

Algebraic and Tensor Methods for Anomaly Detection

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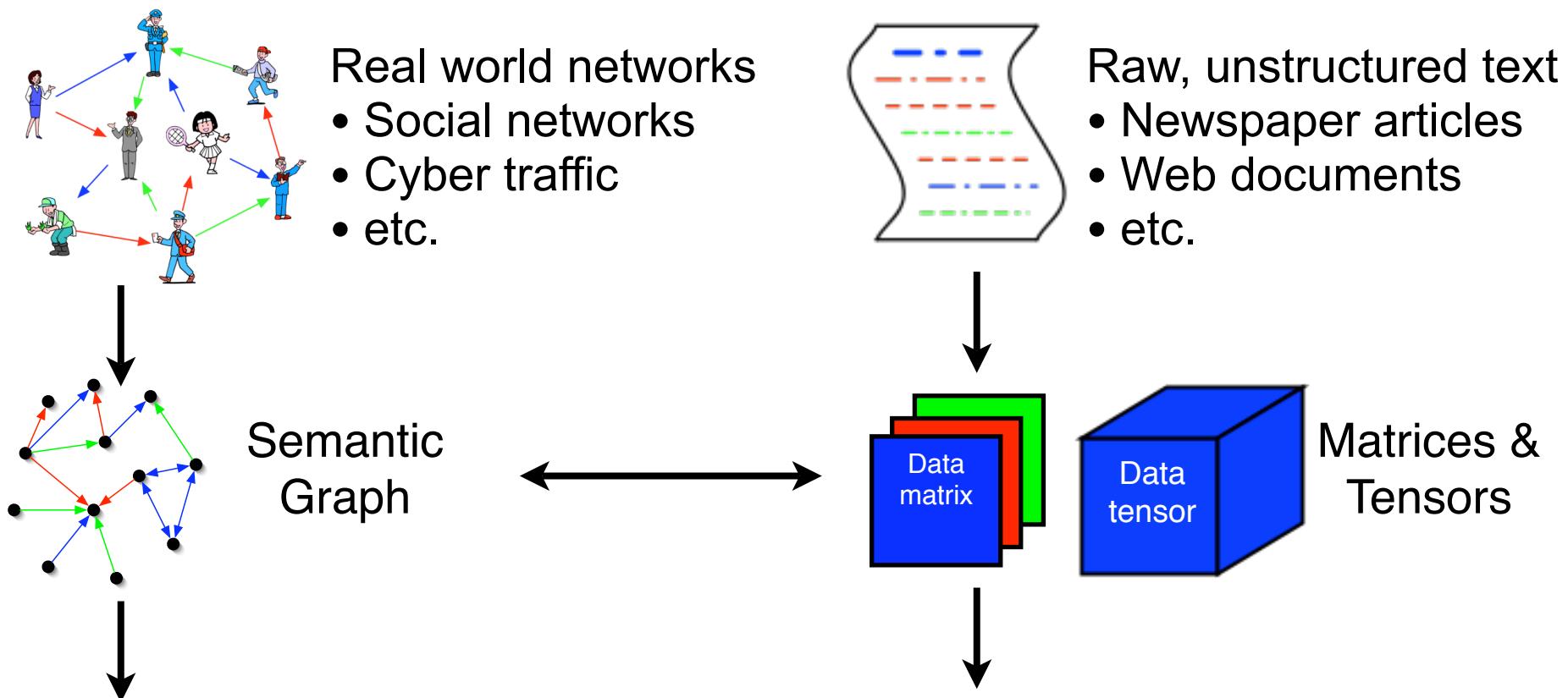

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Robust data analysis requires appropriate data abstractions and algorithms

Sandia uses *semantic graphs* and *tensors* as unifying data abstractions

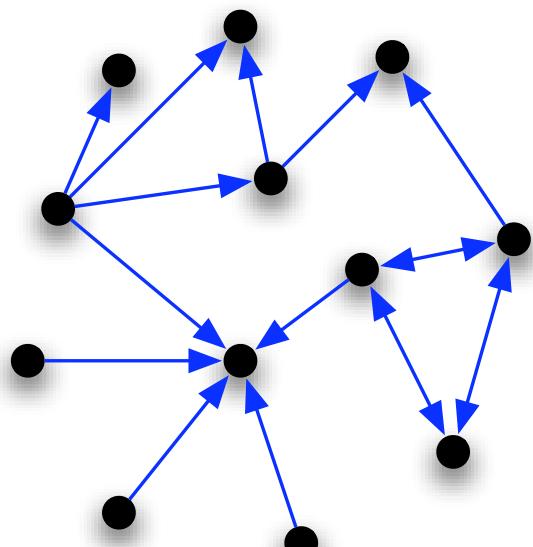
- Supports rich relationship-centered analysis
- Combines large, heterogeneous data corpora
- Different abstractions support different analytics



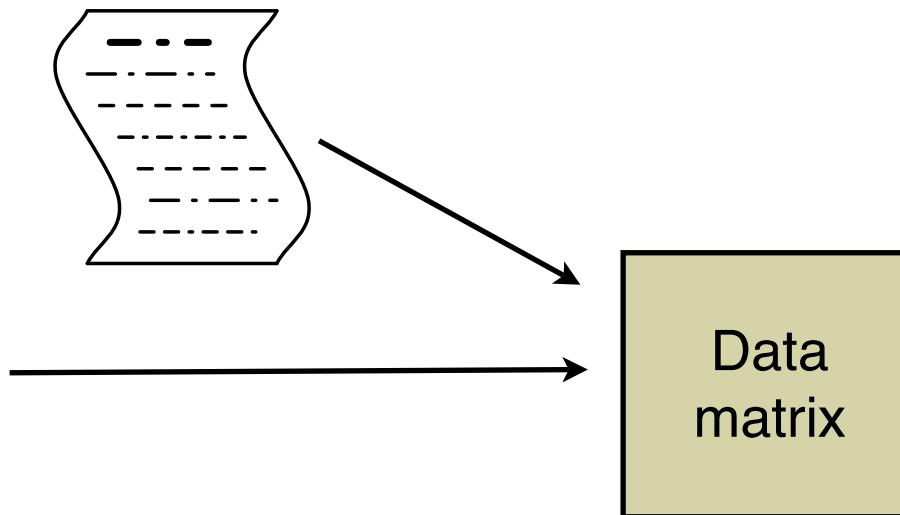
- Graph algorithms, discrete math
- Short paths, connection subgraphs, subgraph isomorphism

- Linear and multilinear algebra, statistics/probability
- Ranking, clustering

Traditional Analysis

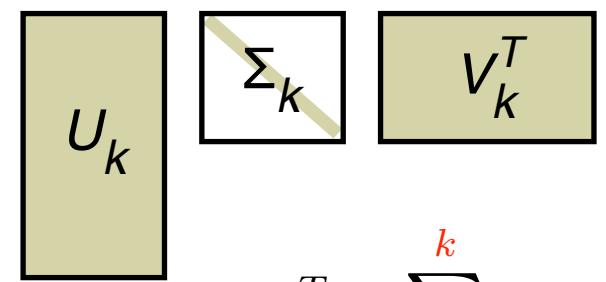


or



Best rank- k matrix filters out noise and captures “latent” information, which improves certain data mining tasks

