



Inference and Signal Processing for Networks

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Outline

- 1. Dealing with the data cube*
- 2. Challenges in multi-site Internet data analysis*
- 3. Dimension reduction approaches*
- 4. Conclusion*



My Current Research Areas

- Dimension reduction, manifold learning and clustering
 - Information theoretic dimensionality reduction (Costa)
 - Information theoretic graph approaches to clustering and classification (Costa)
- Ad hoc networks
 - Distributed detection and node-localization in wireless sensor nets (Costa, Patwari)
 - Distributed optimization and distributed detection (Blatt, Patwari)
- Administered networks
 - Spatio-temporal Internet traffic analysis (Patwari)
 - Tomography (Shih)
 - Topology discovery (Shih, Justice)
- Adaptive resource allocation and scheduling in networks
 - Sensor management for tracking multiple targets (Kreucher)
 - Sensor management for acquiring smart targets (Blatt)
- Inference on gene regulation networks
 - Gene and gene pair filtering and ranking (Jing, Fleury)
 - Confident discovery of dependency networks (Zhu)
- Imaging
 - Image and volume registration (Neemuchwala)
 - Tomographic reconstruction from projections in medical imaging (Fessler)
 - Quantum imaging, computational microscopy and MRFM (Ting)
 - Multi-static radar imaging with adaptive waveform diversity (Raich, Rangajaran)



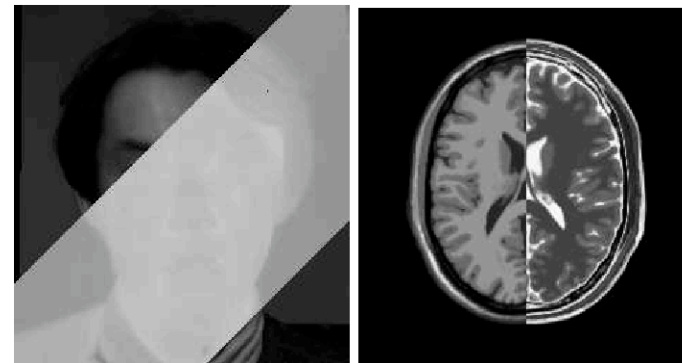
Applications

- Characterization of face manifolds (Costa)



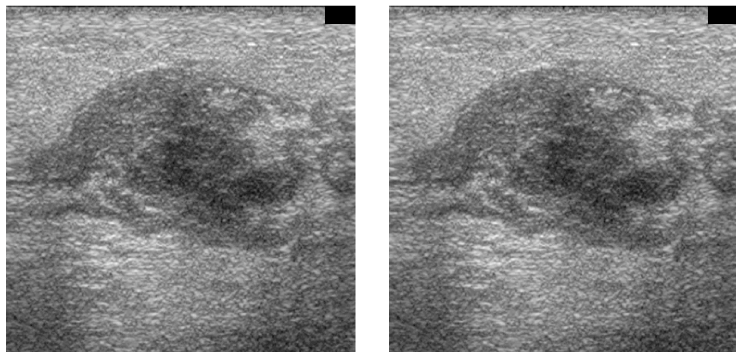
- The set of face images evolve on a lower dimensional imbedded manifold in $128 \times 128 = 16384$ dimensions

- Handwriting (Costa) - Pattern Matching (Neemuchwala)

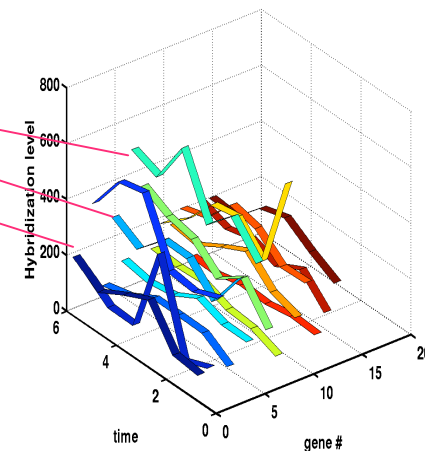
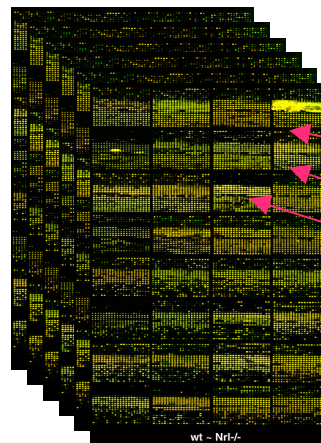




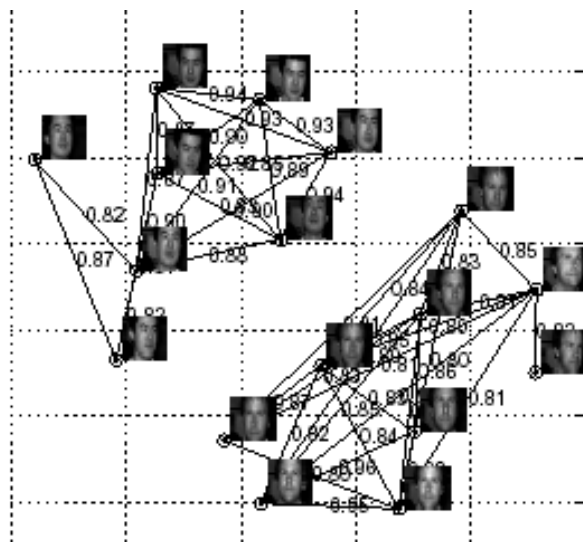
Applications



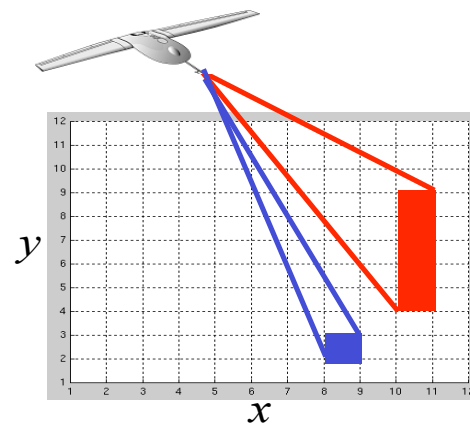
Ultrasound Breast Registration (Neemuchwala)



Gene microarray analysis (Zhu)



Clustering and classification (Costa)

