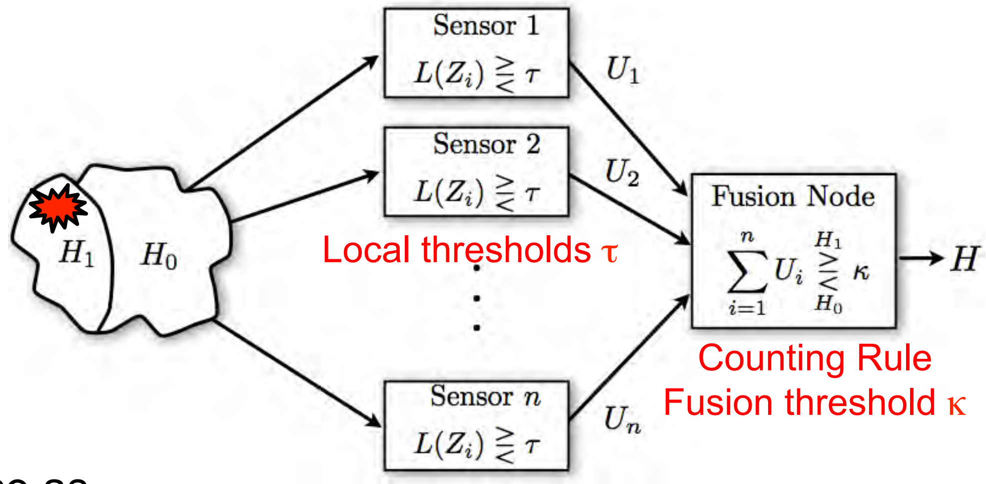
Two axes of progress

- **Progress 1**: Distributed decision fusion:
  - Propose a distributed detection framework to analyze large, random sensor networks
  - [Year2] Analyze performance versus network constraints and under imperfect communications
- **Progress 2** [new]: Distributed/decentralized learning:
  - Learn low-dimensional manifold structure in high dimensions using a mixture of factor analyzers framework.
  - Apply distributed EM from locally sufficient statistics
  - Derive decentralized EM to approximate distributed learning via consensus averaging in network neighborhoods

Progress 1: Distributed decision fusion in single-hop, random sensor networks

Performance analysis of a large sensor network

- Distributed detection of a 'rare' event
- Each sensor observes a source and computes local feature vector
- Local decisions sent to fusion center to estimate state *H*

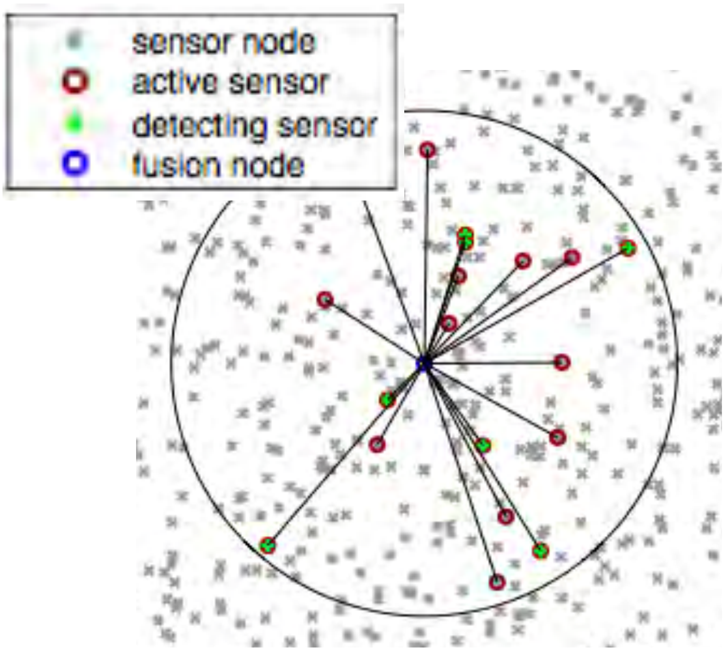


Goal: Quantify fusion detection performance as a function of sensor network density

