

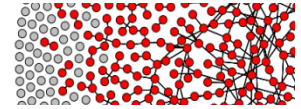
Scalable Methods for the Analysis of Network-Based Data

MURI Project: University of California, Irvine

Project Meeting

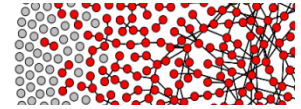
May 25th 2010

Principal Investigator: Padhraic Smyth



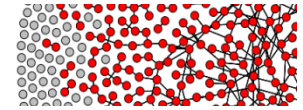
Today's Meeting

- Goals
 - Review our research progress
 - Discussion, questions, interaction
 - Feedback from visitors
- Format
 - Introduction
 - Research talks
 - 20 and 30 minute slots
 - 5 mins at end for questions/discussion
 - Question/discussion encouraged during talks
 - Several breaks for discussion



Project TimeLine

- Project start/end
 - Start date: May 1 2008
 - End date: April 30 2011/2013
- Meetings
 - Nov 2008: All-Hands Kickoff Meeting
 - April 2009: Working Meeting
 - August 2009: Working Meeting
 - December 2009: All-Hands Annual Review
 - May 2010: Working Meeting



MURI Investigators



Padhraic Smyth UCI



David Eppstein UCI



Carter Butts UCI



Michael Goodrich UCI



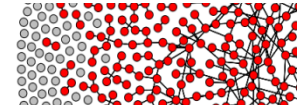
Mark Handcock
UCLA



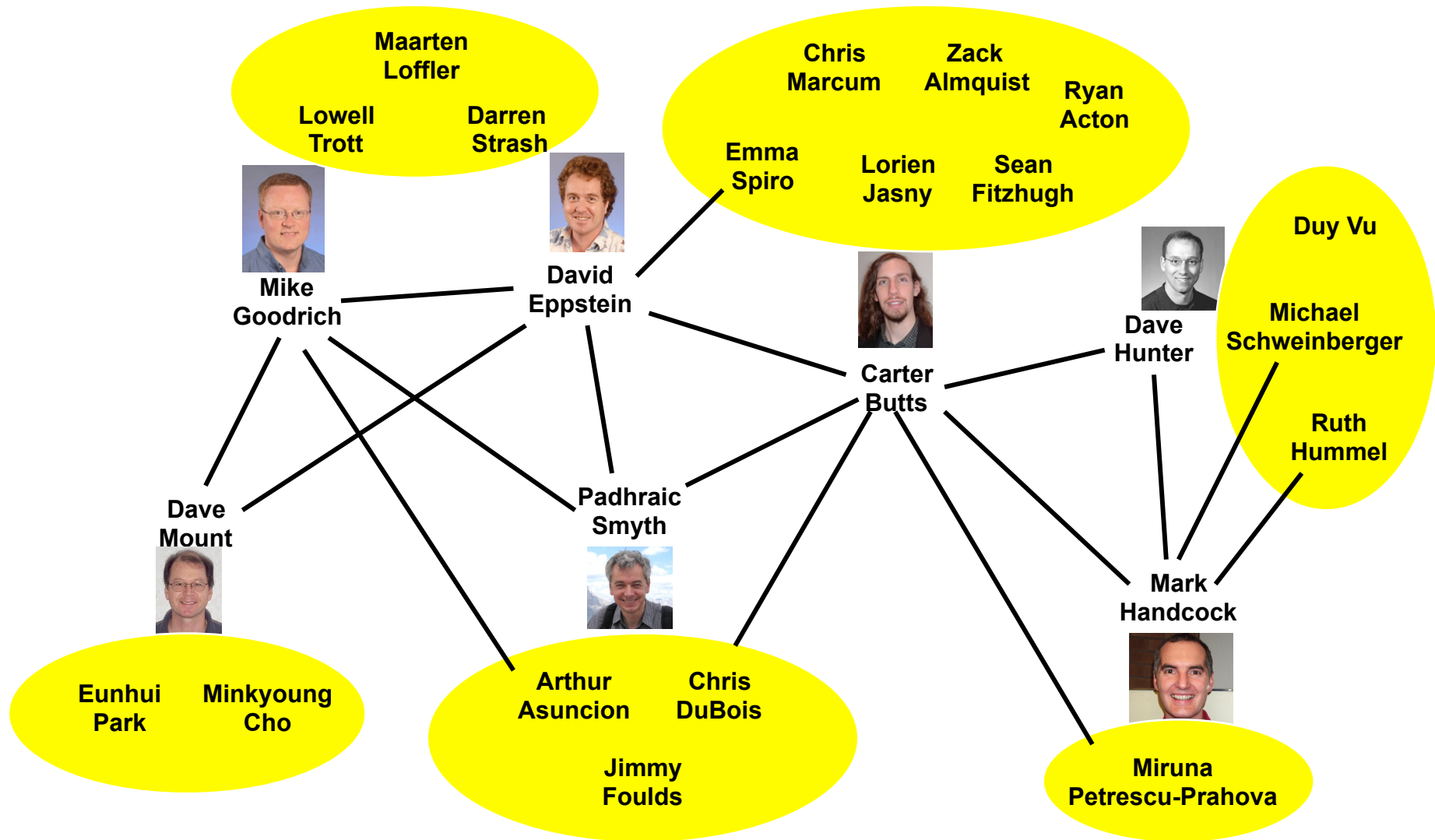
Dave Mount
U Maryland

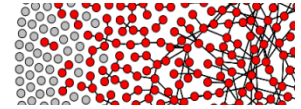


Dave Hunter
Penn State



Collaboration Network

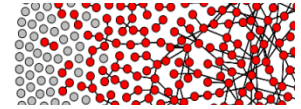




Graduate Student Progress

Highlights

- Presenting talks at multiple international conferences this summer
 - Sunbelt International Social Networks conference (Jasny, Spiro, Fitzhugh, Almquist)
 - ACM SIGKDD Conference (DuBois)
 - American Sociological Meeting (Marcum, Jasny, Spiro, Fitzhugh, Almquist)
 - + more
- Workshop organization/instruction
 - Political Networks Conference (Spiro, Fitzhugh, Almquist)
- Summer school on social network analysis
 - DuBois and Almquist received scholarships to attend
- Faculty position at U Mass Amherst (Acton)
- Best paper awards or nominations (Spiro, Hummel)
- National fellowships (DuBois, Asuncion)



Publications

Fundamentals of Exponential Random Graph Models and Network Analysis

Revisiting the foundations of network analysis, C.T. Butts, *Science*, 325, 414-416, 2009.

Scalable Algorithms for Statistical Network Modeling

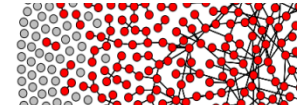
The h-index of a graph and its application to dynamic subgraph statistics, D. Eppstein & E. S. Spiro.

Proceedings of Algorithms and Data Structures Symposium (WADS), Springer-Verlag, Lecture Notes in Computer Science 5664, pp. 278-289, 2009.

A stepwise algorithm for fitting ERGMS, R.M. Hummel, M.S. Handcock, D.R. Hunter, Penn State Department of Statistics Technical Report 10-03, 2010.

Learning with blocks: composite likelihood and contrastive divergence, A. Asuncion, Q. Liu, A. T. Ihler, and P. Smyth. *Proceedings of the 13th International Conference on AI and Statistics*, May 2010.

Particle-filtered MCMC-MLE with connections to contrastive divergence, A. Asuncion, Q. Liu, A. Ihler, and P. Smyth, *Proceedings of the 27th International Conference on Machine Learning (ICML)*, to appear, 2010.