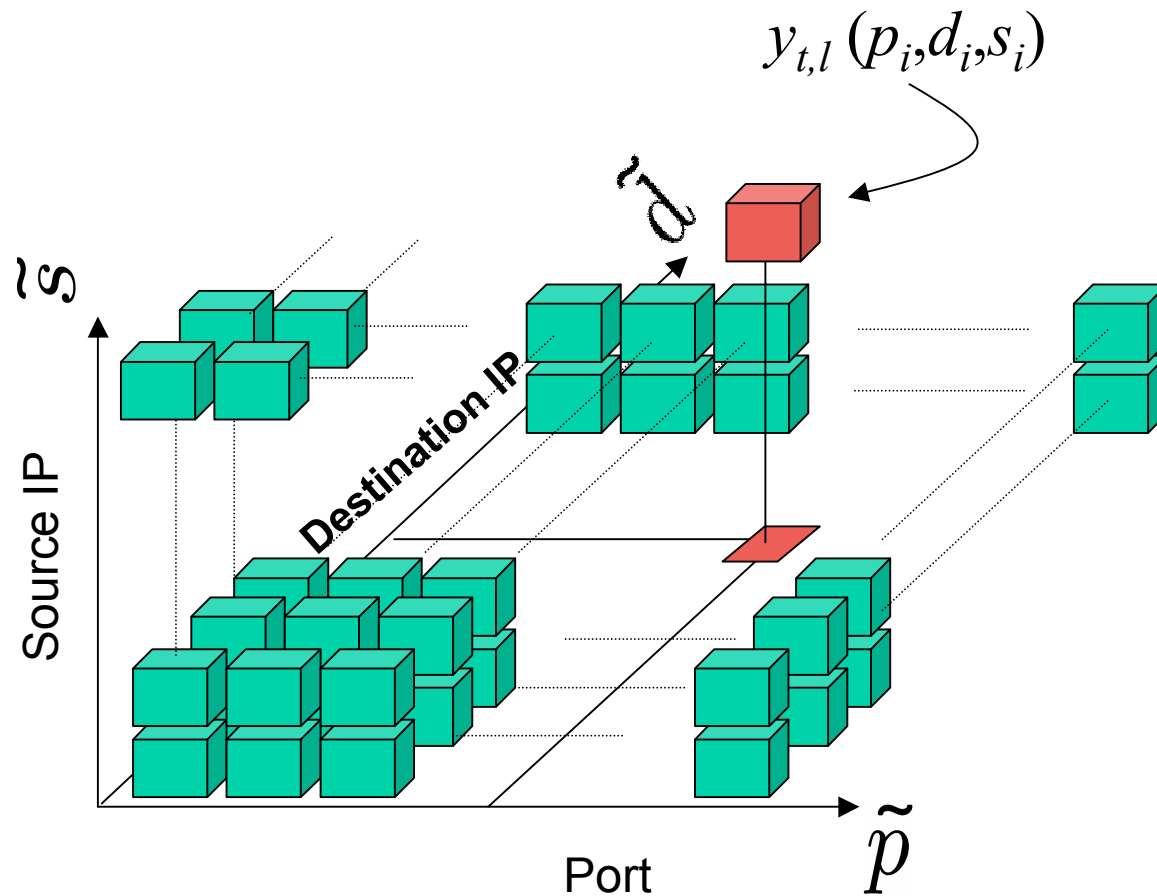


$$\mathbf{x} = [x, y, \dot{x}, \dot{y}]^T$$

Adaptive scheduling of measurements (Kreucher)



1. Dealing with the data cube

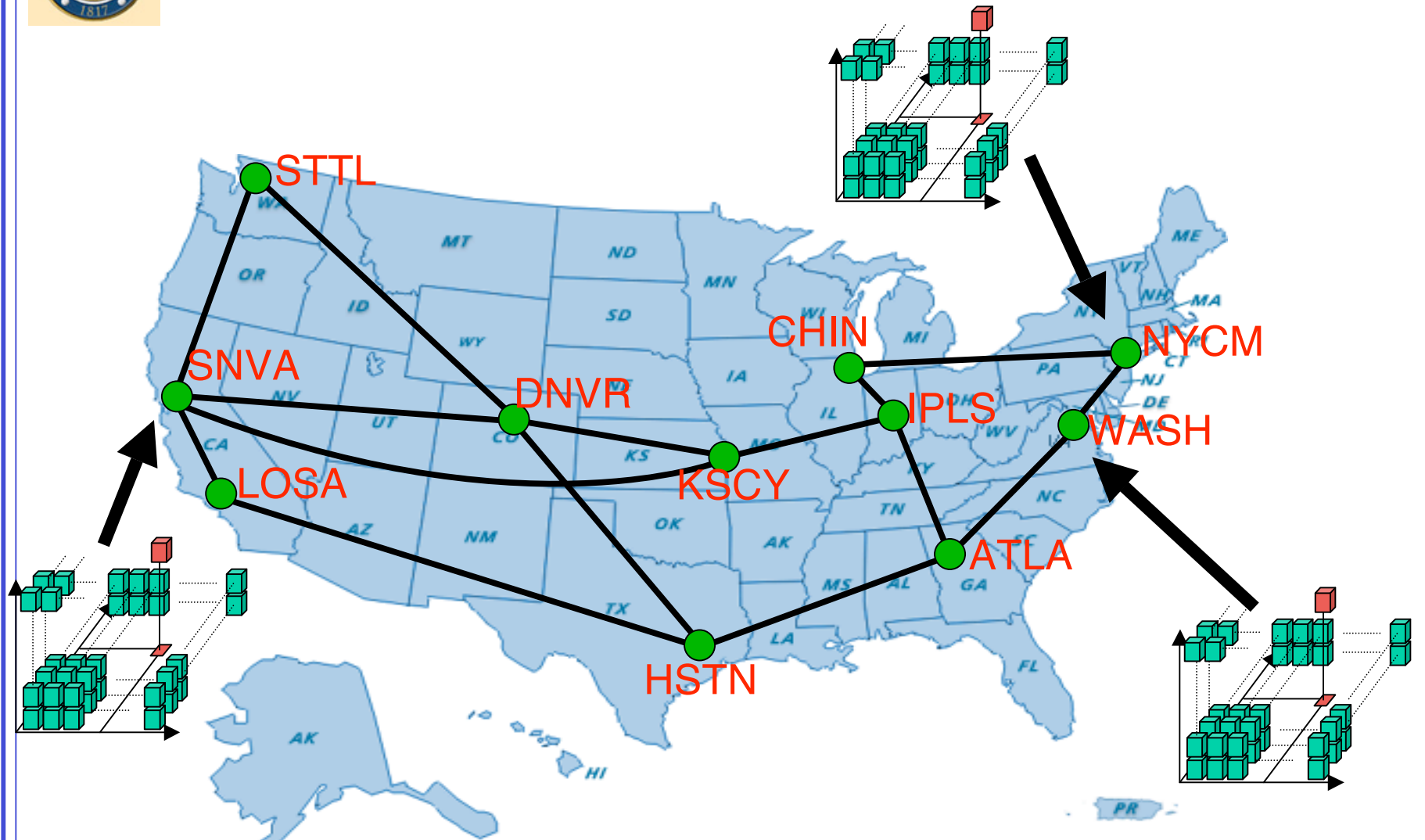


Single measurement site (router)