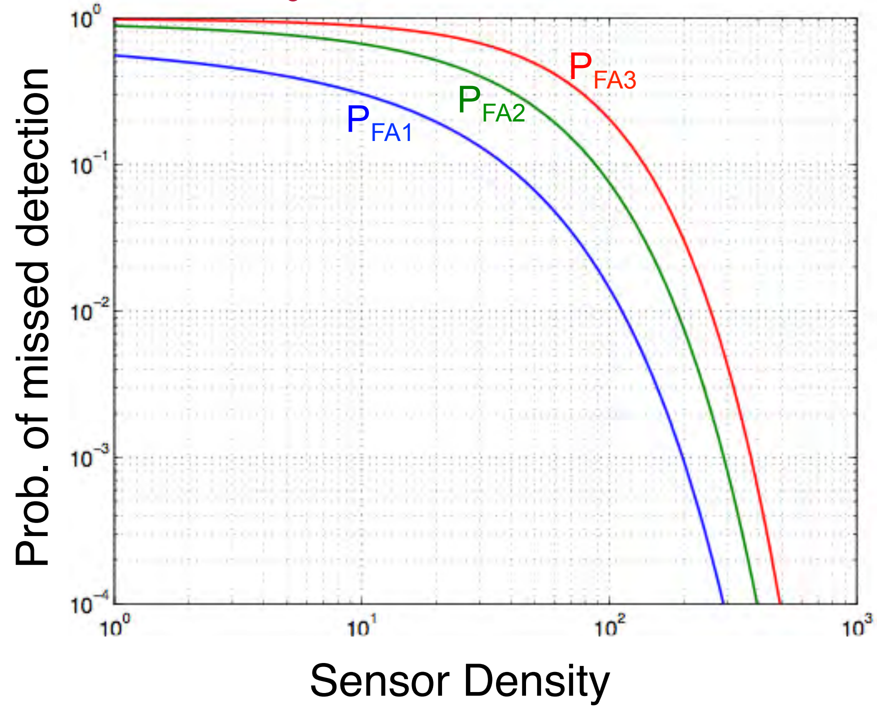
Challenge: Increasing sensor density requires decreasing per node data rate to meet network constraints

- Desensitize local sensor detections (increase τ) as network density increases

Progress 1: Distributed decision fusion in single-hop, random sensor networks



P_M (=1-P_D) vs Sensor Density, Fixed H_0 communication traffic



As sensor node density increases:

- Constrain the rate of sensor reporting to maintain the same average network communication load under H_0
- Quantify performance under H_1

Perfect communications to fusion center.

Progress 1: Distributed decision fusion with communications collisions

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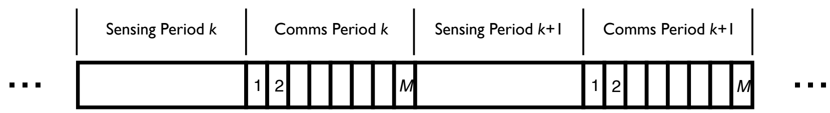
Imperfect communications:
Slotted-ALOHA



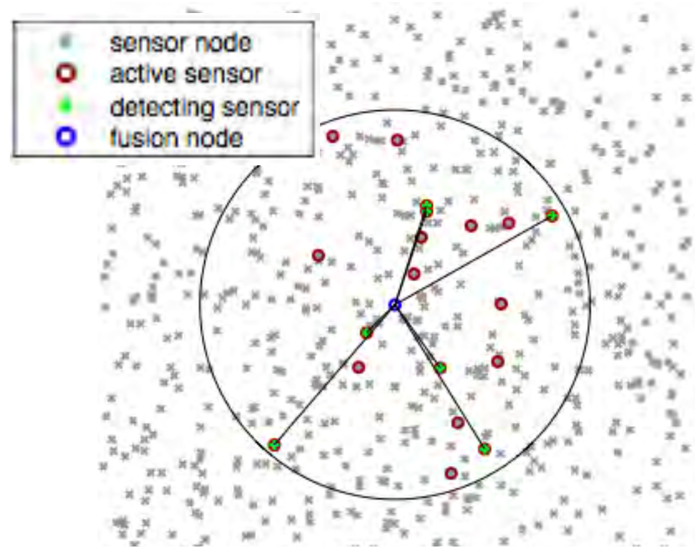
MAC Properties

- Poisson(λ) nodes sharing M slots
    - Fusion delay is proportional to M
- Only sensors with local detections transmit
- Sensor nodes select a slot according to a discrete uniform distribution
- No collision avoidance mechanism is used
- No retransmissions are made if collisions occur

At Fusion Center

- M_0 slots have no transmissions
- M_1 slots have (single) detection transmissions
- M_C slots have collisions (≥1 detection)