Publications

Geometric and Spatial Embedding Methods

Space-time tradeoffs for approximate nearest-neighbor searching, S. Arya, T. Malamatos, and D. M. Mount, *Journal of the ACM*, 57 (2009), 1-54.

Approximate range-searching: the absolute model, G. D. da Fonseca and D. M. Mount, *Computational Geometry*, 43:4, 434—444, 2010.

Approximation algorithm for the kinetic robust center algorithm, S. Friedler and D. M. Mount, *Computational Geometry*, 43(6-7), 572-586, 2010.

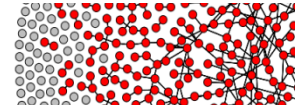
Maintaining nets and net trees under incremental motion, M. Cho, D. M. Mount, and E. Park, in *Proceedings of the 20th Intl. Symp. on Algorithms and Computation (ISAAC 2009)*, 1134-1143, 2009

Particle-based variational inference for continuous systems, A. T. Ihler, A. J. Frank, P. Smyth, *Proceedings of the 22nd Neural Information Processing Conference (NIPS)*, Dec 2009.

Succient greedy geometric routing in the Euclidean plane, M. T. Goodrich and D. Strash, in *Proceedings of the 20th Intl. Symp. on Algorithms and Computation (ISAAC 2009)*, 2009 (to appear).

The effect of corners on the complexity of approximate range searching, S. Arya, T. Malamatos, and D. M. Mount, *Discrete and Computational Geometry*, 41 (2009), 398-443.

Compressing kinetic data from sensor networks, S. Friedler and D. M. Mount, *Algorithmic Aspects of Wireless Sensor Networks (ALGOSENSORS 2009)*, Springer Lecture Notes LNCS 5804, 2009, 191-202.



Publications

Dynamic and Relational Event Models

Change and external events in computer-mediated citation networks: English language Weblogs and the 2004 electoral cycle, C. T. Butts and B. R. Cross, *Journal of Social Structure*, 10, 2010.

Modeling relational events via latent classes, C. DuBois and P. Smyth, *Proceedings of the 16th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, July 2010, in press.

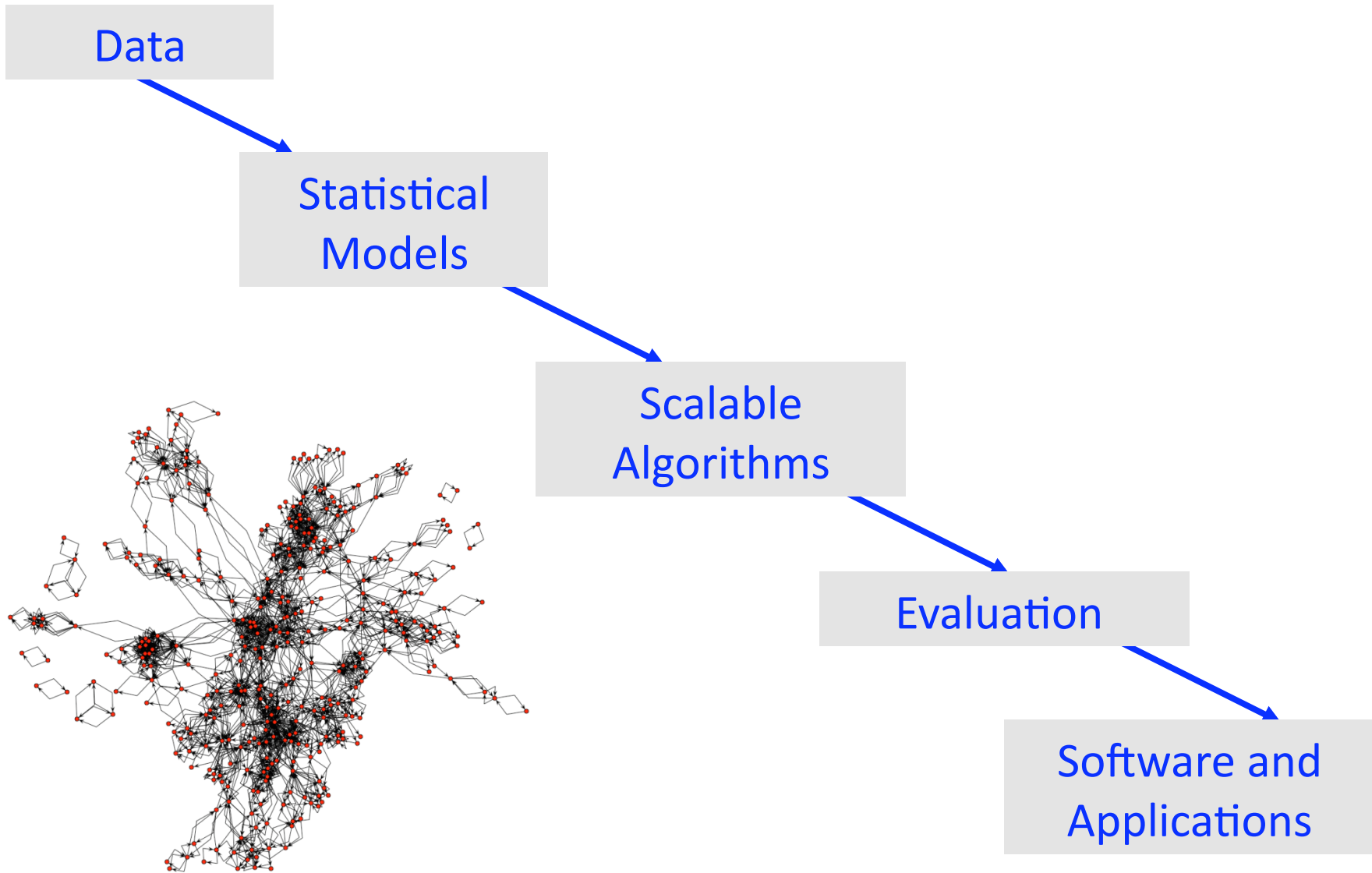
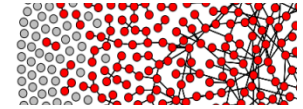
Statistical Modeling of Text and Networks

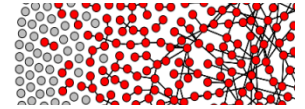
Distributed algorithms for topic models, D. Newman, A. Asuncion, P. Smyth, M. Welling, *Journal of Machine Learning Research*, 1801-1828, 2009.

Asynchronous distributed estimation of topic models for document analysis, , A. Asuncion, P. Smyth, M. Welling, *Statistical Methodology*, in press, 2010.