Truncated SVD



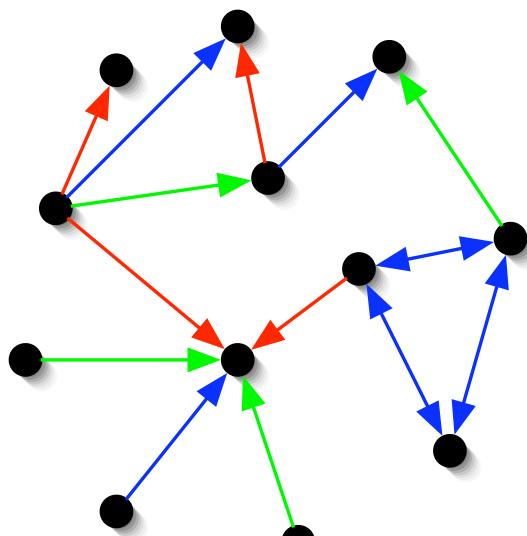
$$A_k = U_k \Sigma_k V_k^T = \sum_{i=1}^k \sigma_i u_i v_i^T$$

Examples:

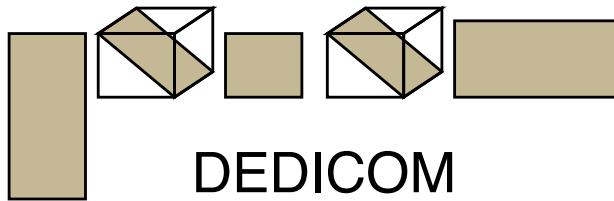
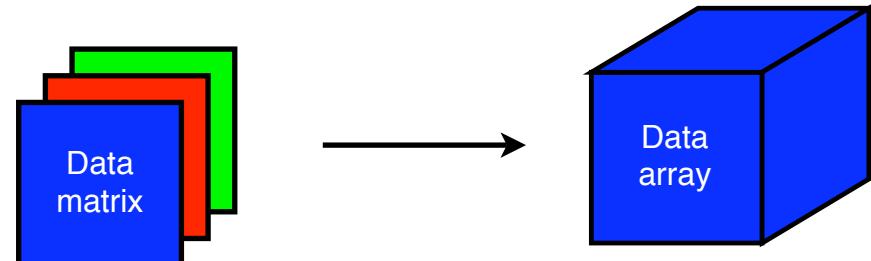
- Latent Semantic Analysis
- Text Analysis (LSI)
- Web search (HITS)
- Clustering

But there may be more useful information in the data!

New Paradigm: “Multidimensional Data Mining”

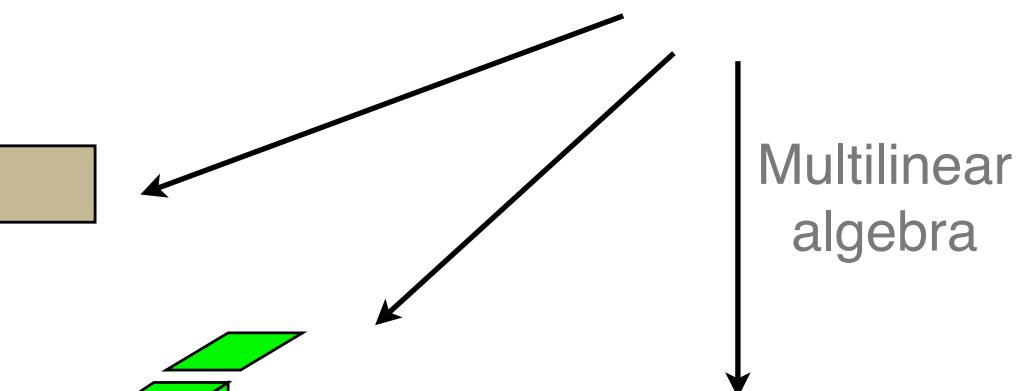


Build a “data array” such that there is a data matrix for each link type.

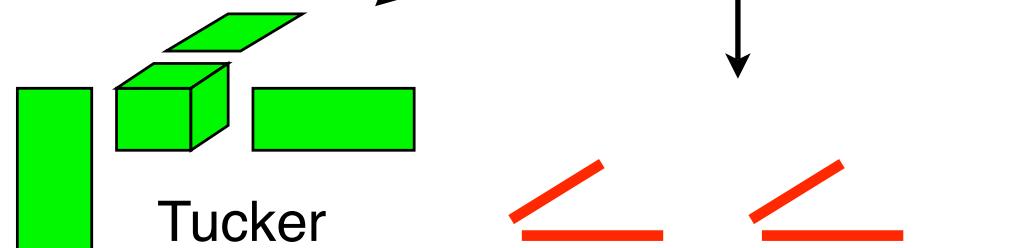


DEDICOM

Third dimension offers more explanatory power: uncovers new latent information and reveals subtle relationships



Multilinear algebra



Tucker



PARAFAC



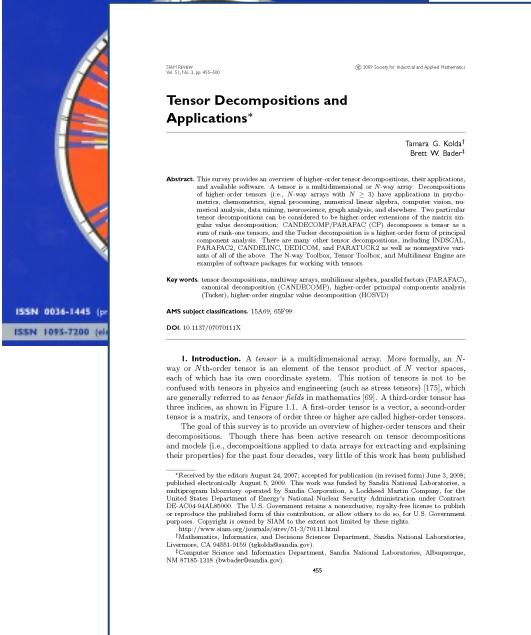
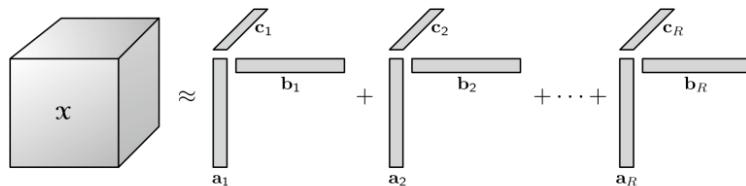
Unique data mining capability developed at Sandia