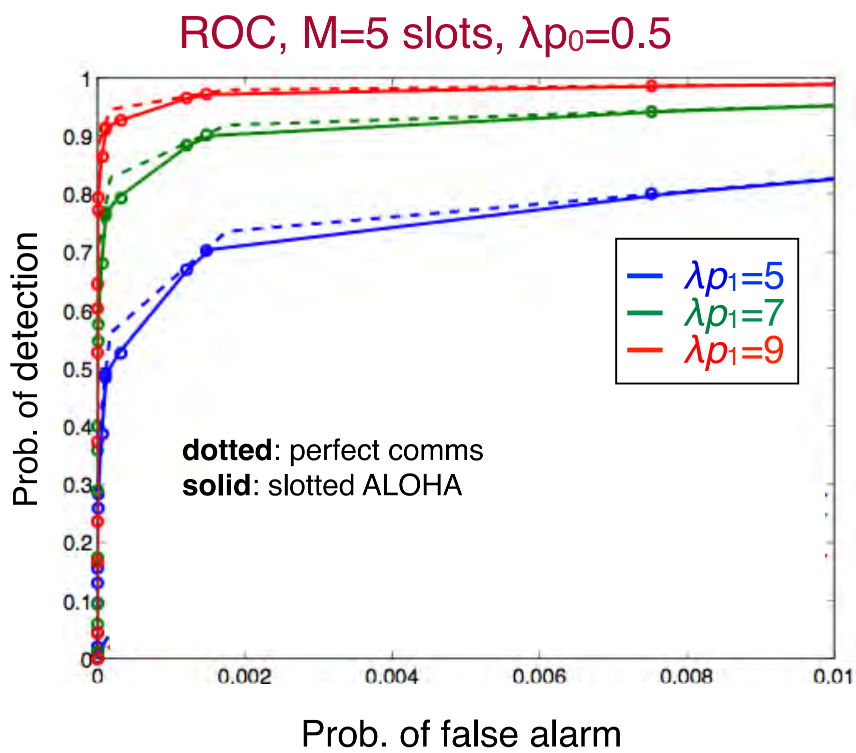
S-ALOHA,
λ_H avg. nodes transmit

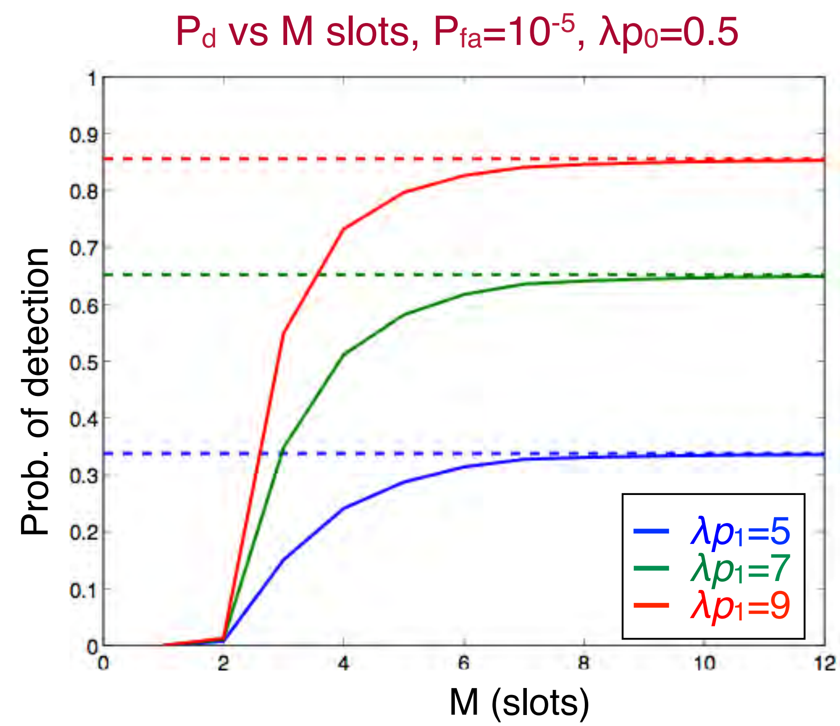


Only sensors with detections transmit

For assumed target parameters:
Optimal Fusion Rule: $\alpha M_1 + \beta M_C$

Progress 1: Distributed decision fusion with communications collisions



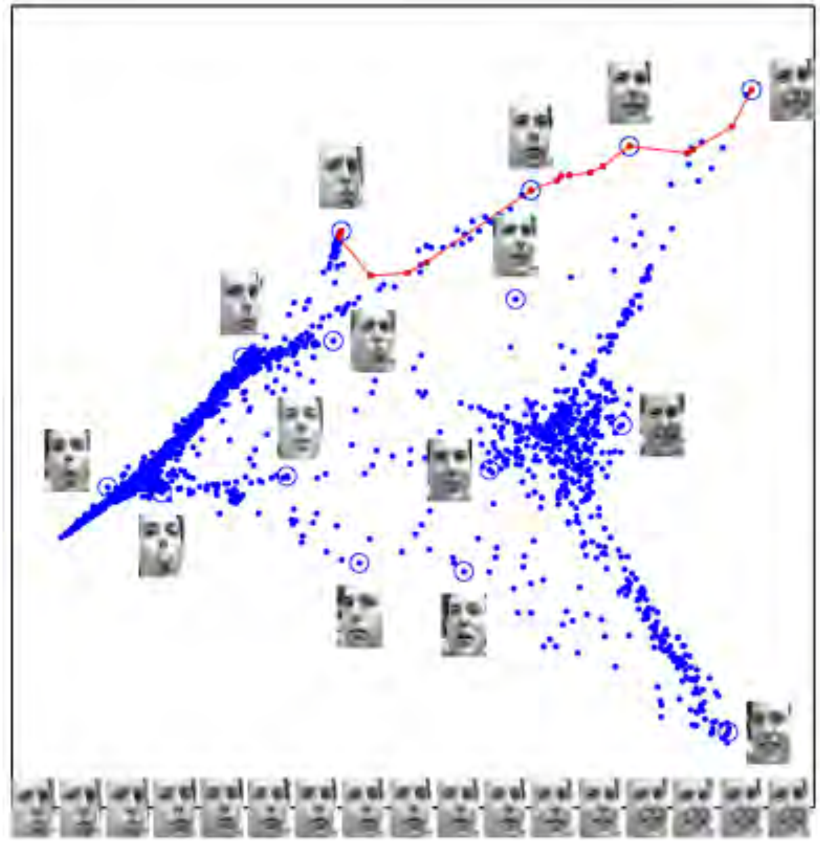


Progress 2: Distributed learning of a mixture of factor analyzers

Learning low-dimensional manifolds:

- Distributed and decentralized unsupervised learning of low dimensional manifold from high dimensional observations
- Each sensor observes its environment and computes local sufficient statistics
- Local statistics sent to fusion center (distributed) or a neighborhood (decentralized) to estimate global model

Goal: Design unsupervised learning methods and study convergence properties



Data lives on a lower dimensional subspace

From: Saul, L. and Roweis, S., Think Globally, Fit Locally: Unsupervised Learning of Nonlinear Manifold, Technical Report MS CIS-02-18, University of Pennsylvania,

Progress 2: Distributed learning of MFAs

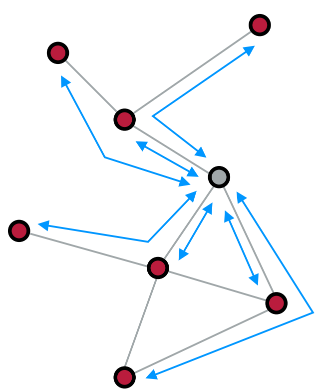
Approach: Gaussian Mixture Model (GMM) representation

- Locally linear approximation: Mixture of Factor Analyzers (MFA)
  - Roweis, S., *et al.*, 2001; Verbeek 2006
- Fusion of GMM;
  - Local sensors see only a subset of data modes
  - Sensor estimate MFA means and low-rank covariances
  - Consensus is used to align local estimates
    - Express needed MFA representation as functions of means
- Modes are initialized by distributed or decentralized k-means