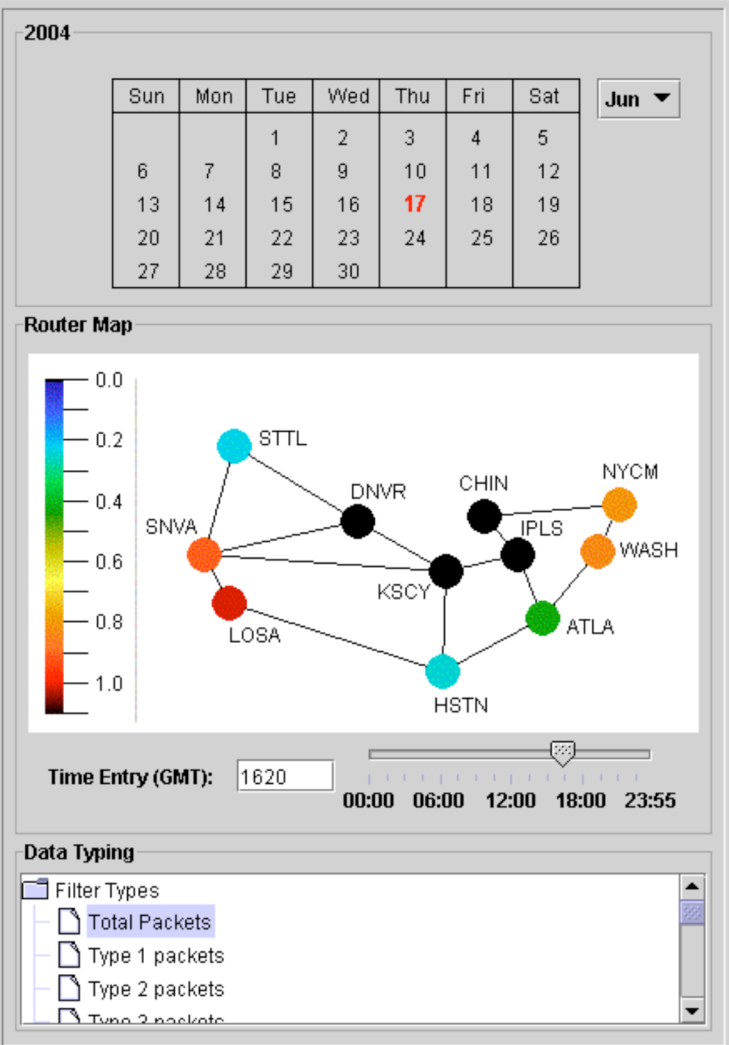
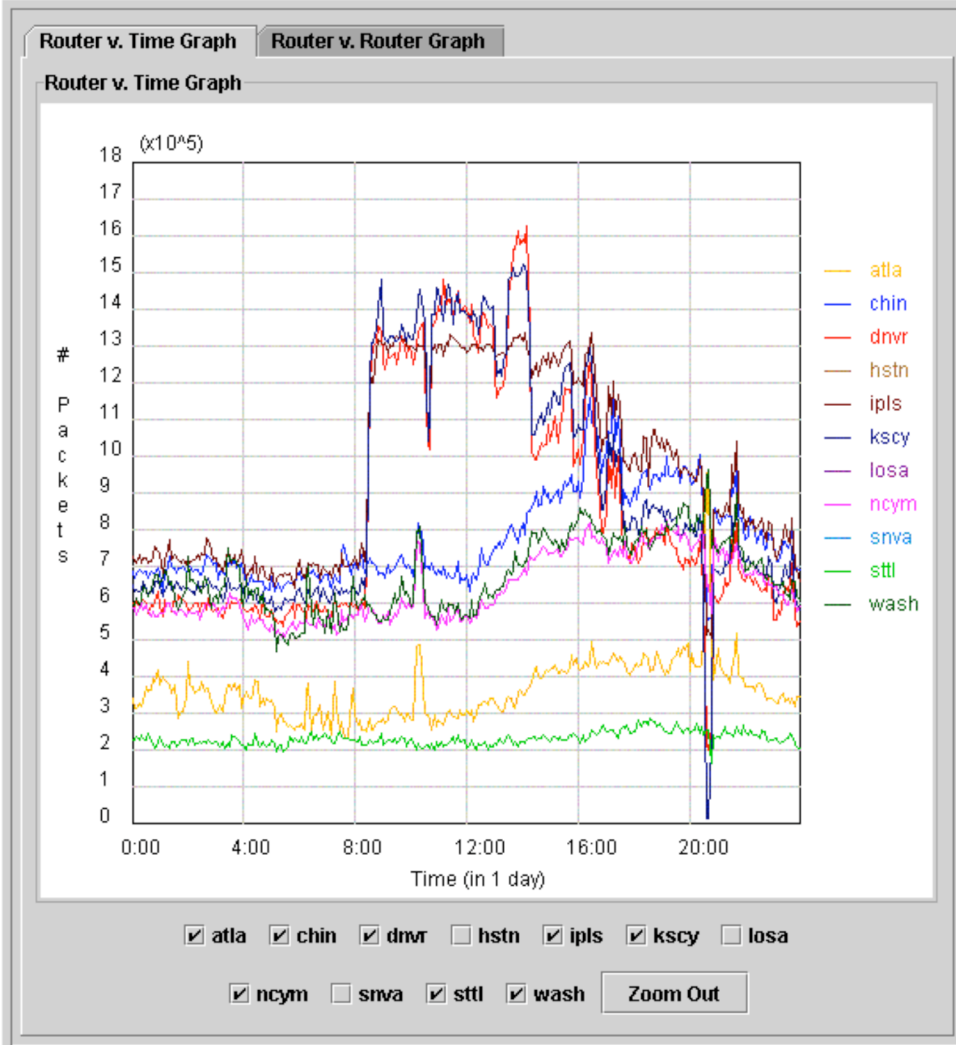
Ports, applications, protocols > dozens of dimensions



Dealing with the data cube



Multiple measurement sites (Abilene)



Source: Felsen, Pacholski

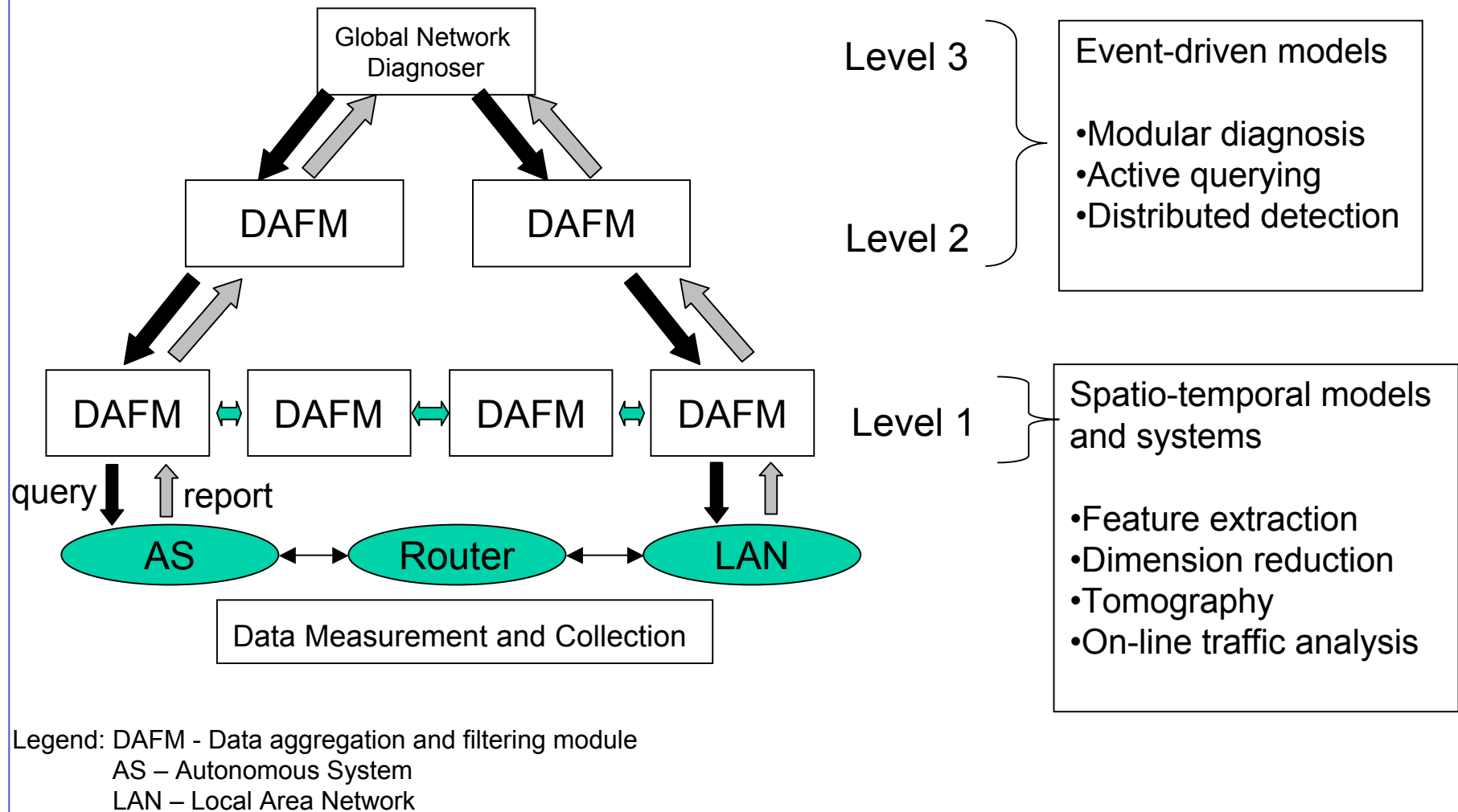


2. Internet SP Challenges

- What makes multisite Internet data analysis hard from a SP point of view?
 - Bandwidth is always limited
 - Sampling will never be adequate
 - Spatial sampling: cannot measure all link/node correlations from passive measurements at only a few sites
 - Temporal sampling: full bit stream cannot be captured
 - Category sampling: only a subset of all field variables can be monitored at a time
 - Measurement data is inherently non-stationary
 - Standard modeling approaches are difficult or inapplicable for such massive data sets
 - Little ground truth data is available to validate models
- General robust and principled approach is needed:
 - Adopt hierarchical multiresolution modeling and analysis framework
 - Task-driven dimension reduction