Measurement of Large Scale Networks

A walk in Facebook: uniform sampling of users in online social networks, M. Gjoka, M. Kurant, C. T. Butts, A. Markopoulou, *Proceedings of the IEEE Infocom Conference*, 2010





Statistical Modeling of Network Data

Statistics = principled approach for inference from noisy data

Integration of different sources of information

- e.g., combining edge information with node attributes

Basis for optimal prediction

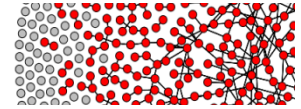
- computation of conditional probabilities/expectation

Principles for handling noisy measurements

- e.g., noisy and missing edges

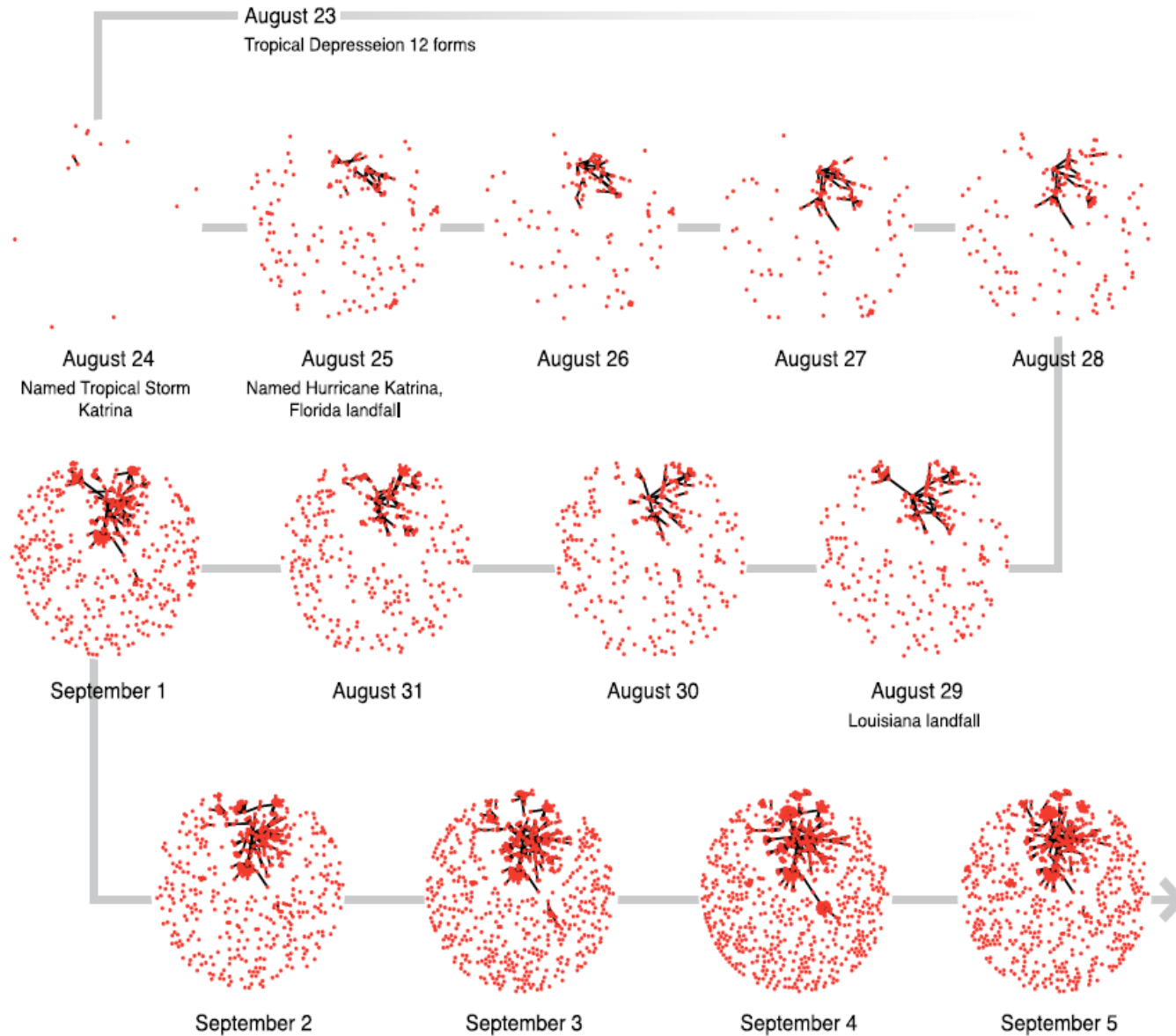
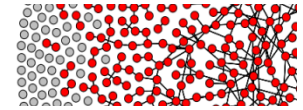
Quantification of uncertainty

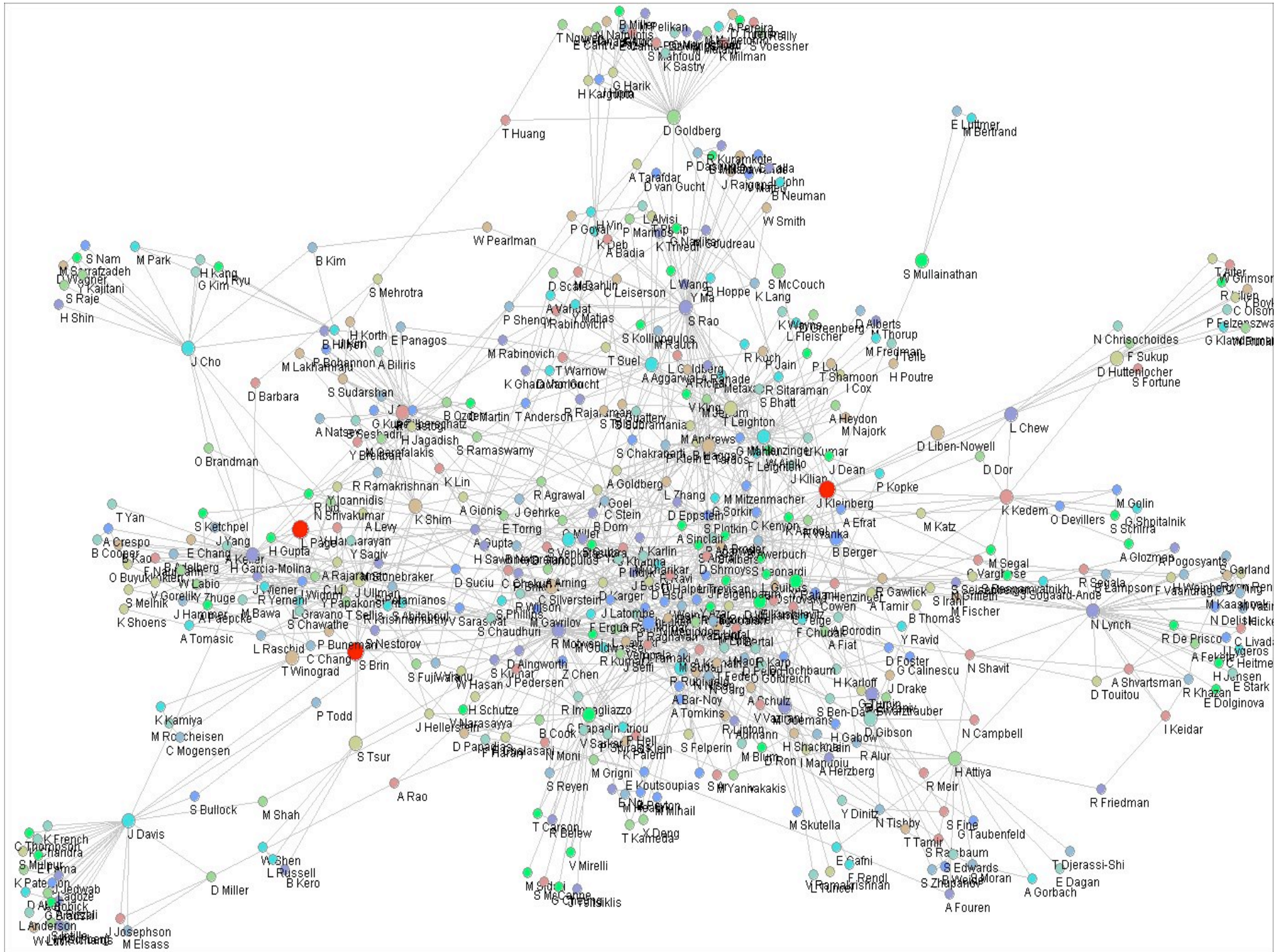
- e.g., how likely is it that network behavior has changed?

