MS157: Advances in Dynamic Graphs: Algorithms, Applications and Challenges

Part I 09:10-10:50

09:10-9:30	**Advances in algorithms and applications for dynamic graphs** **<u>A. Kalyanaraman</u>, M. Halappanavar**
09:35-09:55	**Dynamic networks for microbial biofilms** **R. Marculescu, <u>C. Lo</u>**
10:00-10:20	**Dynamic brain networks** **<u>K. Eschenberg</u>, T. Grabowski, D. Haynor**
10:25-10:45	**Quantitative assessment of transportation network vulnerability with dynamic traffic simulation methods** **<u>V. Shekar</u>, S. Chatterjee, M. Halappanvar, L. Fiondella**

MS184: Advances in Dynamic Graphs: Algorithms, Applications and Challenges

Part II 13:30-15:10

13:30-13:50	**Models for principled characterization of dynamic, spatially embedded, multiscale networks** **D.S. Bassett, <u>R. Betzel</u>**
13:55-14:15	**Scalable algorithms for graph matching and edge cover computations** **A. Pothen, <u>A. Khan</u>**
14:20-14:40	**Massive scale streaming analytics for dynamic graphs** **<u>D.A. Bader</u>**
14:45-15:45	**Dynamic network analysis: From inference to insight** **<u>T. Berger-Wolf</u>**

Advances in Algorithms and Applications for Dynamic Graphs

Ananth Kalyanaraman
Associate Professor,
Boeing Centennial Chair in CS,
School of EECS, Washington State University, Pullman, WA

Mahantesh Halappanavar
Senior Scientist,
Data Science group,
Pacific Northwest National Lab.
Richland, WA

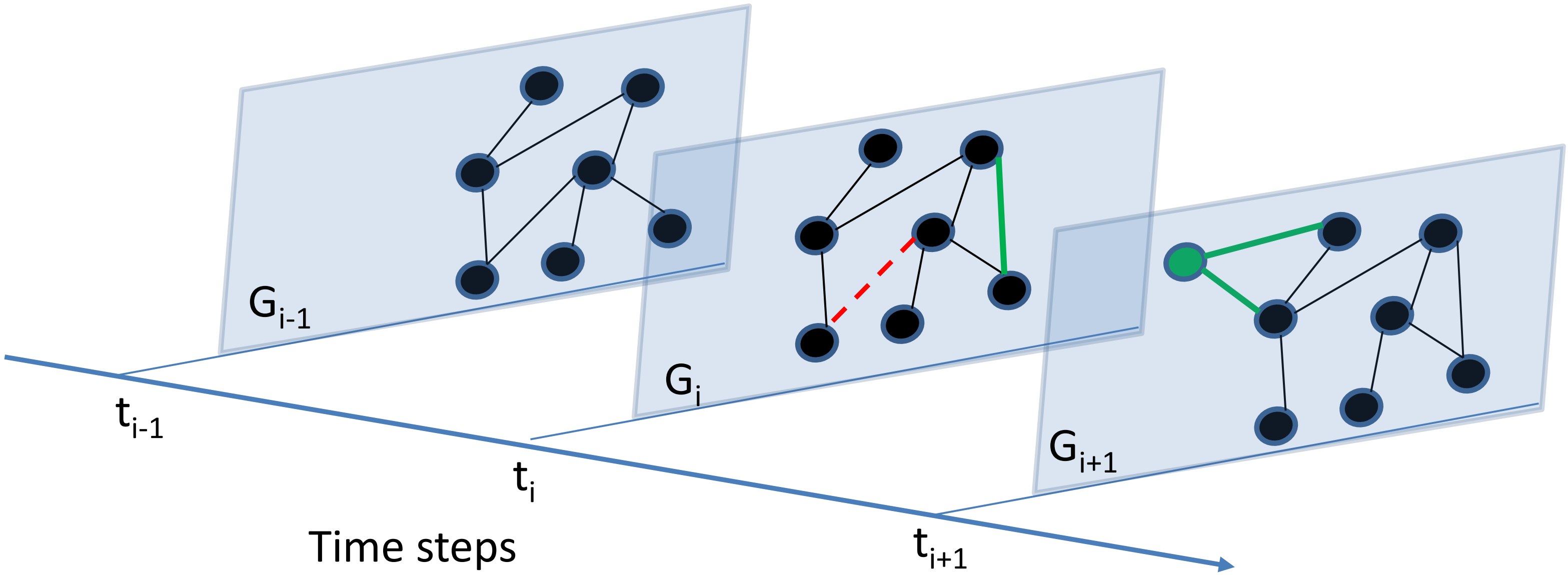
SIAM CSE, Advances in Dynamic Graphs, Minisyposium, Atlanta, GA
March 1, 2017