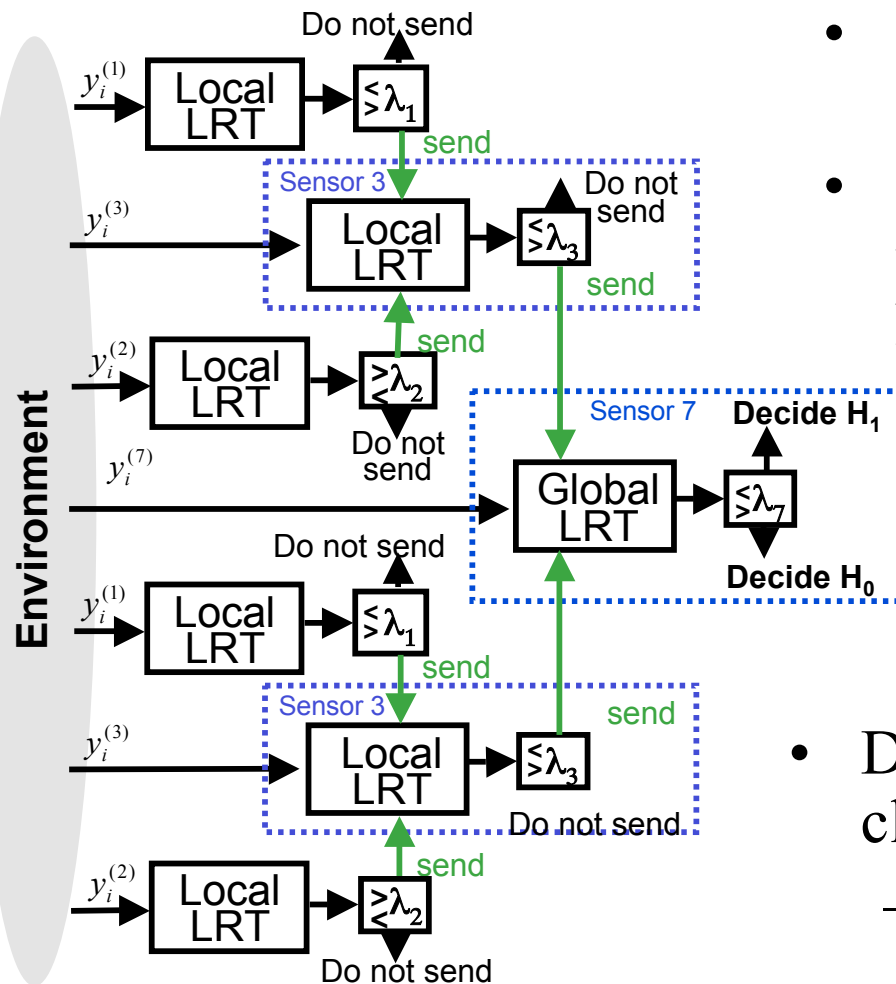


Hierarchical Network Measurement Framework





Example: distributed anomaly detection



- Multi-hop is desirable for energy efficiency, cost
- Censored test can be iterated to match arbitrary multi-hop 'tree' hierarchy

$\forall \rho = 1 \Leftrightarrow$ centralized

- $0 < \rho < 1 \Leftrightarrow$ data fusion, reduce data bottleneck at the root

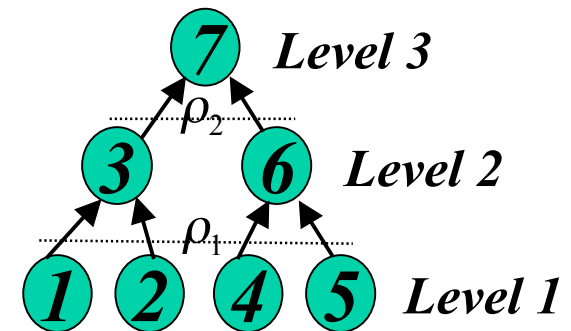
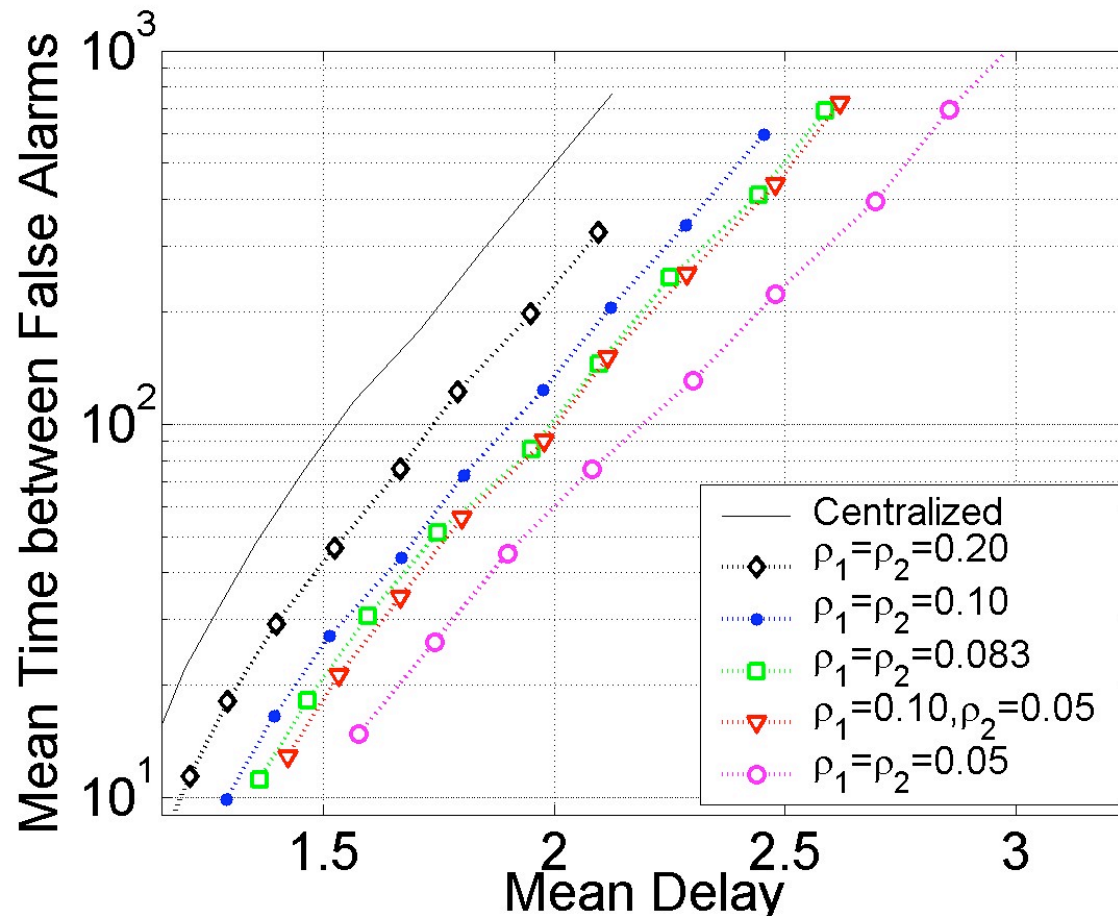
- Detection performance can be close to optimal [1]
 - Even $\rho = 0.01$ sensors greatly improve performance

[1] N. Patwari, A.O. Hero III, "Hierarchical Censoring for Distributed Detection in Wireless Sensor Networks", IEEE ICASSP '03, April 2003.