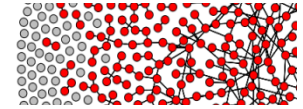


Limitations of Prior Work

- Network data over time
 - Relatively little work on dynamic network data
- Heterogeneous data
 - e.g., few techniques for incorporating text, spatial information, etc, into network models
- Computational tractability
 - Many network modeling algorithms scale exponentially in the number of nodes n
 - Limits practical network sizes to order of $n = 100$ nodes

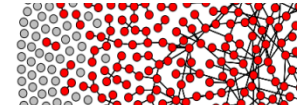






Computational Efficiency

- Parameter estimation can scale from $O(ne)$ to $O(2^{n(n-1)})$
- Algorithms and data structures for efficient computation
 - H-index for change-score statistics
 - Nets and net-trees
 - Efficient clique-finding algorithms



Example

- $G = \{V, E\}$

V = set of n nodes

E = set of directed binary edges

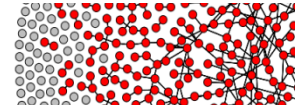
- Exponential random graph (ERG) model

$$P(G | \theta) = f(G; \theta) / \text{normalization constant}$$

The normalization constant = sum over all possible graphs

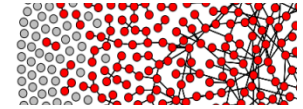
How many graphs? $2^{n(n-1)}$

e.g., $n = 50$, we have $2^{2450} \sim 10^{245}$ graphs to sum over

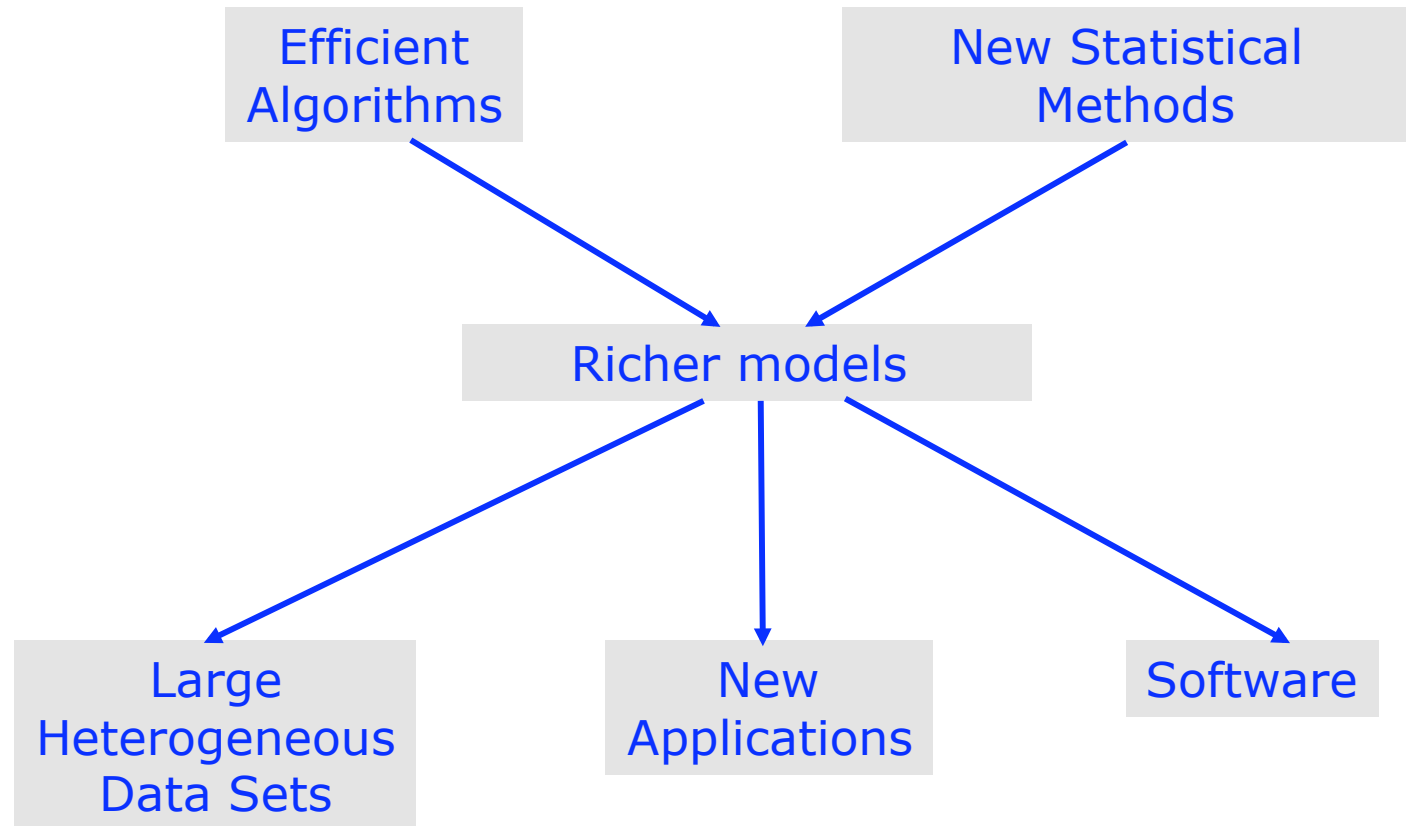


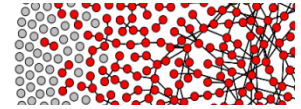
Key Themes of our MURI Project

- Research on new statistical estimation techniques and models
 - e.g., principles of modeling and predicting networks over time
- Faster algorithms
 - e.g., efficient data structures and algorithms for very large data sets
- New algorithms for heterogeneous network data
 - Incorporating spatial information, text, other covariates
- Software
 - Make network inference software publicly-available (in R)