Talk outline

- Dynamic networks – an overview
- Applications
- Representations
- Measures
  - Connectivity measures
  - Mesoscale measures
  - Information spread
- Challenges
- References

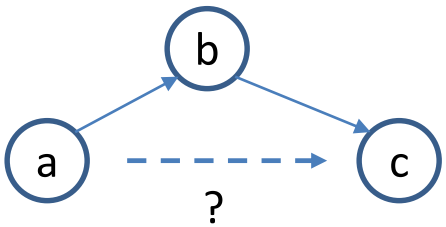
Dynamic networks

- Dynamic graphs
  - Abstract graph representations used to capture *dynamical systems*
  - Evolving networks
    - Vertices and edges can be added/removed
    - Multi-stage, time-varying (temporal)

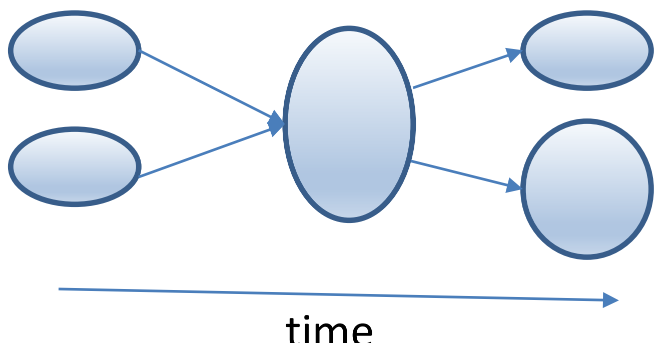


Dynamic vs. Static Networks

- Dynamic networks are different from static networks in multiple ways
  - Edge transitivity
    - Contact sequence



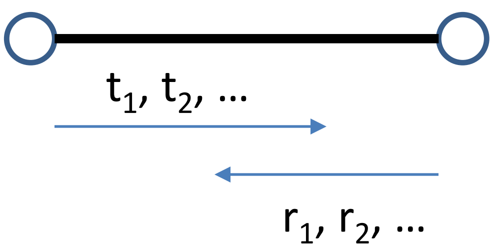
  - Structural properties may evolve
    - e.g., random to structured
    - Variable resolution needed



  - Goal is to study and track the network, to make inferences about an underlying dynamical system

Two Types of Dynamic Graphs

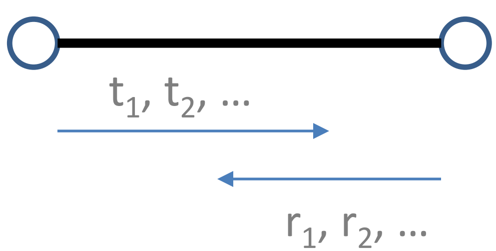
- *(topology)* Links persist
- *(contact)* Link traffic varies over time
  - Active vs. Idle
- E.g., internet