Example: distributed anomaly detection

- Parameter ρ selected to constrain mean time btwn false alarms





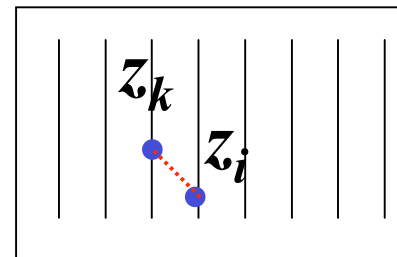
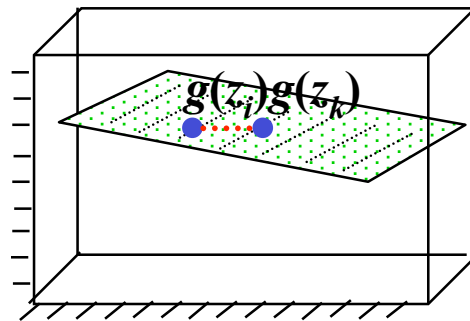
Research Issues

- Broad questions
 - Anomaly detection, classification, and localization
 - Model-driven vs data-driven approaches
 - Partitioning of information and decisionmaking (Multiscale-multiresolution decision trees)
 - Learning the “Baseline” and detecting deviations
 - Feature selection, updating, and validation
 - Multi-site measurement and aggregation
 - Remote monitoring: tomography and topology discovery
 - Multi-site spatio-temporal correlation
 - Distributed optimization/computation
 - Dynamic spatio-temporal measurement
 - Sensor management: scheduling measurements and communication
 - Passive sensing vs. active probing
 - Adaptive spatio-temporal resolution control
 - Dimension reduction methods
 - Beyond linear PCA/ICA/MDS...

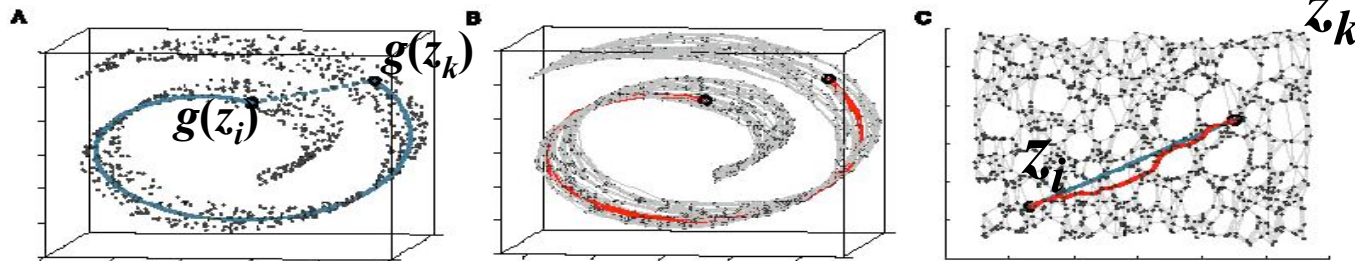


3. Dimension Reduction

- Manifold domain reconstruction from samples: “the data manifold”
 - Linearity hypothesis: PCA, ICA, multidimensional scaling (MDS)



- Smoothness hypothesis: ISOMAP, LLE, HLLE

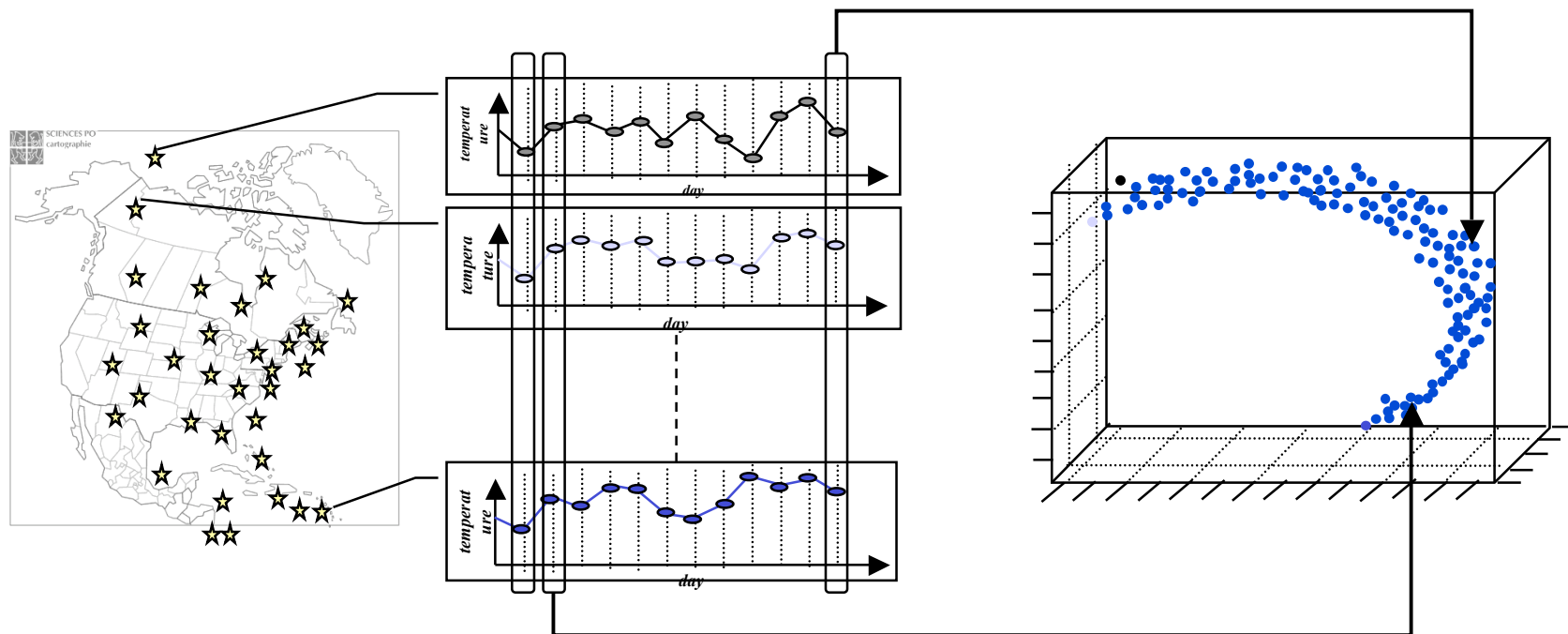


- Dimension estimation: infer degrees of freedom of data manifold
- Infer entropy, relative entropy of sampling distribution on manifold