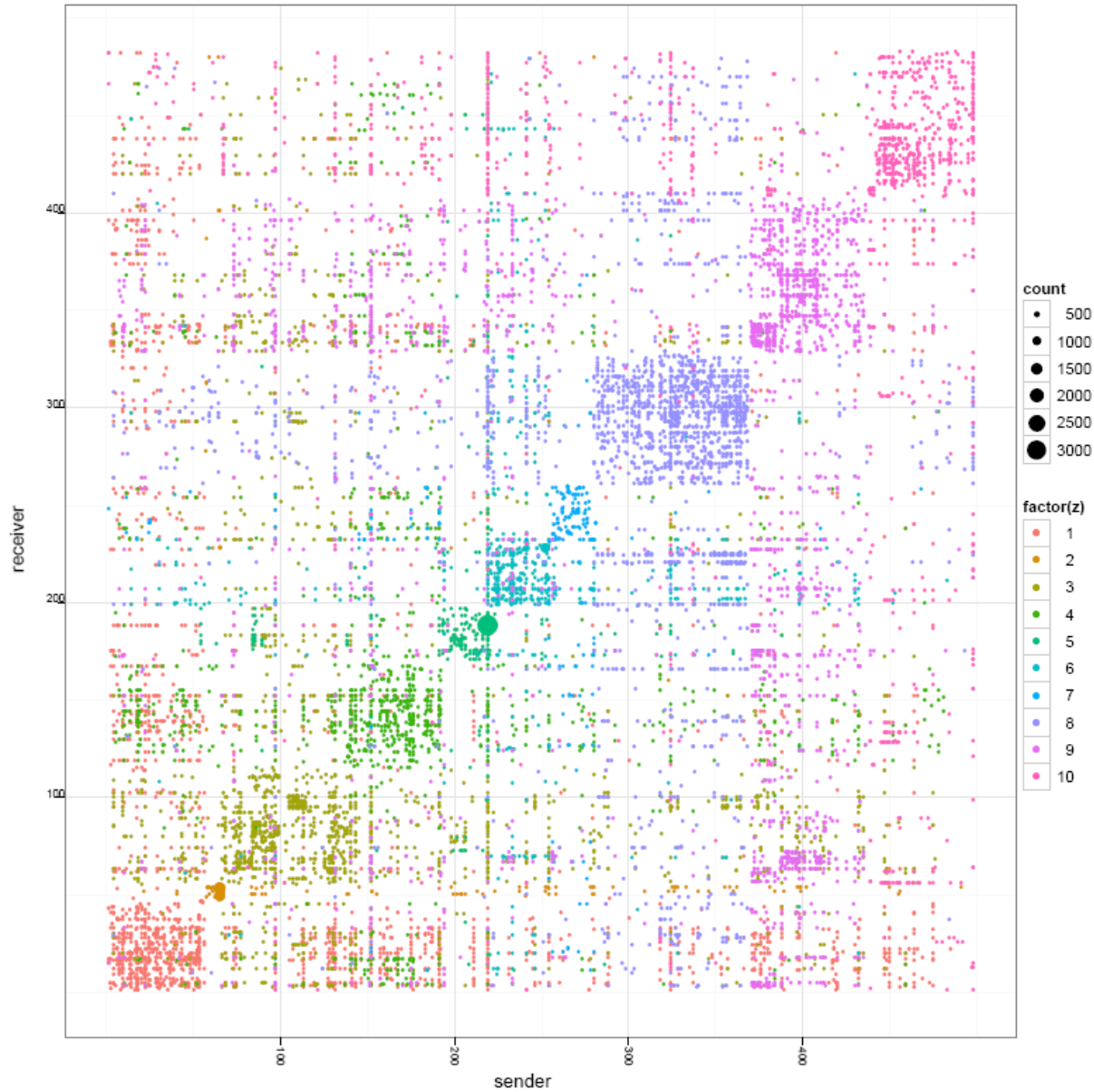
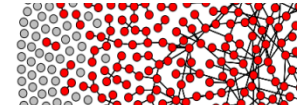
Key Themes of our MURI Project



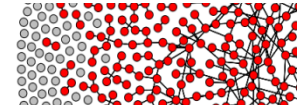


Complexities of Real Network Data

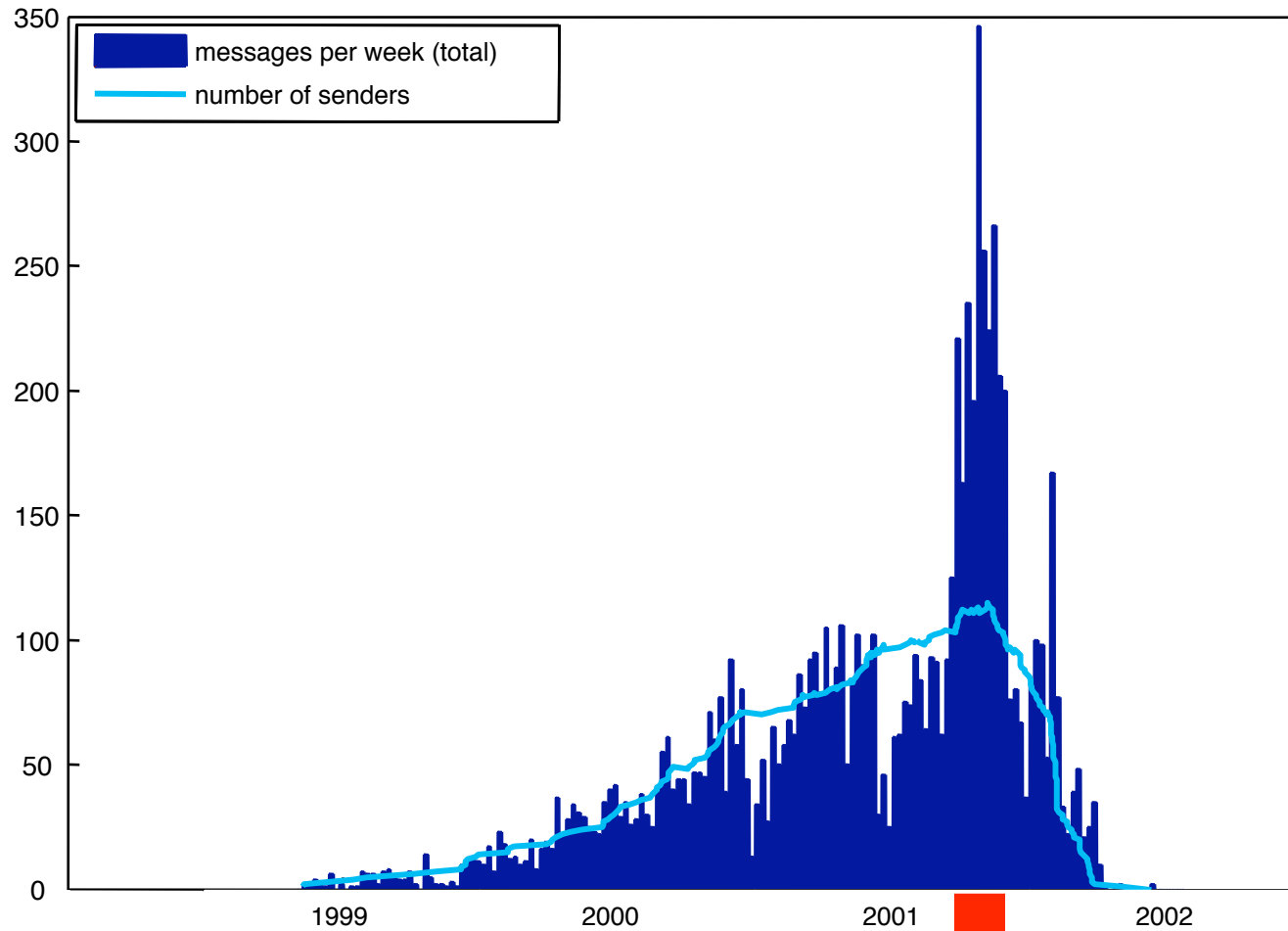
- Data types
 - Actors and ties
 - Covariates
 - Temporal events
 - Spatial
 - Text
- Structure
 - Hierarchies and clusters
- Measurement issues
 - Sampling
 - Missing data