If traffic is much faster
than topological changes
=> Static modeling adequate

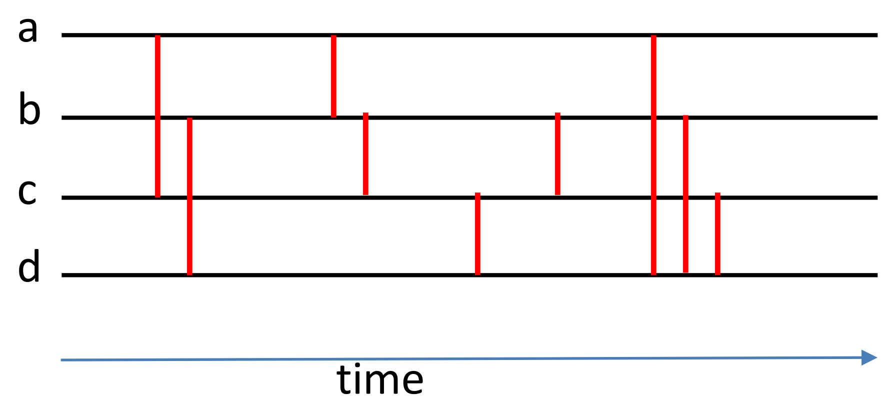
Two Types of Dynamic Graphs

- (topology) Links persist
- (contact) Link traffic varies over time
  - Active vs. Idle
- E.g., internet



If traffic is much faster
than topological changes
=> Static modeling adequate

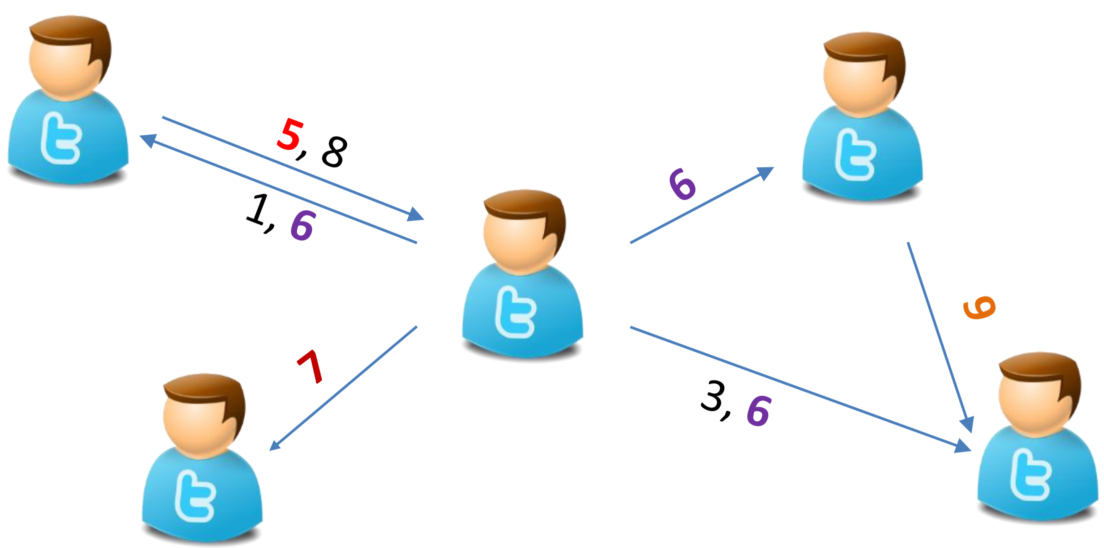
- Topology changes with time and contact
- *Time-varying networks*