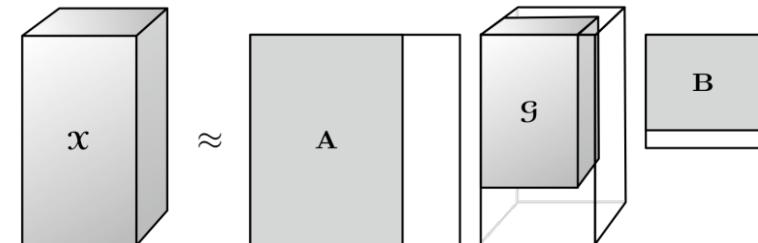
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Many Types of Tensor Decompositions

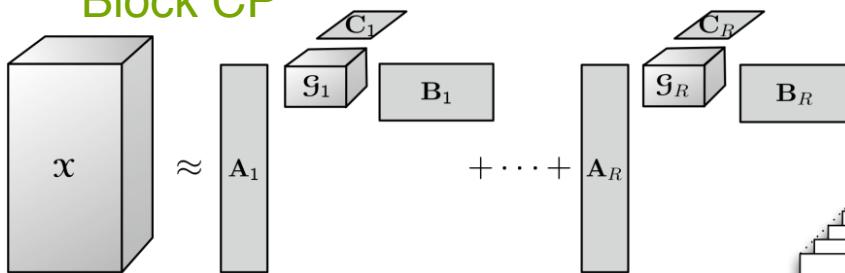
CANDECOMP/PARAFAC (CP)



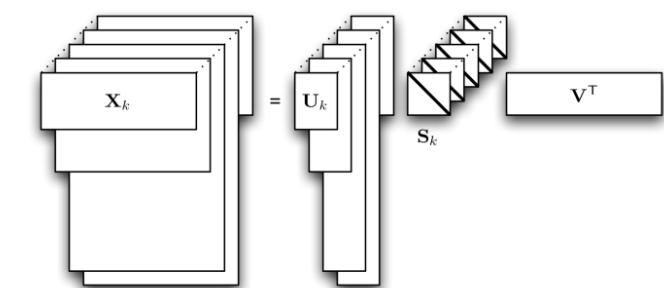
Tucker



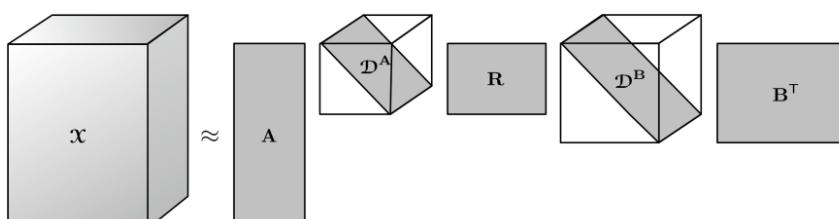
Block CP



PARAFAC2



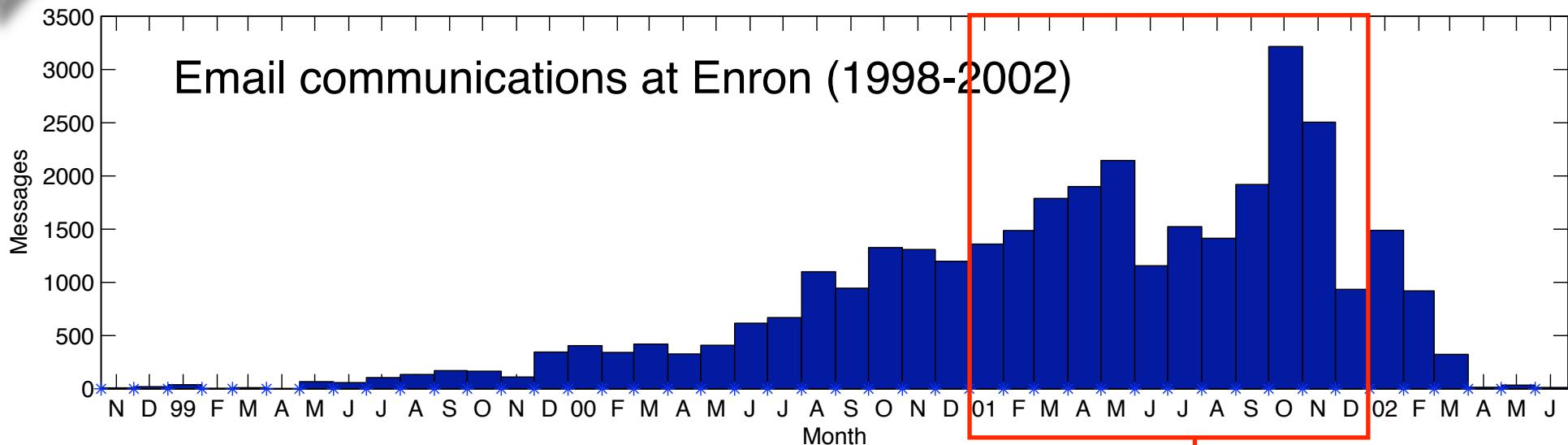
PARATUCK2 (DEDICOM3)



Kolda & Bader, Tensor Decompositions and Applications, SIAM Review, 2009

Each decomposition provides a different interpretation of the data

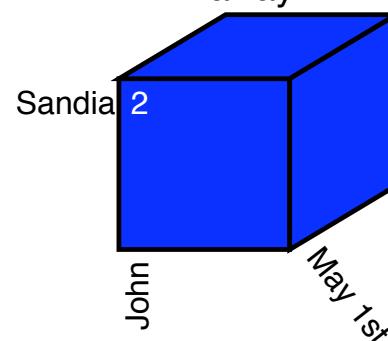
Case Study: Discussion Tracking in Email