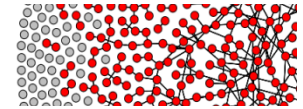
DuBois and Smyth, 2010



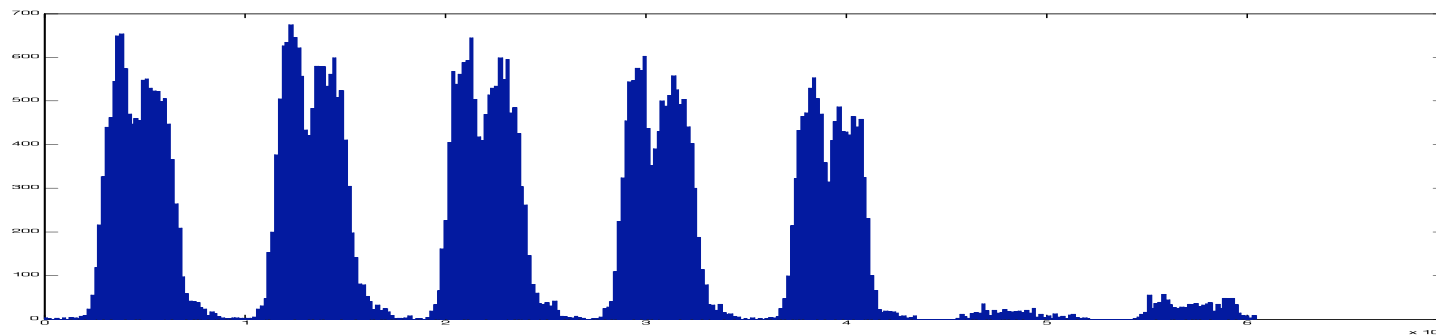
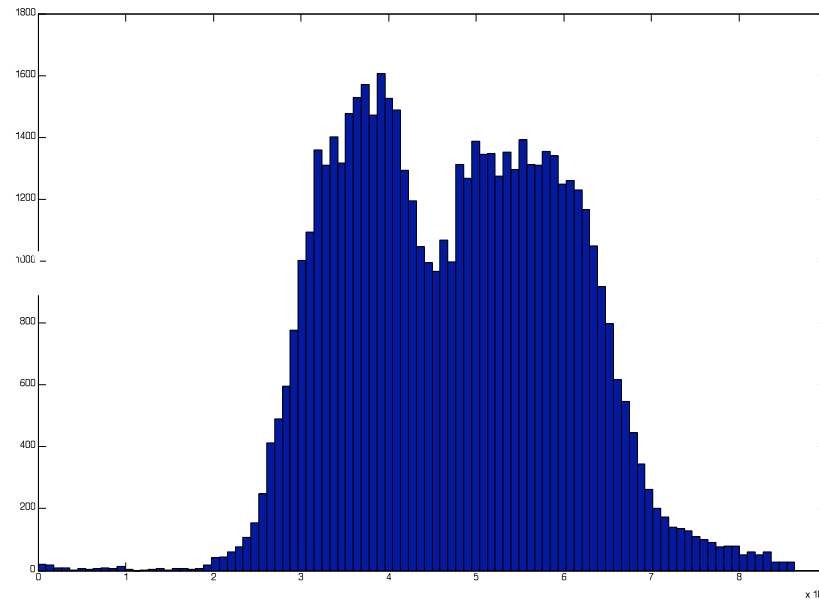
Enron Email Data

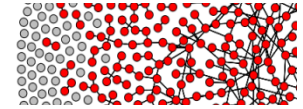


Sept 2001 (scandal revealed) to Dec 2001 (bankruptcy)



Daily and weekly variation

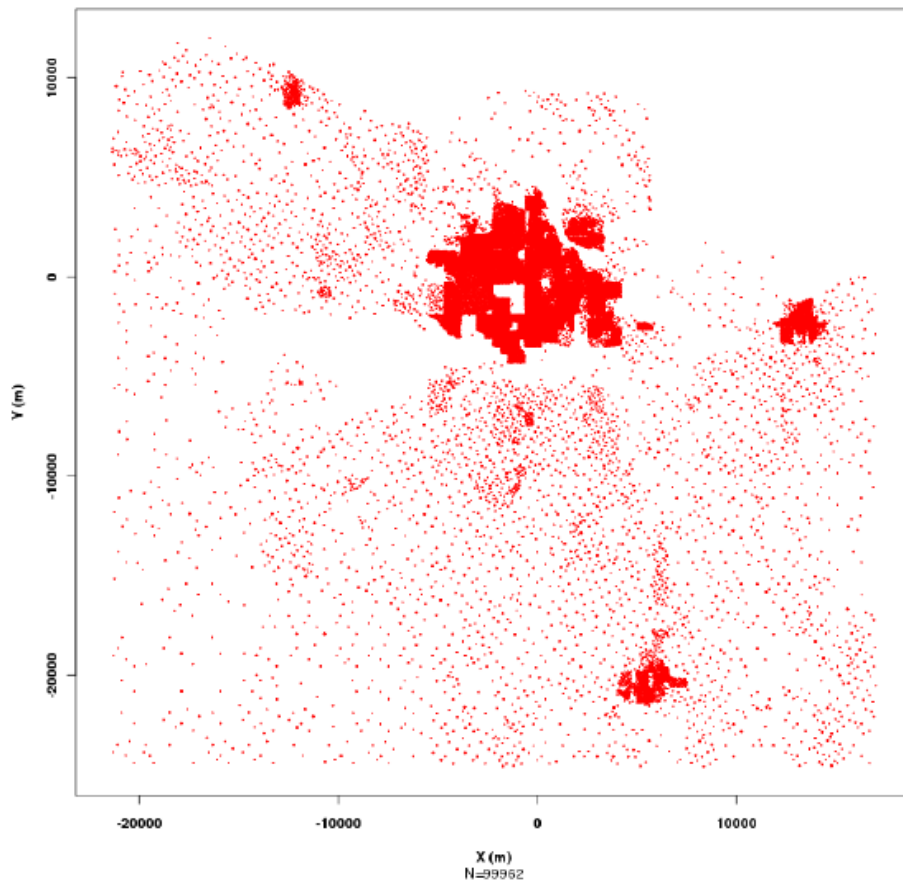




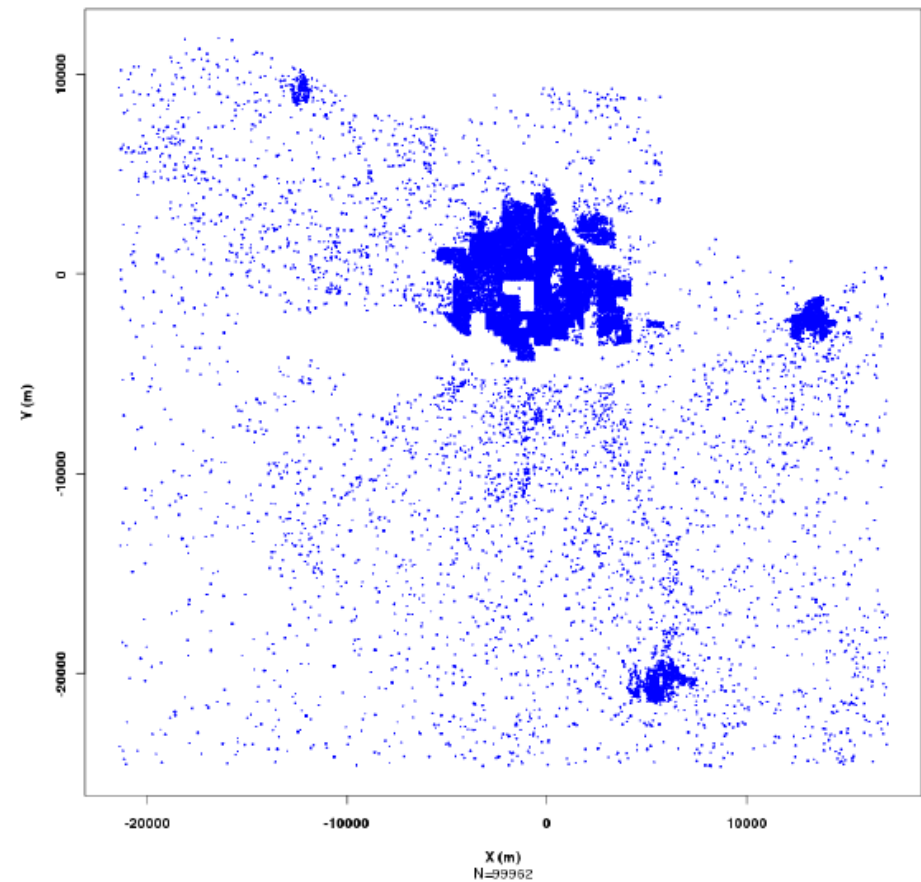
Spatially-Embedded Network Data

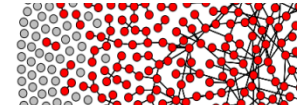
Butts, Acton, Almquist, 2009

Quasi-random Model



Uniform Model





Missing Data

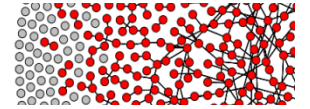
Handcock and Gile, 2008

$Y =$

	A	B	C	D
A	-	1	0	0
B	0	-	1	1
C	0	0	-	0
D	1	1	1	-

$Y_{\text{obs}} =$

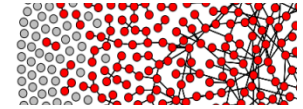
	A	B	C	D
A	-	?	?	?
B	?	-	?	?
C	0	0	-	0
D	1	1	1	-