Contact sequence: <a,c,t_1>
(edges) <b,d,t_2>
<a,b,t_3>
<b,c,t_4>
…

Applications: Digital Communication

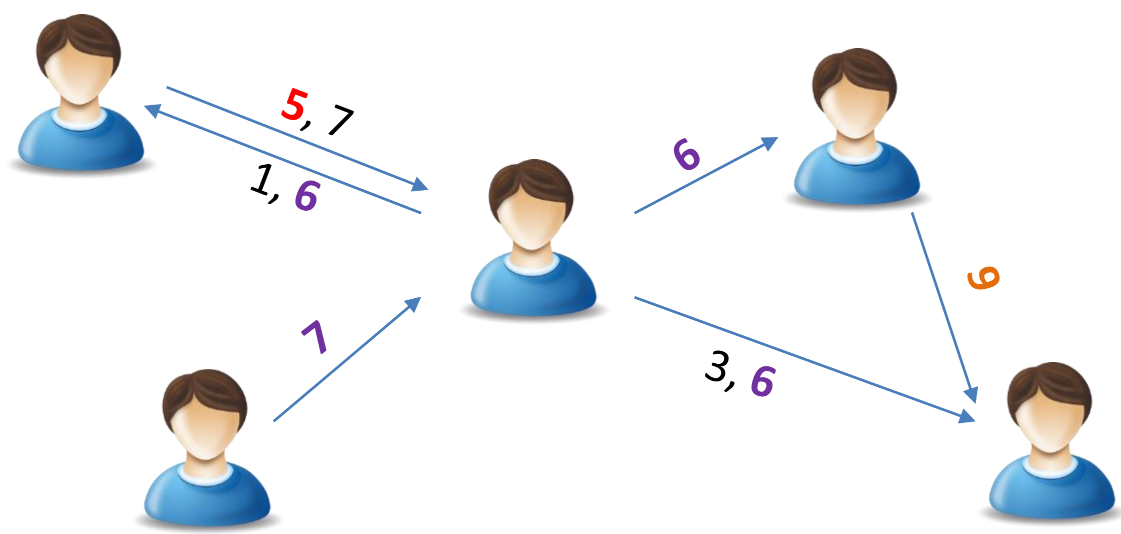
- <u>Nodes:</u> People/Users
- <u>Edges:</u> Person-person communication



Contact sequence matters

Applications: Contagion Networks

- Infectious disease epidemics can be modeled with a human contact network
- Nodes: human (+ other species)
- Edges: contact

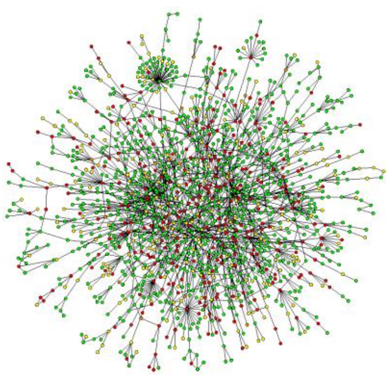


Infection spread
=
f(
Sequence of contact,
Duration of contact,
Type of contact,
Burstiness of contact
)

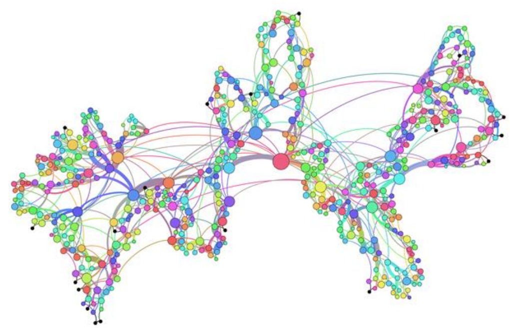
Outbreak prediction, HAIs (e.g., MRSA), Host-Pathogen exchanges

Applications: Biological Networks

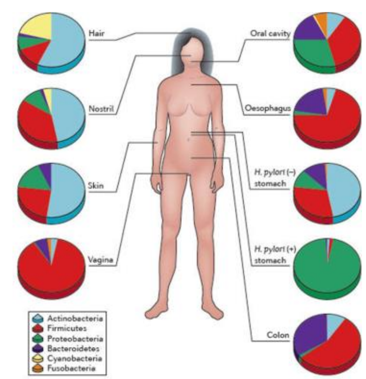
- Molecules and cells interact to form complexes and bioproducts
- <u>Nodes:</u> proteins/metabolites/cells/organisms
- <u>Edges:</u> molecular/cellular interaction and exchanges



Protein-Protein Int.
(static)



Metabolic networks
(dynamic)



Microbiomes
(dynamic)

Image credits: quantamagazine.org

Applications: Brain Networks

- Brain imaging (EEG, fMRI) captures neuron activities in different regions of the brain (spatio-temporal networks)
- <u>Nodes:</u> brain voxels
- <u>Edges:</u> neuron signaling, functional correlation

- Other examples:
  - Ecological networks
  - Transportation networks
  - Power grid