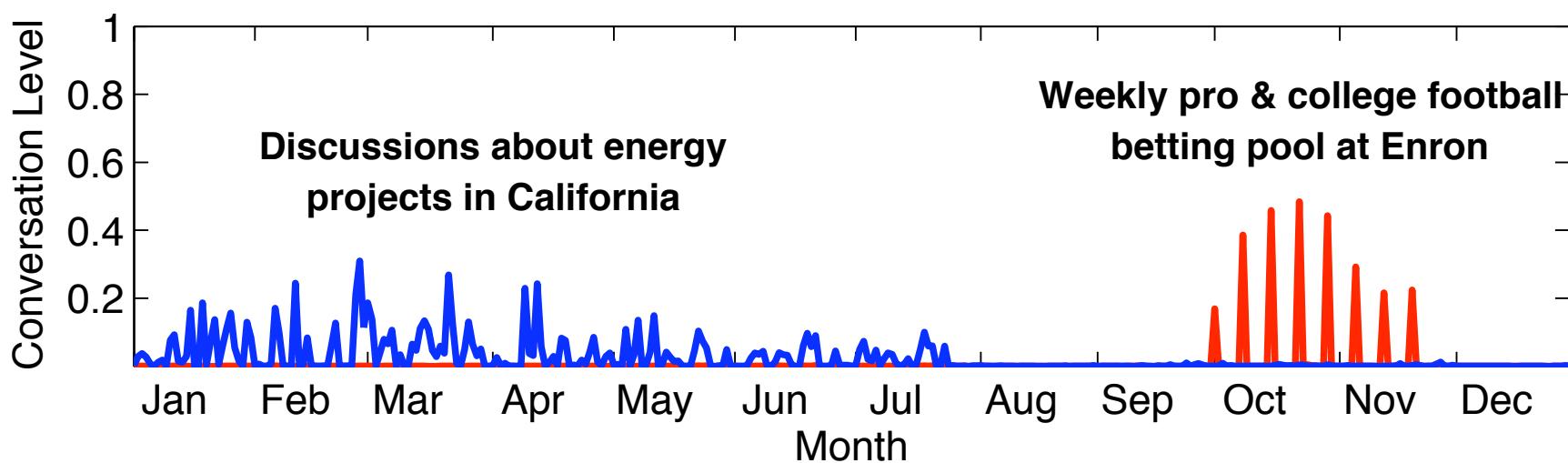
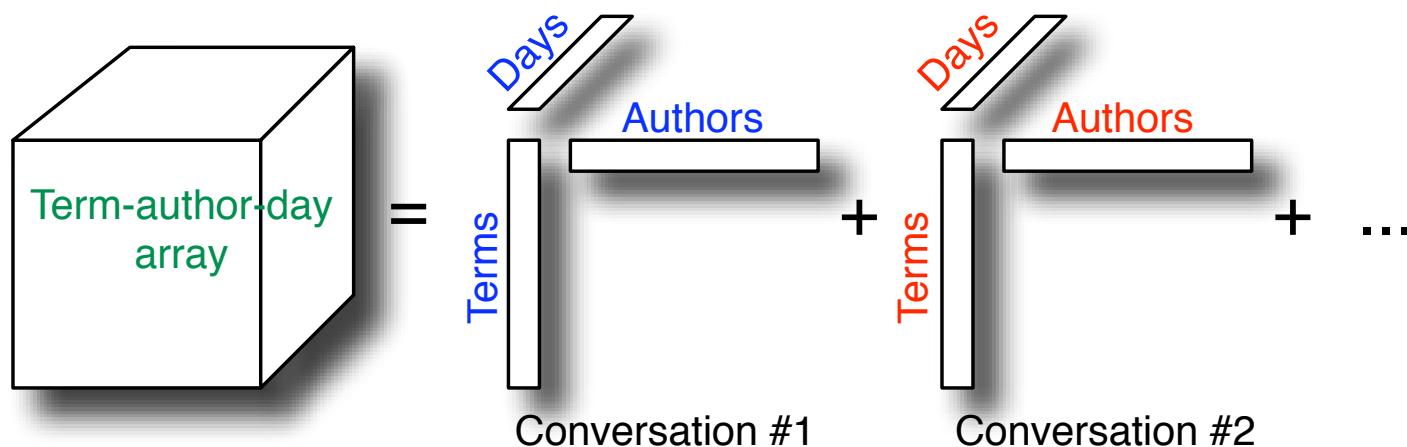
- Situational awareness
- What can we learn from these email conversations?
 - **What** are the major topics of conversations?
 - **Who** are the major participants?
 - **When** are they taking place?

53,733 messages
from 184 employees

term-author-time
array



Tensor analysis finds unusual activity by associating terms with people over time



Key terms: California, power, utilities, energy, utility, governor, market

Key authors: J. Steffes, S. Kean, J. Dasovich, R. Shapiro, P. Allen, ...

games, week, missed, picked, prize, wins, scored, upsets

A. Pace, L. Campbell, C. Dean



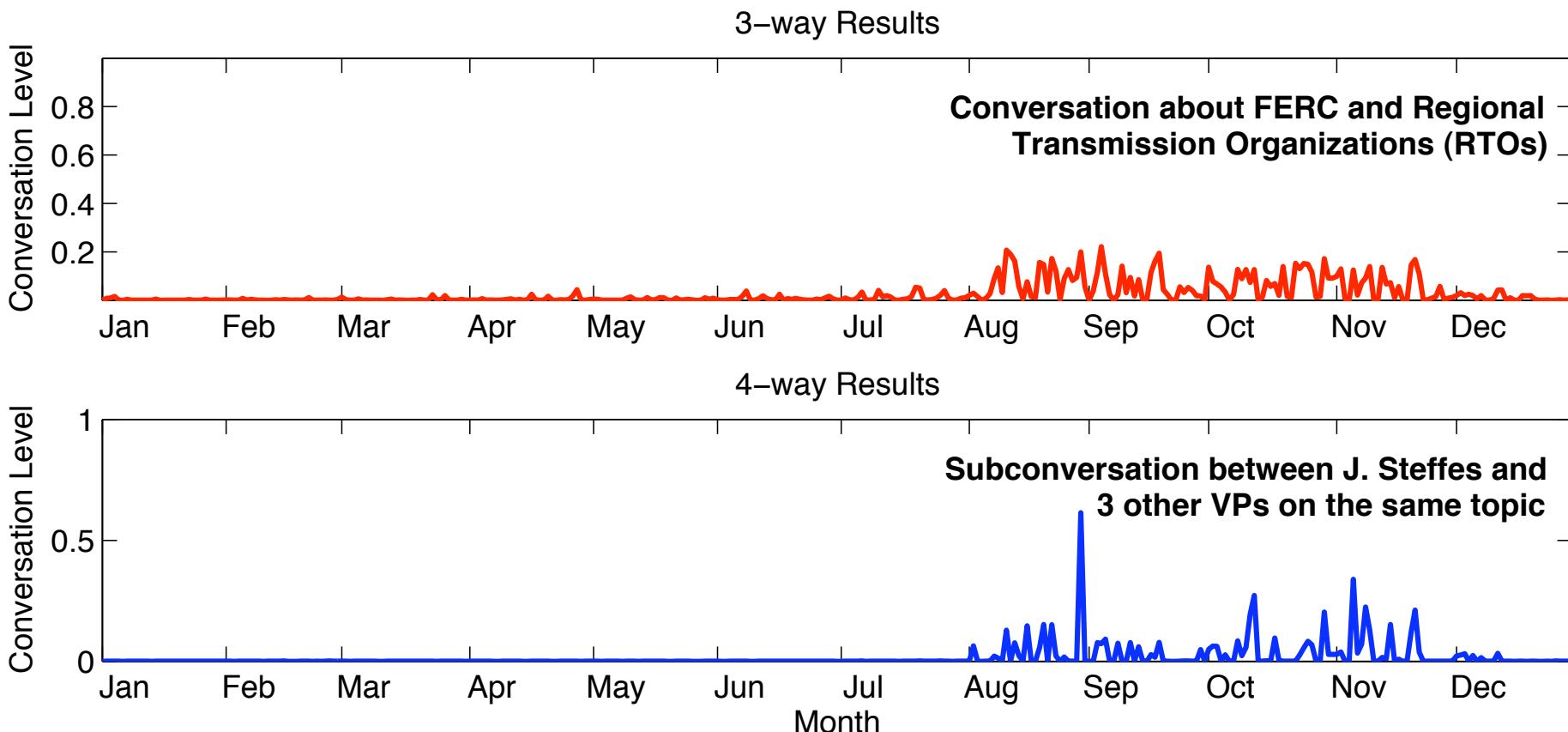
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Four-way analysis shows deeper relationships