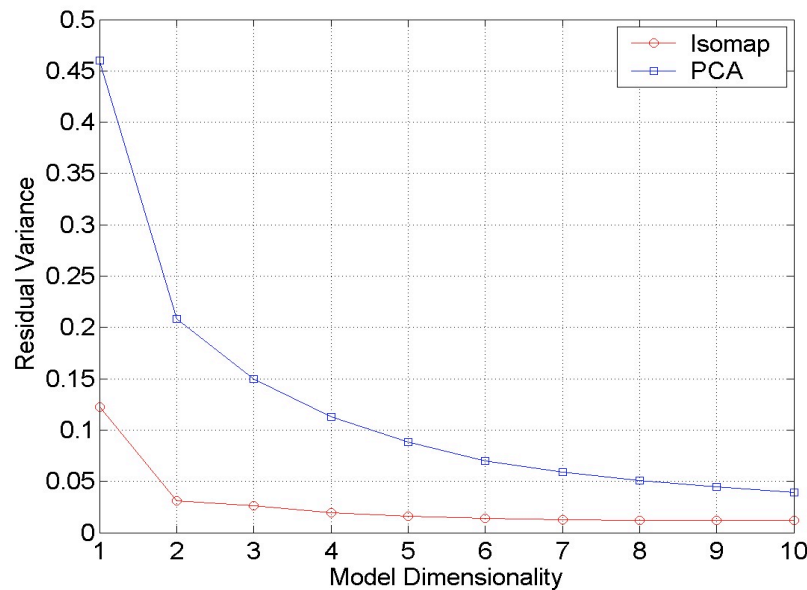
Application: Internet Traffic Visualization

- Spatio-temporal measurement vector:

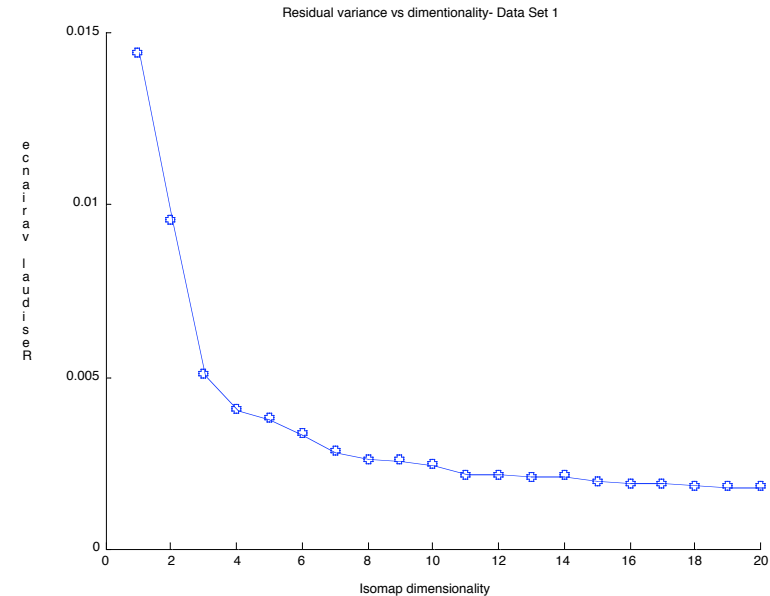




Key problem: dimension estimation



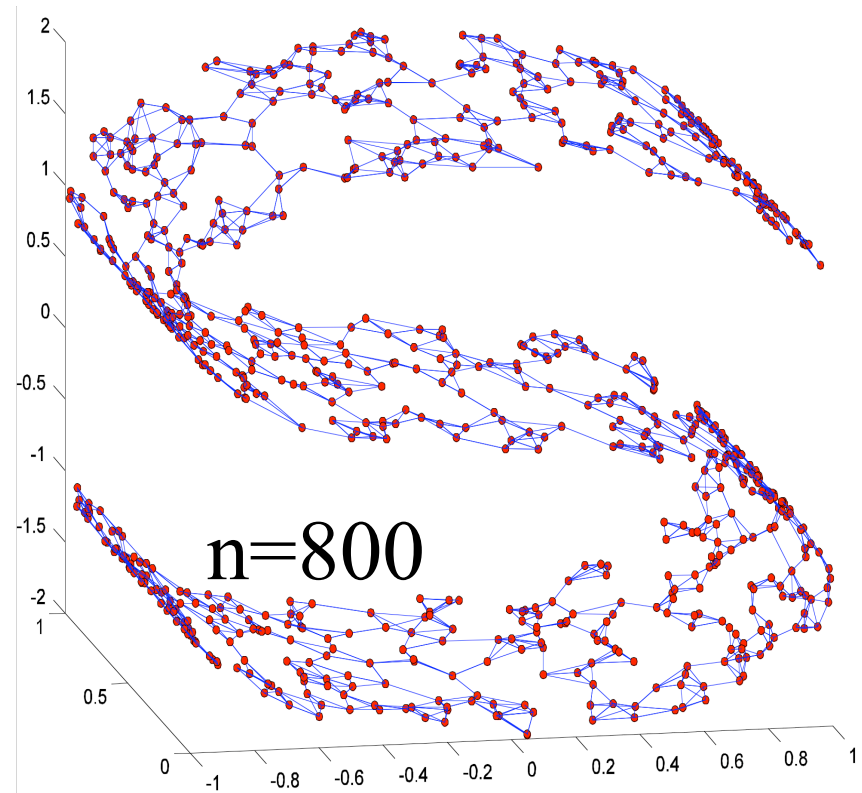
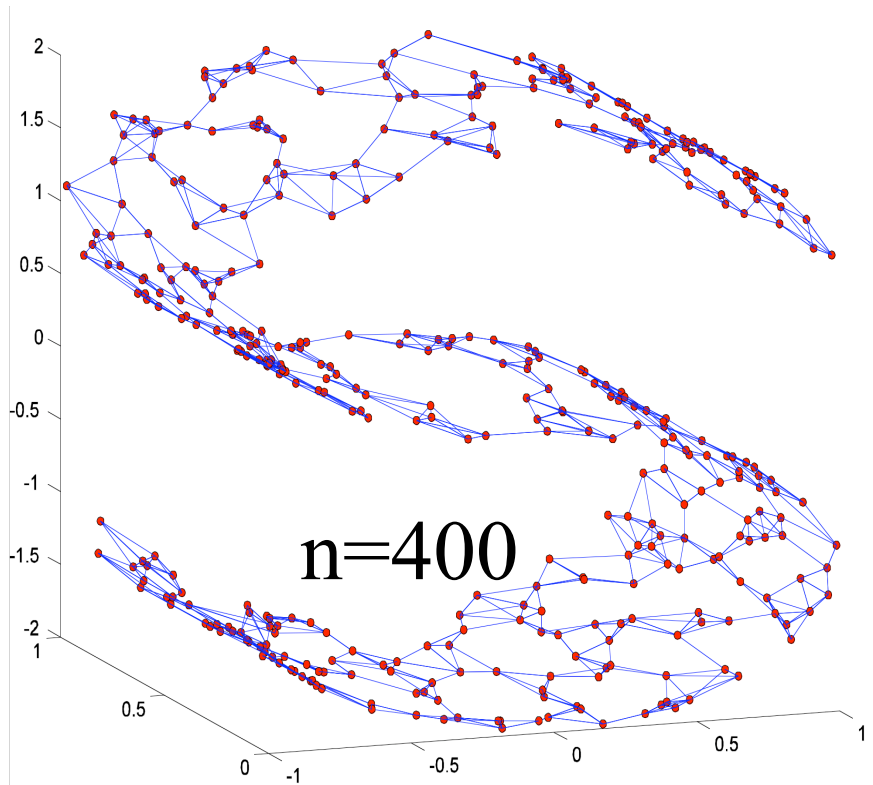
Residual fitting curves
for $11 \times 21 = 231$ dimensional
Abilene Netflow data set



ISOMAP residual curve
for $41 + 11 = 51$ dimensional
Abilene OD link data
(Lakhina, Crovella, Diot)