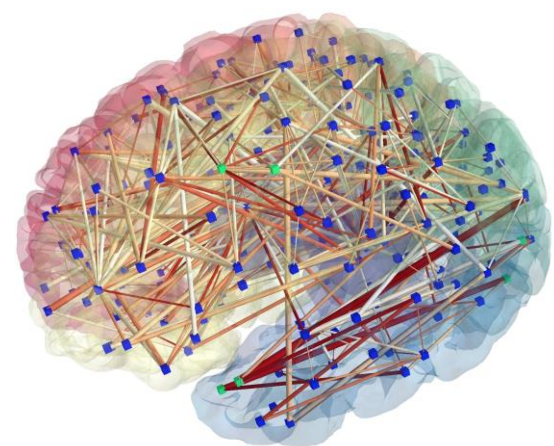
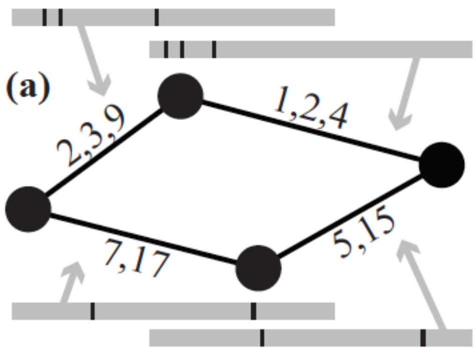


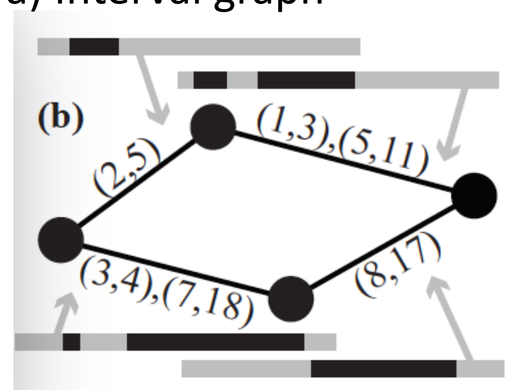
Image credits: Patric Hagmann, CHUV-UNIL, Lausanne, Switzerland

Dynamic Graph **Representations**

a) Contact sequence



a) Interval graph



c) Graphs at different time slices

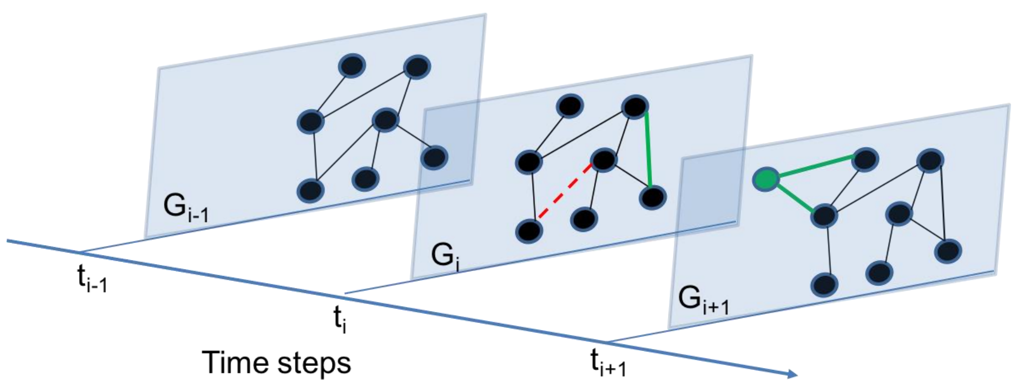


Image credits: Holme, P. and Saramäki, J., 2012. Temporal networks. *Physics reports*, *519*(3), pp.97-125.