4-way array: Author x Recipient x Terms x Time

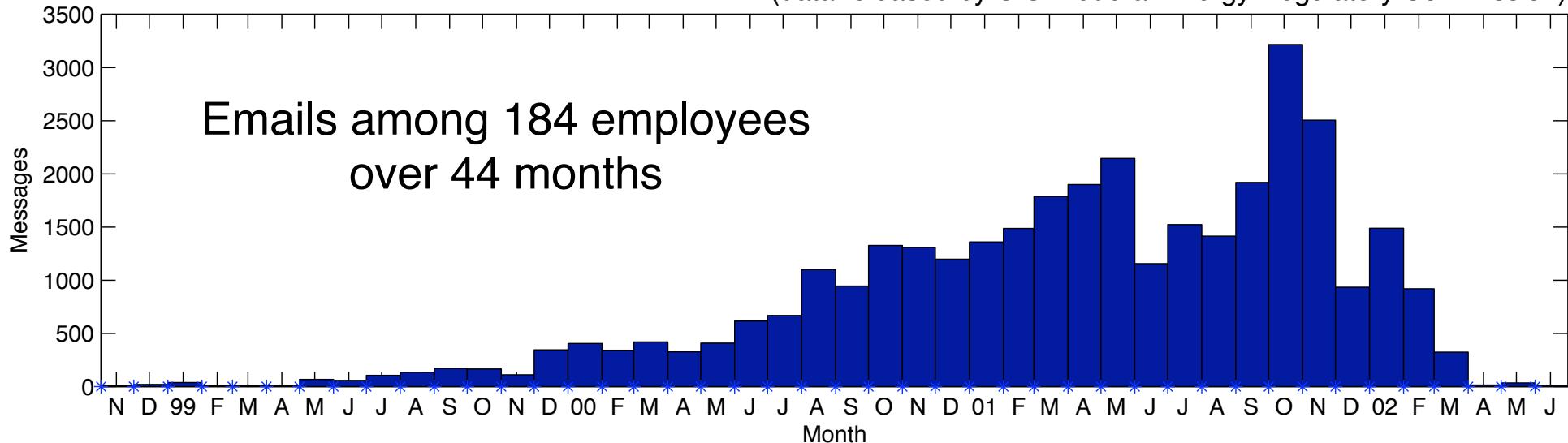
- 4-way analysis may track subconversation already found by 3-way analysis
- Provides context and temporal patterns of social network



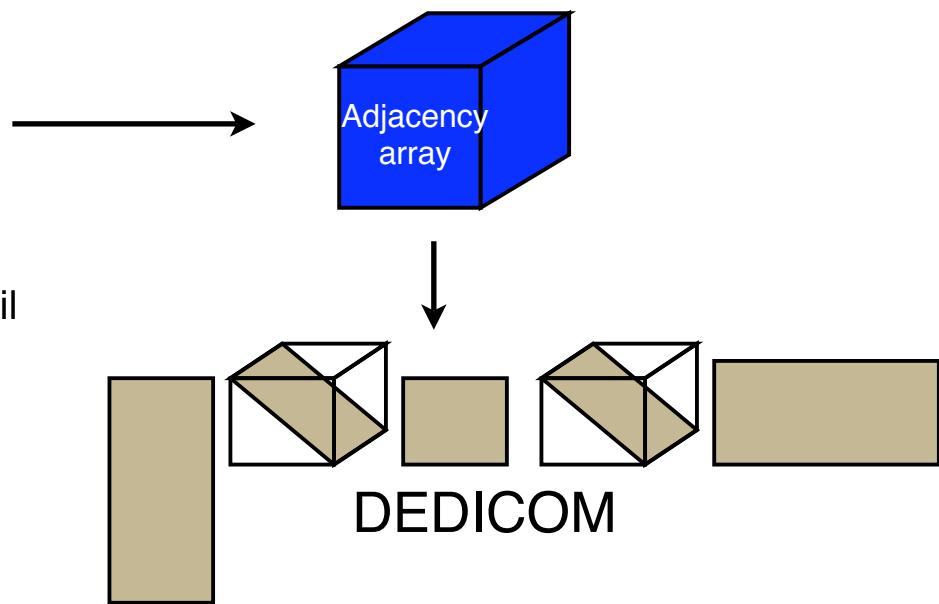
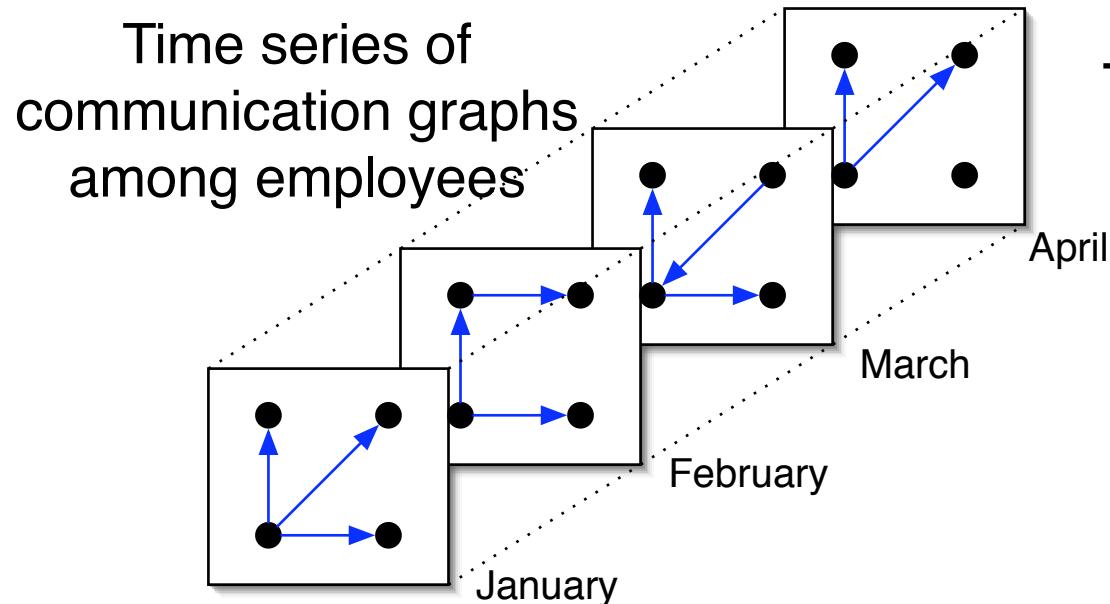
Case Study: Pattern Analysis in Email Networks

Email communications at Enron (1998-2002)