Statistical Modeling Frameworks

- Exponential random graph models
- Latent-space models
- Relational event models

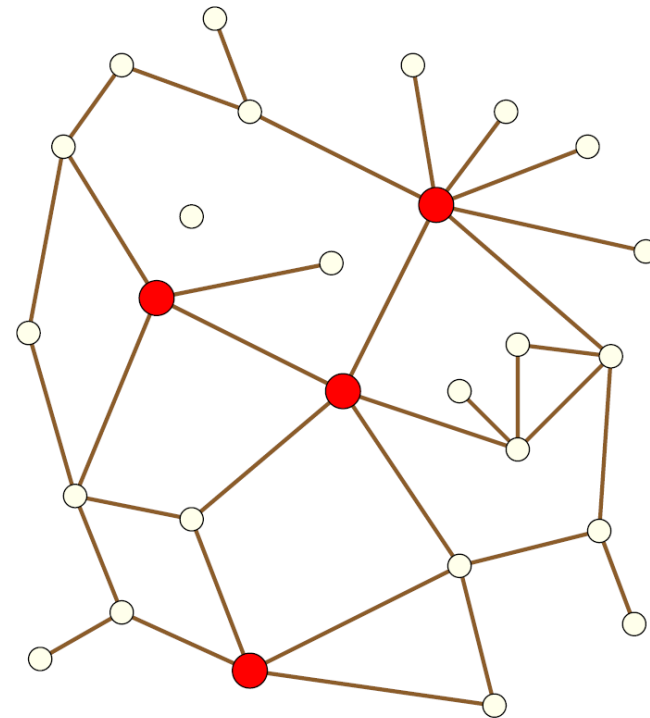
All 3 frameworks are related – many talks today will touch on at least one of these frameworks

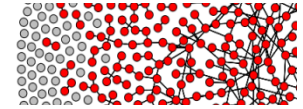


h-index Data Structures

Eppstein and Spiro, 2009

h-index = maximum number such that
h vertices each have at least h neighbors





h-index Data Structures

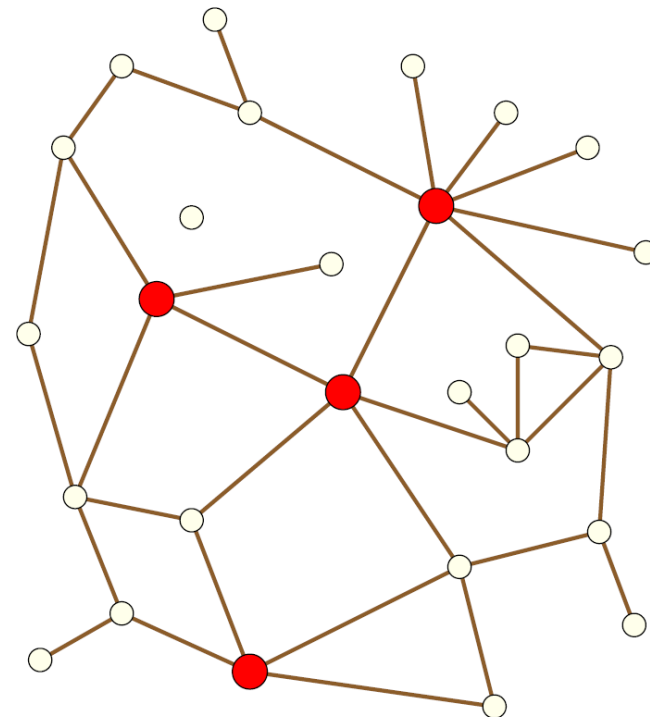
Eppstein and Spiro, 2009

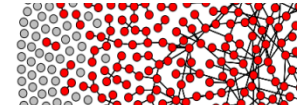
h-index = maximum number such that
h vertices each have at least h neighbors

H = set of h high-degree vertices

L = remaining vertices

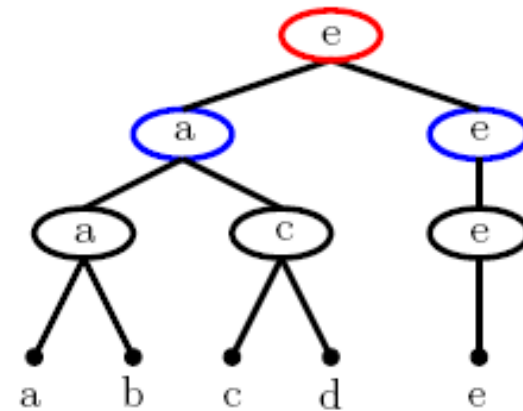
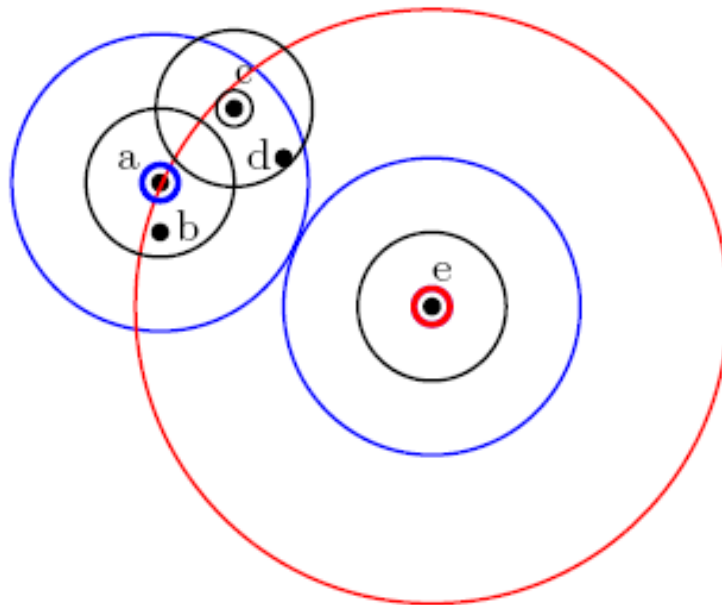
Can use H/L partitioning to efficiently
compute and track graph statistics in
statistical estimation algorithms