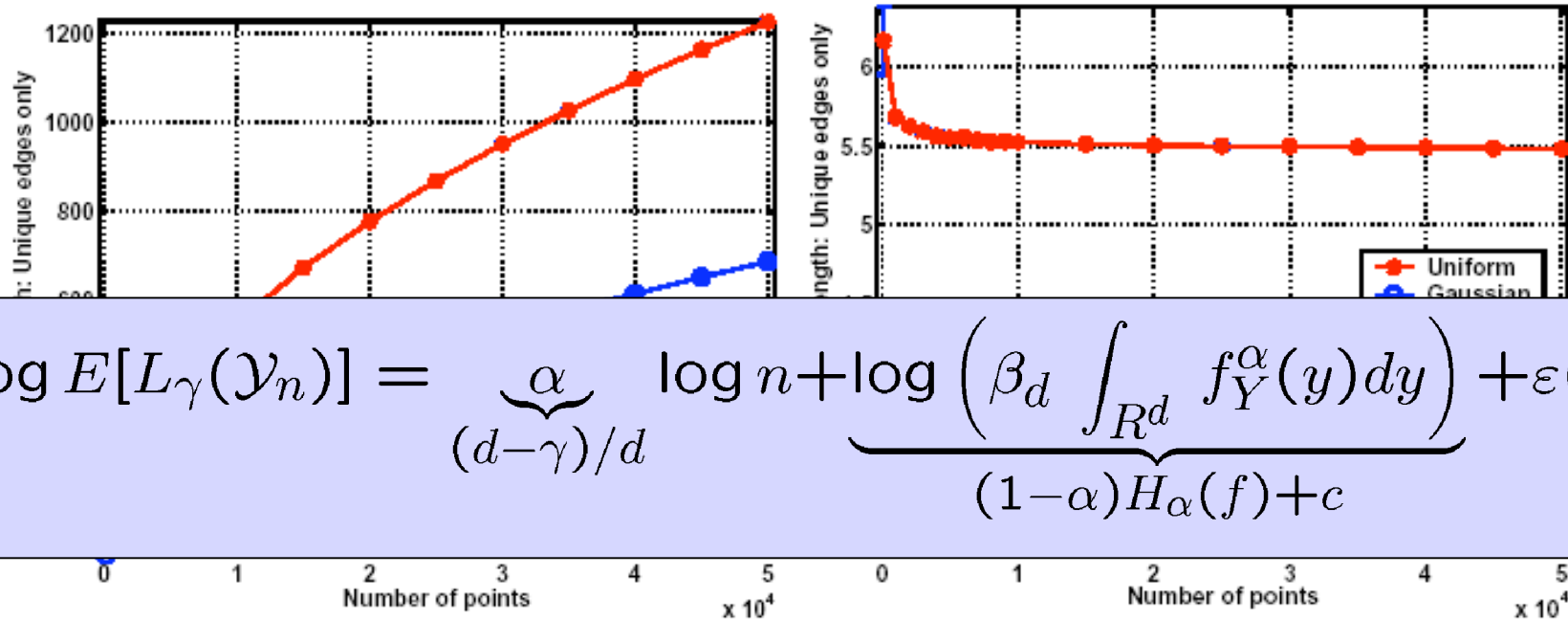
GMST Rate of convergence=dimension, entropy



Rate of increase in length functional of MST should be related to the intrinsic dimension of data manifold



BHH Theorem



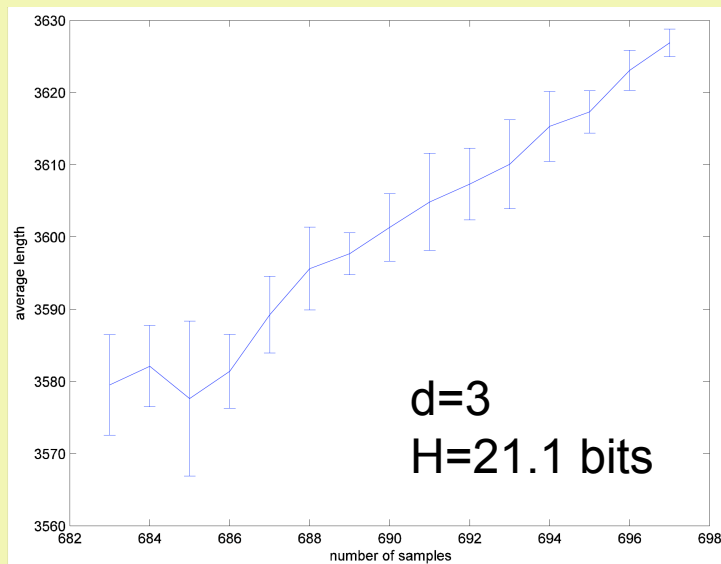
$$\log E[L_\gamma(\mathcal{Y}_n)] = \underbrace{\alpha}_{(d-\gamma)/d} \log n + \underbrace{\log \left(\beta_d \int_{\mathbb{R}^d} f_Y^\alpha(y) dy \right)}_{(1-\alpha)H_\alpha(f) + c} + \varepsilon(n)$$

Extended BHH Theorem (Costa&Hero):

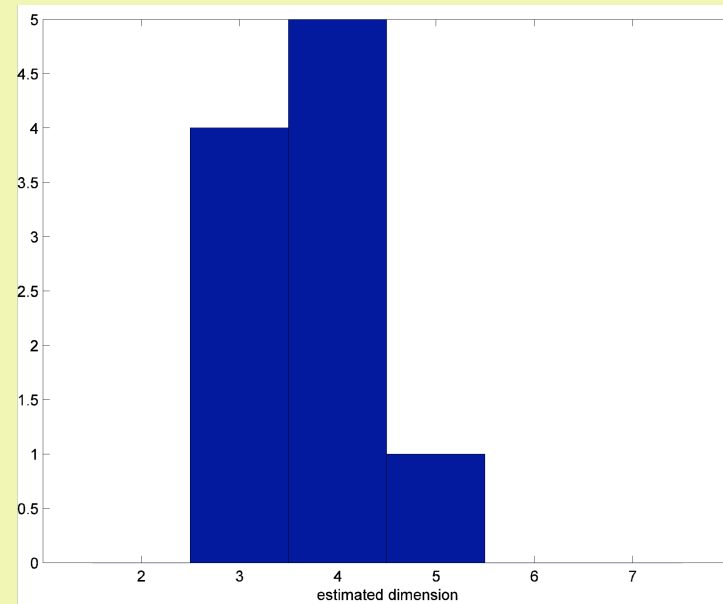
$$L_\gamma(\mathcal{Y}_n)/n^\alpha \rightarrow \beta_d \underbrace{\int_S f_Y^\alpha(y) dy}_{H_\alpha(f_Y)} \quad \alpha = (d - \gamma)/d$$