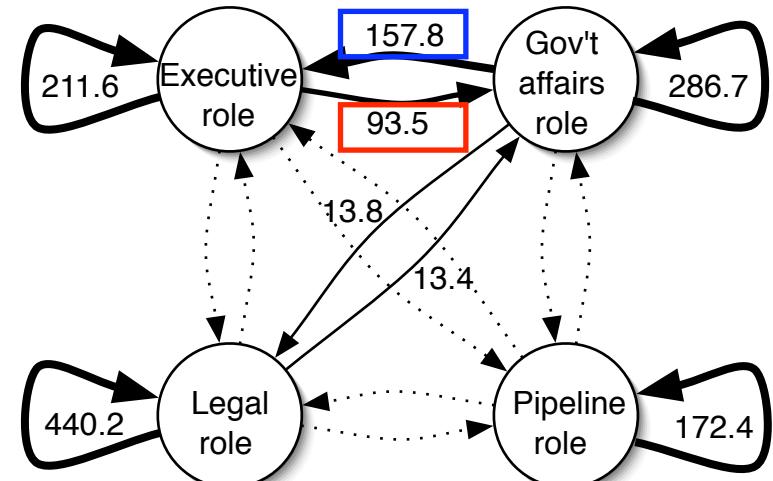
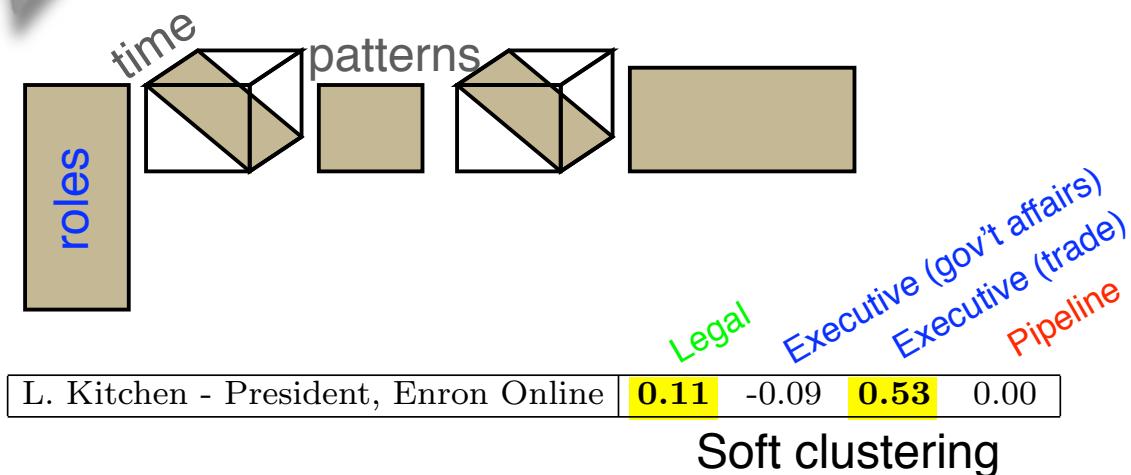
(data released by U.S. Federal Energy Regulatory Commission)



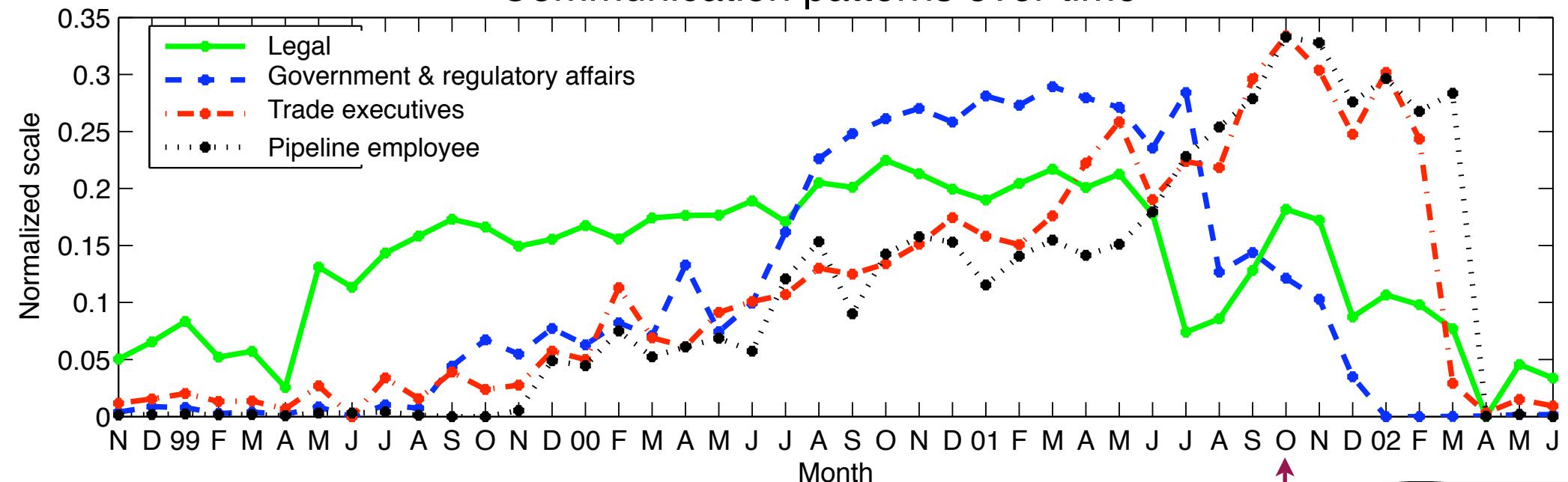
Emails among 184 employees
over 44 months



Analysis shows employee roles and communication patterns



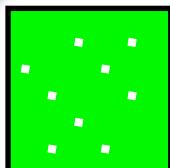
Communication patterns over time



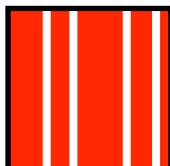
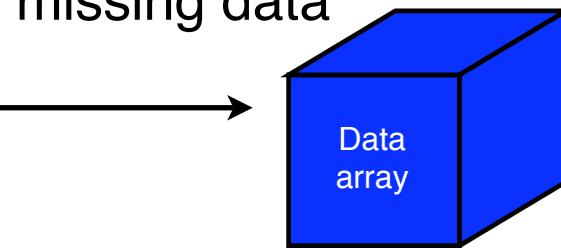
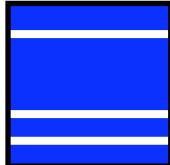
Bader, Harshman, Kolda, Temporal analysis of semantic graphs using ASALSAN, in ICDM 2008.

Enron crisis breaks;
investigation begins

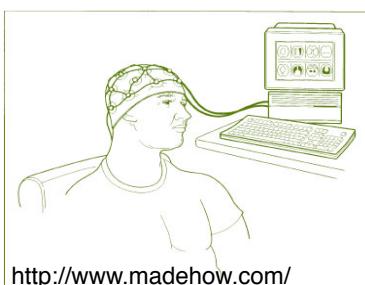
Our algorithms can handle missing data



Random or systematic patterns of missing data



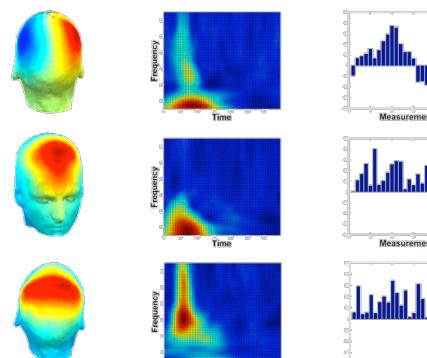
Fit model using derivative-based algorithms



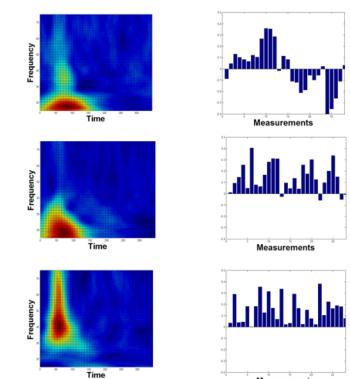
64 channels 28 exps 4392 time-freq.