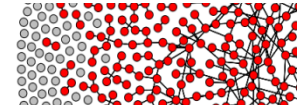




Nets and Net Trees

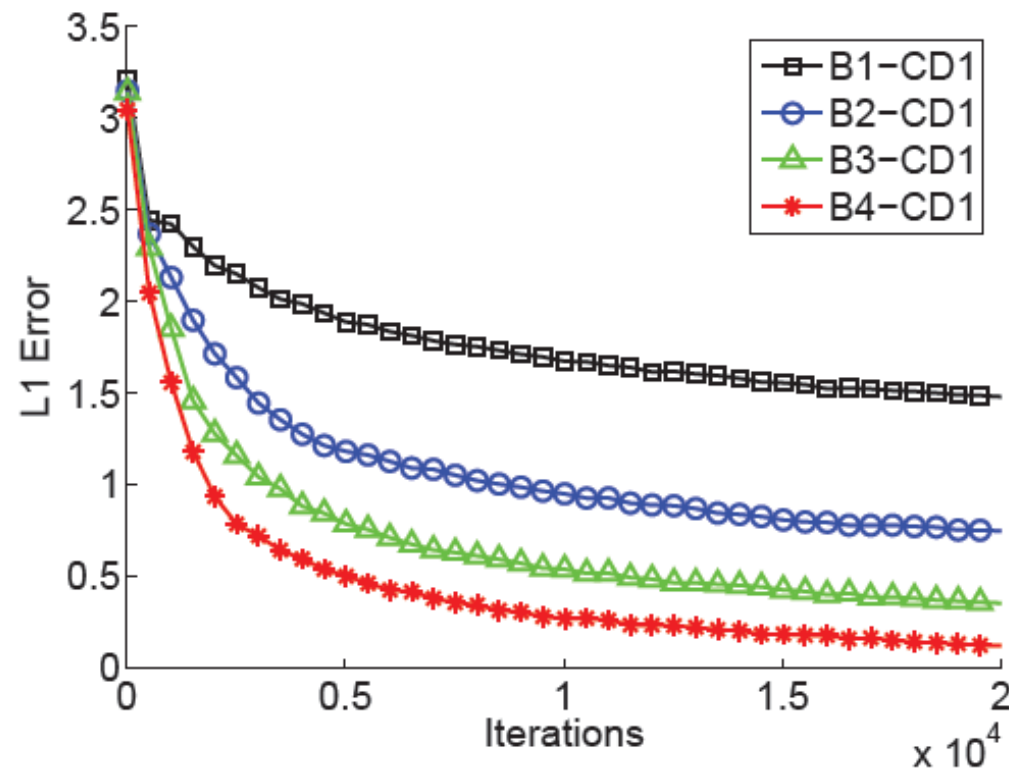
Cho, Mount, Park, 2009

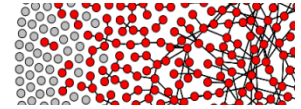




Fast Sampling Methods

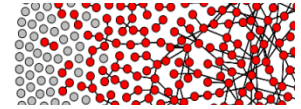
Asuncion et al, 2009





Evaluation and Prediction

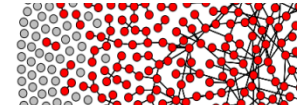
- Evaluate algorithms on large real-world data sets
 - Disaster response
 - Katrina communication networks, World Trade Center disaster response data
 - Networks of documents
 - Political blogs, Wikipedia
 - Social activities on the Web
 - Twitter data, Facebook networks, email communication networks
 - International relations
 - ... and more
- Evaluation metrics
 - Computational efficiency
 - Goodness of fit and predictive accuracy



ONR Interests

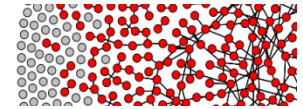
(adapted from presentation/discussion in Nov 2008 by Martin Kruger, ONR)

- How does one select the features in an ERG model?
- How can one uniquely characterize a person or a network?
- Can a statistical model (e.g., a relational event model) be used to characterize the trajectory of an individual or a network over time?
- Can one do “activity recognition” in a network?
- Can one model the effect of exogenous changes (e.g., “shocks”) to a network over time?
- Importance of understanding social science aspect of network modeling: what are human motivations and goals driving network behavior?



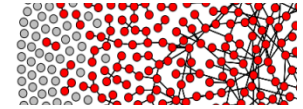
Morning Session I

- 9:00 Introduction and review of project progress
Padhraic Smyth (UCI)
- 9:20 Implementation issues for latent-space embeddings
David Mount (U Maryland)
- 9:40 Near-optimal fixed parameter tractability of the Bron-Kerbosch
algorithm for maximal cliques
Darren Strash (UCI)
- 10:10 Methods for analysis of behavioral time-use data
Chris Marcum (UCI)
- 10:30 BREAK



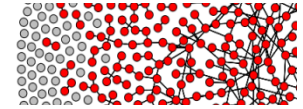
Morning Session II

- 10:50 Mixture models for event-based network data
Chris DuBois (UCI)
- 11:10 Static and dynamic robustness in emergency-phase communication networks
Sean Fitzhugh (UCI)
- 11:30 Bernoulli graph bounds for general random graph models
Carter Butts (UCI)
- LUNCH BREAK
- 12:00 Lunch for ALL meeting participants in 4011



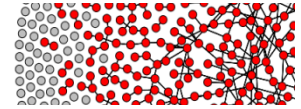
Afternoon Session I

- 1:30 Social network analysis of Twitter data
Emma Spiro (UCI)
- 2:00 Logistic network regression for scalable analysis of dynamic relational data:
an overview and case study
Zack Almquist (UCI)
- 2:20 Latent feature models for network data over time
Jimmy Foulds (UCI)
- 2:40 New directions in greedy routing on social networks: the membership dimension
Lowell Trott (UCI)
- 3:10 BREAK



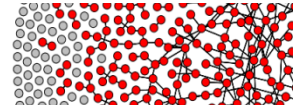
Afternoon Session II

- 3:30 Bias-adjusted maximum likelihood estimation methods
Dave Hunter (Penn State)
- 3:50 Composite likelihood methods for network estimation
Arthur Asuncion (UCI)
- 4:10 Discussion and Wrap-up
- AHM meeting in November/December
 - collaborative activities
 - action items
- 4:30 ADJOURN

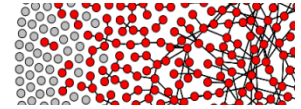


Logistics

- Meals
 - Lunch in this room, 12 noon
 - Refreshment breaks at 10:30 and 3:10
- Wireless
 - Should be able to get 24-hour guest access from UCI network
- Slides will be posted online on the project Web site
www.datalab.uci.edu/muri
- **Questions and discussion are encouraged during talks!**



Questions?



Preprints

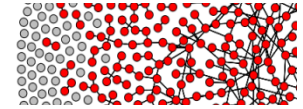
R.M. Hummel, M.S. Handcock, D.R. Hunter, A steplength algorithm for fitting ERGMs, submitted, 2009

C. T. Butts, A behavioral micro-foundation for cross-sectional network models, preprint, 2009

C. T. Butts, A perfect sampling method for exponential random graph models, preprint, 2009

A. Asuncion and M. Goodrich, Turning privacy leaks into floods: Surreptitious discovery of Facebook friendships and other sensitive binary attribute vectors, submitted, 2009.

A. Asuncion, Q. Liu, A. Ihler, P. Smyth, Learning with blocks: composite likelihood and contrastive divergence, submitted, 2009.



Tasks

A: Fast network estimation algorithms

Eppstein, Butts

B: Spatial representations and network data

Goodrich, Eppstein, Mount

C: Advanced network estimation techniques

Handcock, Hunter

D: Scalable methods for relational events

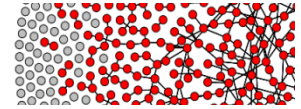
Butts

E: Network models with text data

Smyth

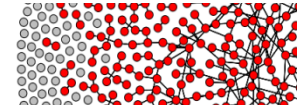
F: Software for network inference and prediction

Hunter



Estimation Algorithms

- We want $P(\text{parameters} \mid \text{data})$
- Exact algorithms are rare
- Approximate search
 - E.g., Markov chain Monte Carlo
- Exact solution of simpler objective function
 - E.g., pseudolikelihood v. likelihood



Collaboration Network