Network information flow

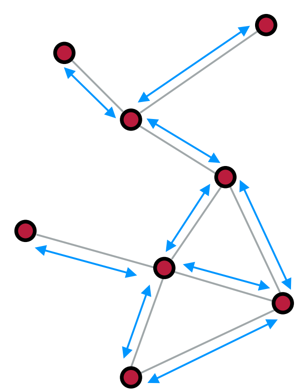
Distributed

Each node has a comm path to a fusion center



Decentralized

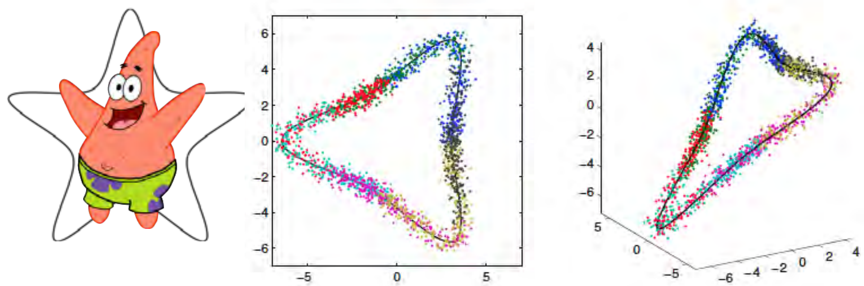
Nodes are connected; no fusion center



Progress 2: Distributed learning of a mixture of factor analyzers

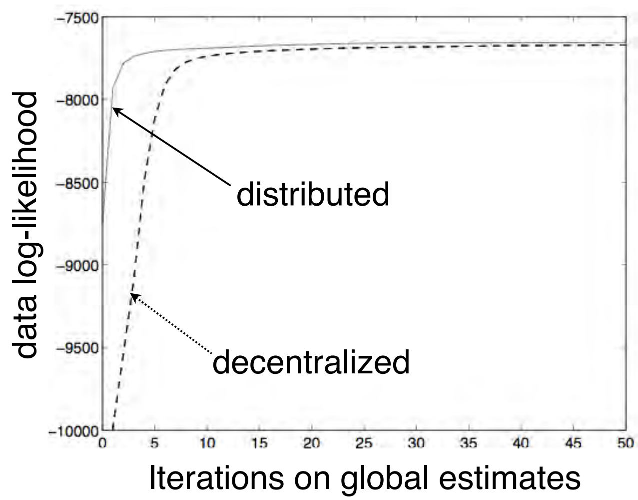
Synthetic data example

21 Sensor nodes, 6D data; 1D NL manifold



This is a depiction of the manifold in 2, 3 of the dimensions.

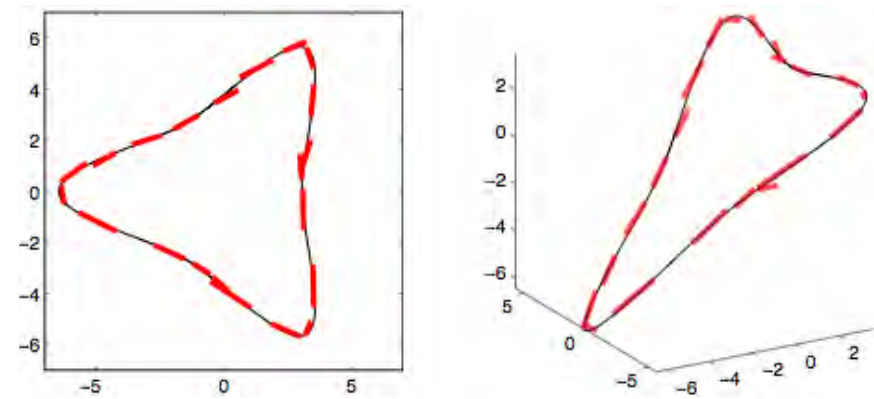
Increases data likelihood



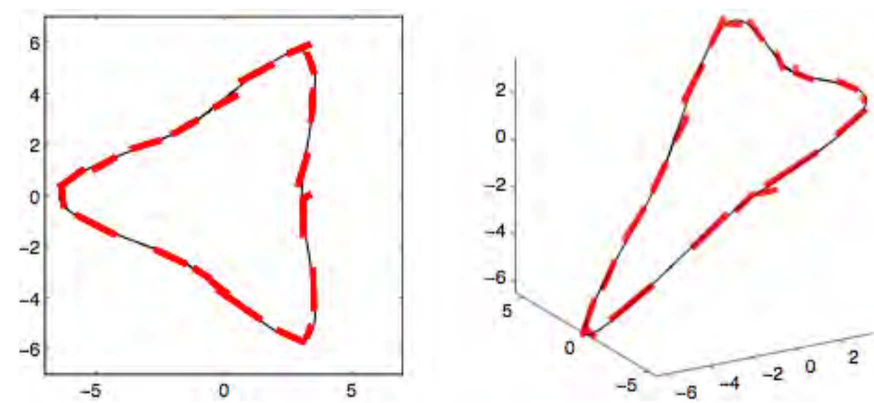
(decentralized: consensus iterations for each global iterate)

Unconstrained parameter estimates

1-σ lines centered on local means



Distributed



Decentralized

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Future and ongoing focus areas and collaborations

- Study VoI performance tradeoffs with respect to: network density, data complexity (number of mixtures), and network structure
- Study convergence rates of data representations with respect to network connectivity and data representation complexity.
- Investigate model order learning and adaptation in decentralized setting
- Investigate extensions to multiple sensor modalities.
- Compare alternative strategies for target manifold learning (Hero + Ertin)