- Simultaneous analysis in 3 ways will fill in the gaps
- Our approach is faster than alternatives
- Specialized algorithm for large-scale problems
 - $500 \times 500 \times 500$ with 99% missing data (1.25M nonzeros)
 - $1000 \times 1000 \times 1000$ with 99.5% missing data (5M nonzeros)

No Missing Data

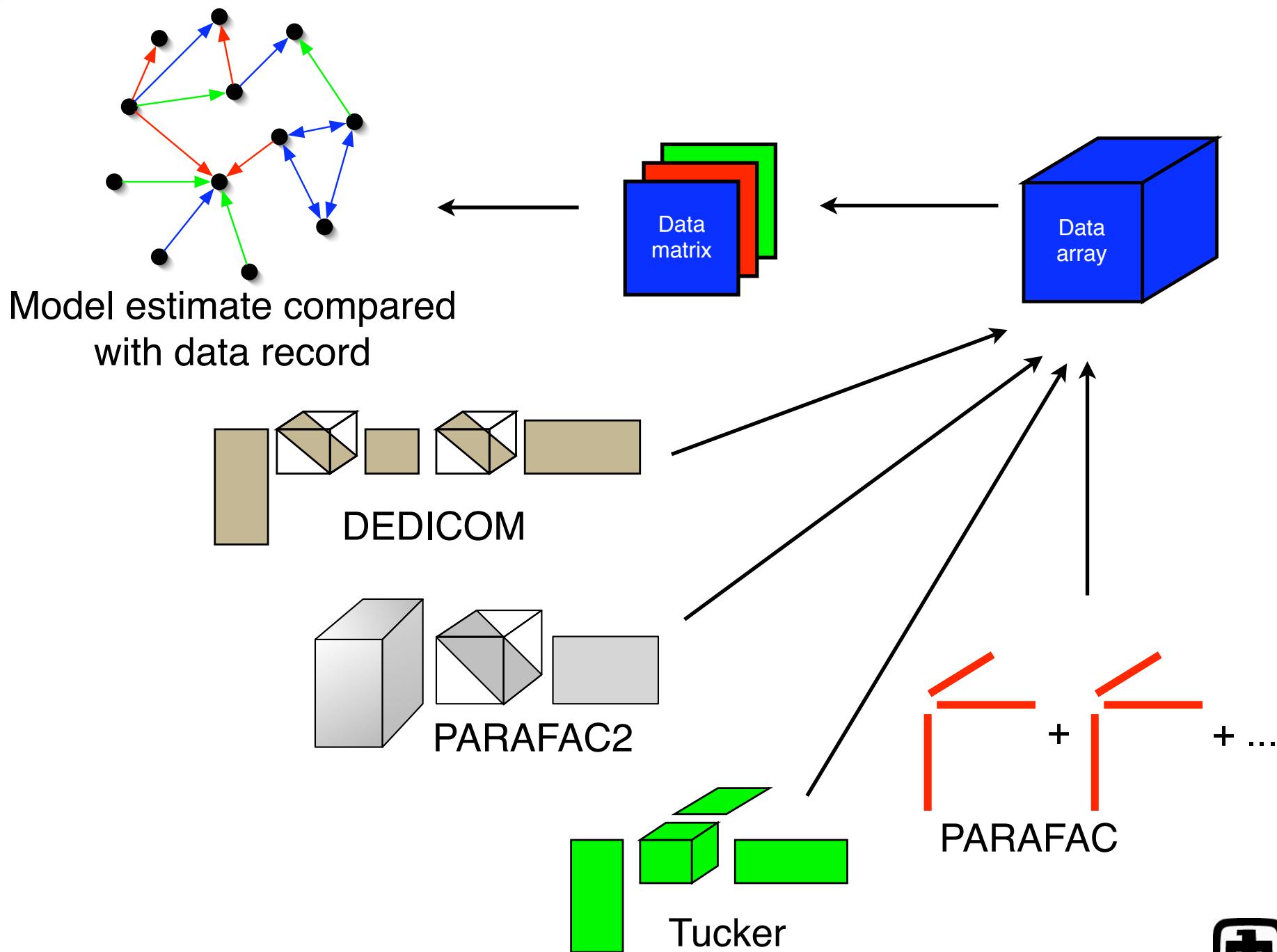


46% Missing Data



- Acar, Dunlavy, Kolda, Mørup, Scalable Tensor Factorization with Missing Data, SDM2010.
- Acar, Dunlavy, Kolda, Mørup, Scalable Tensor Factorization with Incomplete Data, in revision, 2010.

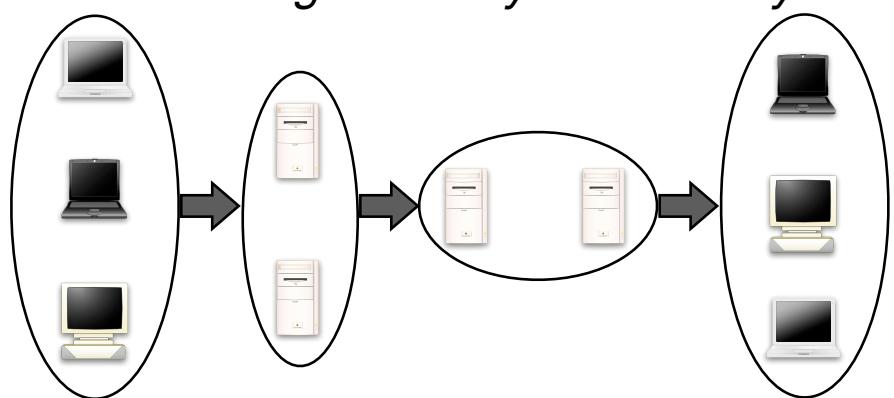
Missing data facilitates another approach to anomaly detection