Application: ISOMAP Database



Mean GMST Length Function

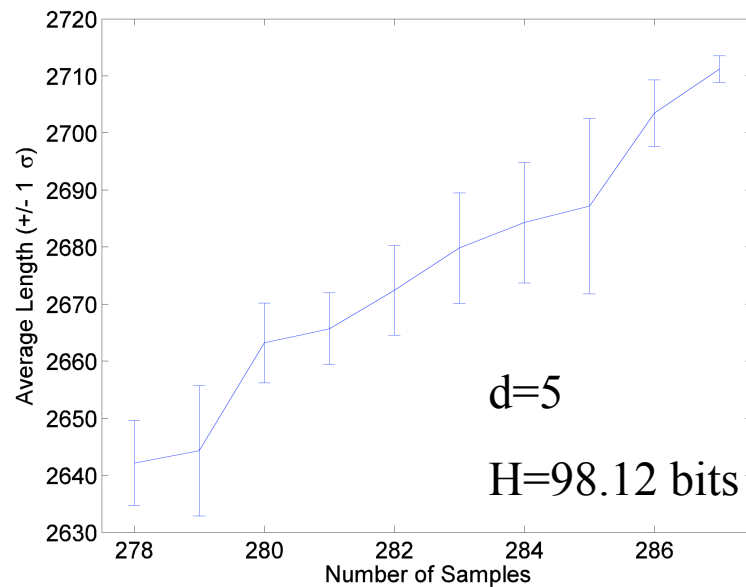


Resampling Histogram of \hat{d}

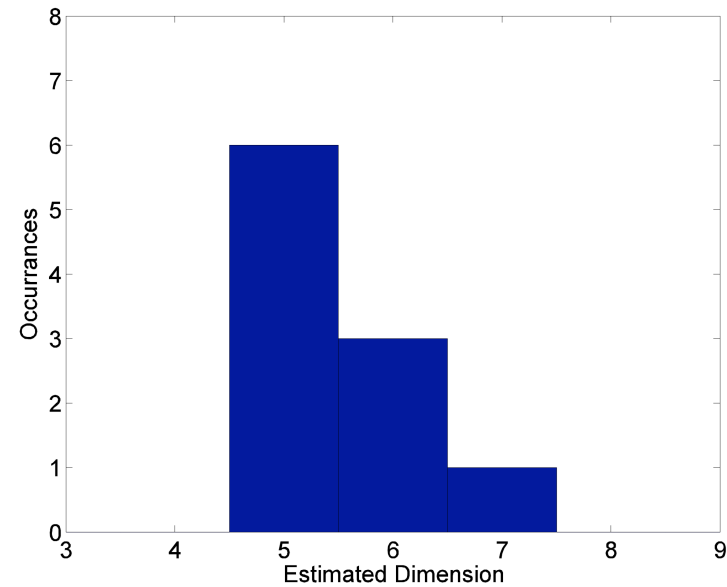


Illustration: Abilene Netflow

- 11 routers and 21 applications = each sample lives in 231 dimensions
- 24 hour data block divided into 5 min intervals = 288 samples



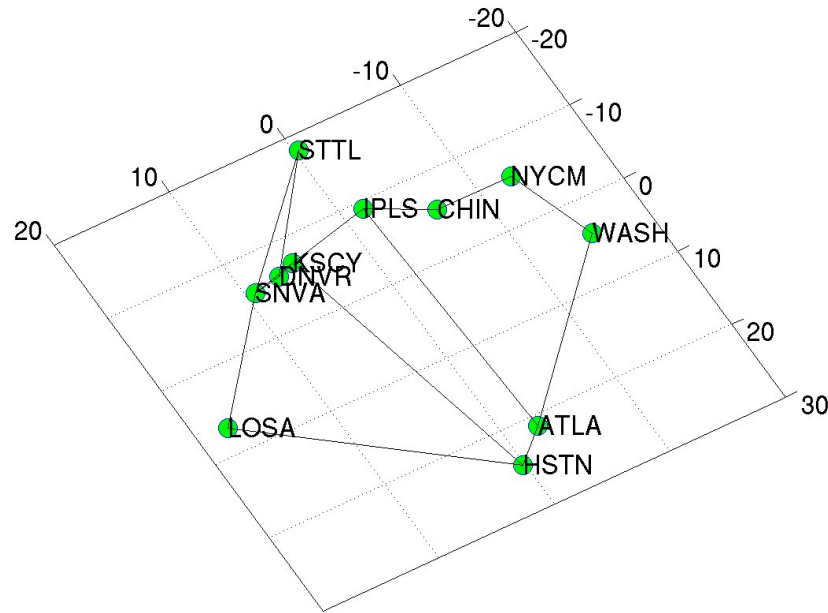
Mean GMST Length Function



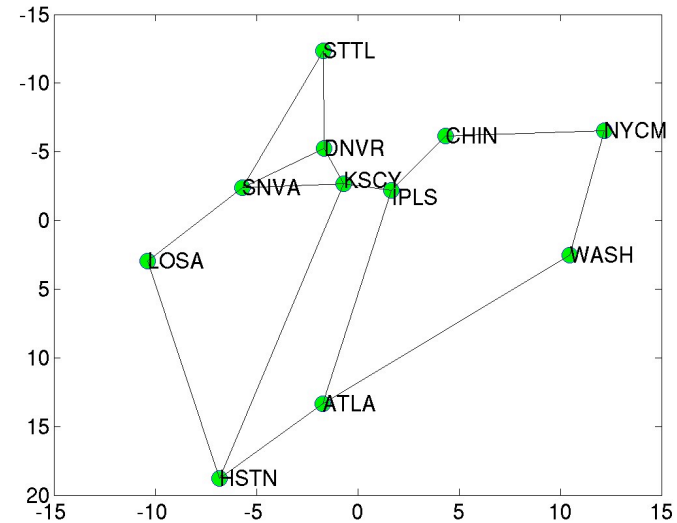
Resampling histogram of \hat{d}



dwMDS embedding/visualization



Abilene Network Isomap
(Centralized computation)



Abilene Network DW MDS
(Distributed computation)

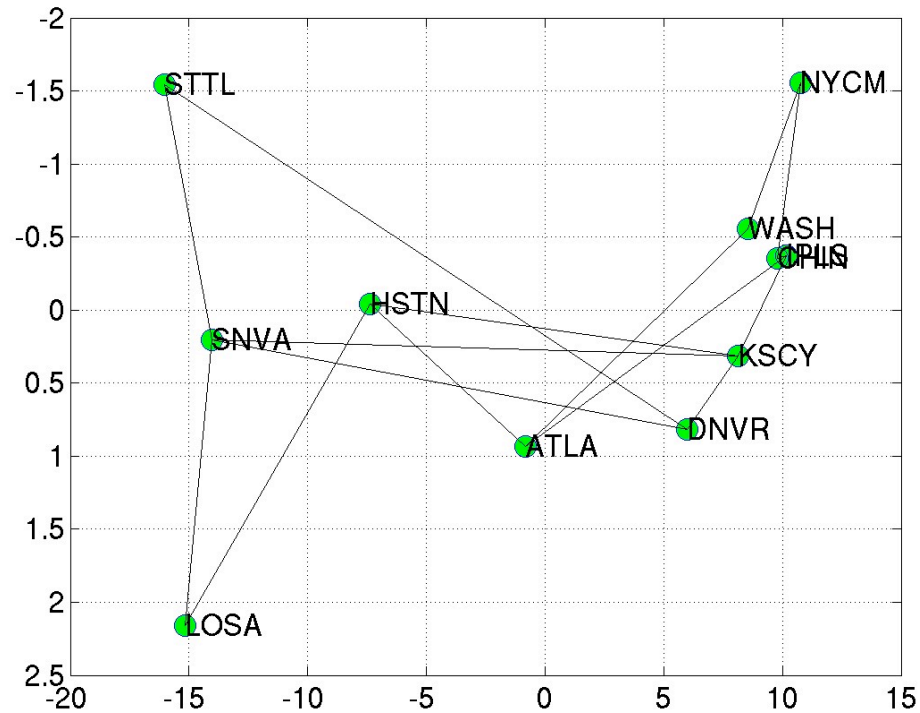
Data: total packet flow over 5 minute intervals 10 june '04

Isomap(Tennbaum): $k=3$, 2D projection, L2 distances

DW MDS(Costa&Patwari&Hero): $k=5$, 2D projection, L2 distances



dwMDS embedding/visualization



Abilene Network MDS (linear)
(Centralized computation)

Data: total packet flow over 5 minute intervals 10 june '04
MDS: 2D projection, L2 distances



4. Conclusions

- Interface of SP, control, info theory, statistics and applied math is fertile ground for network measurement/data analysis
- SP will benefit from scalable hierarchical multiresolution modeling and analysis framework
 - Multiresolution modeling, communication, decisionmaking
- Task-driven dimension reduction is necessary
 - Go beyond linear methods (PCA/ICA)
 - What is goal? Estimation/Detection/Classification?
 - Subspace constraints (smoothness, anchors)?
 - Out-of-sample updates?
 - Mixed dimensions?
- Validation is a critical problem: annotated classified data or ground truth data is lacking.