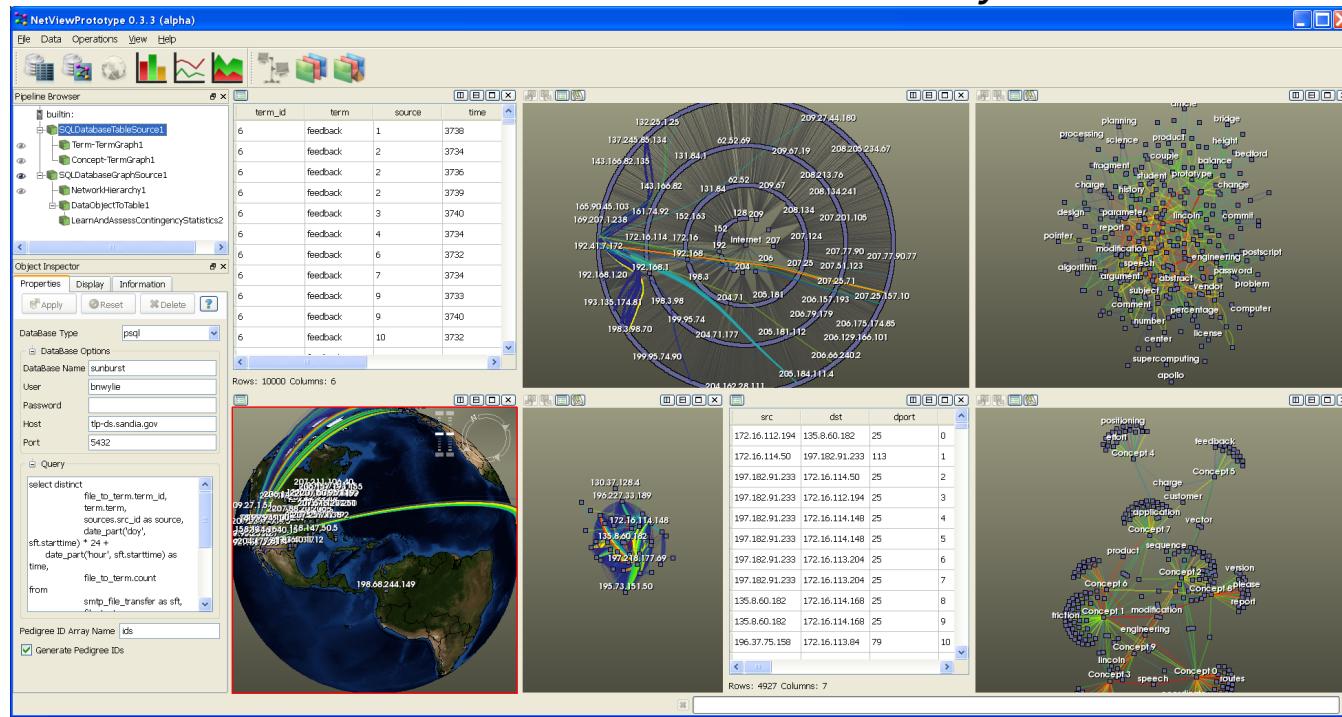
Related Analysis Projects

- Multilingual document analysis and classification
- Uncovering plots buried in text (scenario discovery)
- IP address characterization (trace route analysis)
- Network traffic analysis (cyber, phone)
- Cyber data exfiltration analysis
- Link prediction
- Higher-order web link analysis

Clustering nodes by their activity

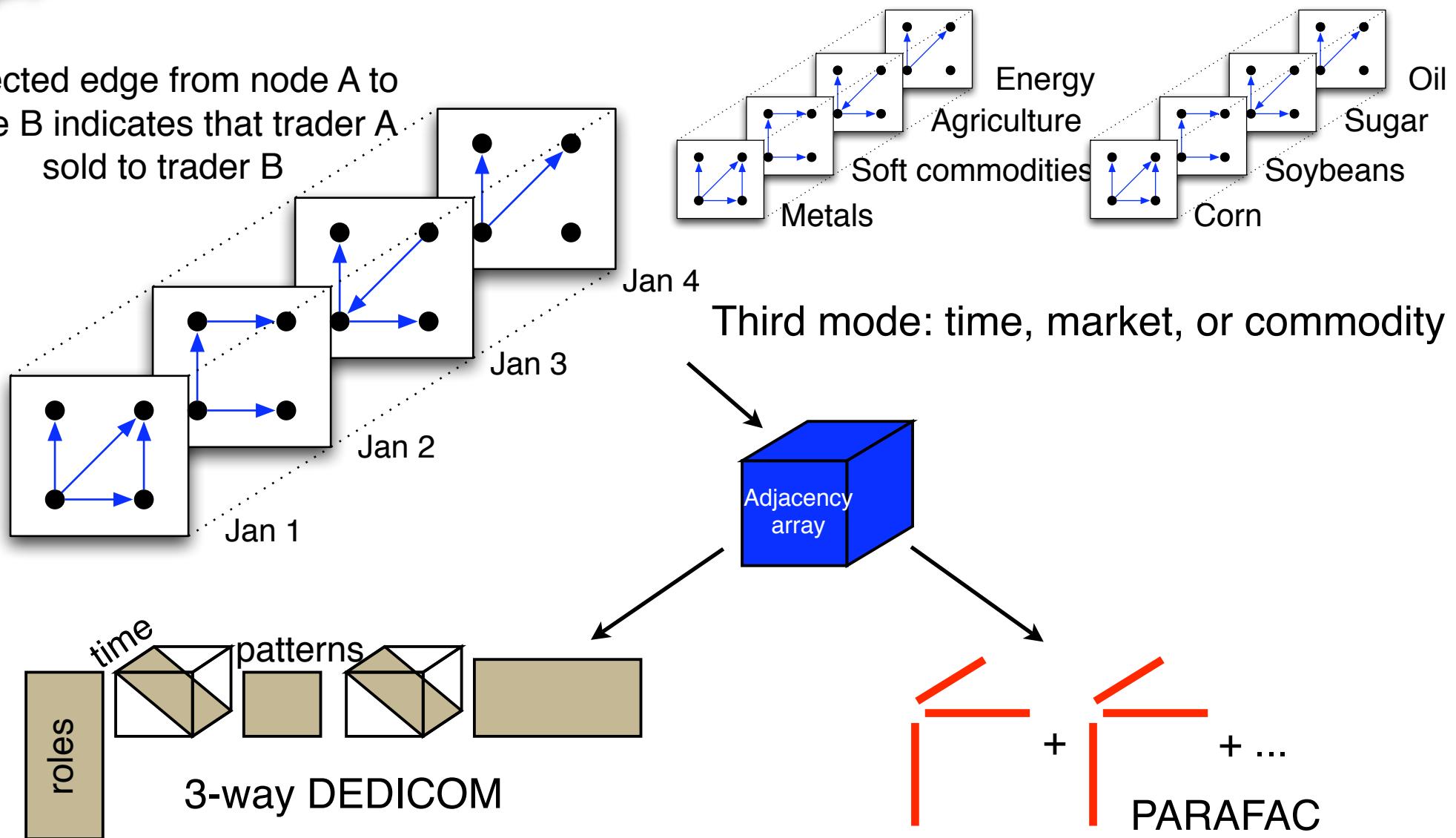


Network traffic and content analysis



Preliminary Ideas for Trading Networks

Directed edge from node A to node B indicates that trader A sold to trader B



- Soft clustering of traders by their activity
- Aggregate trading patterns among clusters
- Behavior over time or by market
- Traders characterized by their “authority”
- Patterns in time or by market