Structural **Measures**

- **Path enumeration** methods need to be time-respecting
  - Identification of time-respecting paths (Kempe et al. 2000)
  - Identification of strongly and weakly connected components (Nicosia et al. 2012)
- **Distance** measures
  - Shortest path computations have a connotation in time (latency, time steps required for message propagation)
  - Identification of temporally shortest paths (Pan, Saramaki, 2011)

Centrality and Random Walk

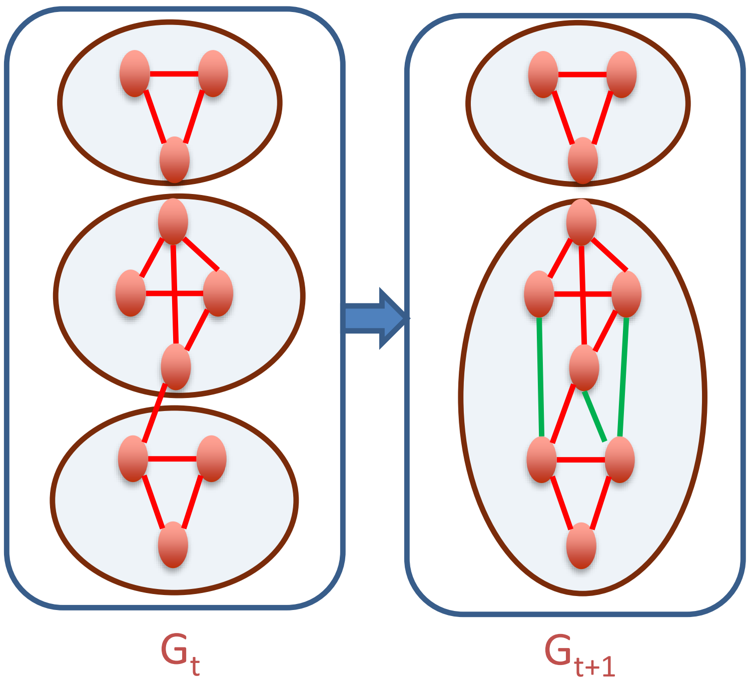
- **Time-dependent centrality** of an edge (or vertex) is related to the temporal role of that edge (vertex)
  - Notion of time-dependent centrality (Moody, 2002)
  - Reduciblity to a static network with directed flow problem (Kim, Anderson, 2012)
- **Random walk** explorations are known to be slower on temporal networks (Starnini et al. 2012, Avin et al. 2008)

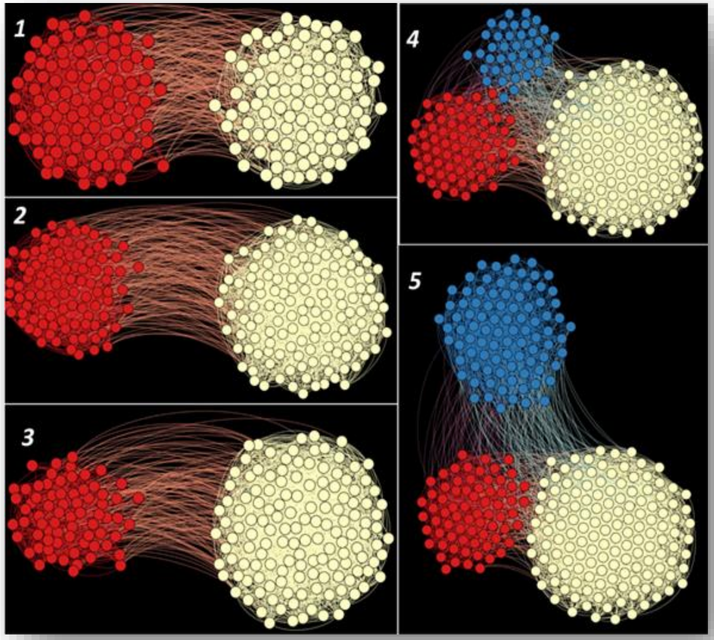
Mesoscale Properties

- **Small-world** properties of temporal networks defined based on links being clustered in time (Tang et al. 2010)
- Dynamic **community detection**
  - Community tracking
  - Merges, Splits, Exchanges
  - Birth, Death, Resurgence
- Algorithms and modularity measures redefined
  - Mucha et al. 2010, Berger-Wolf et al. 2010

Community Detection for Dynamic Graphs

- Parallel clustering frameworks
  (seeded vs. unseeded analysis)
- Generation of synthetic benchmarks



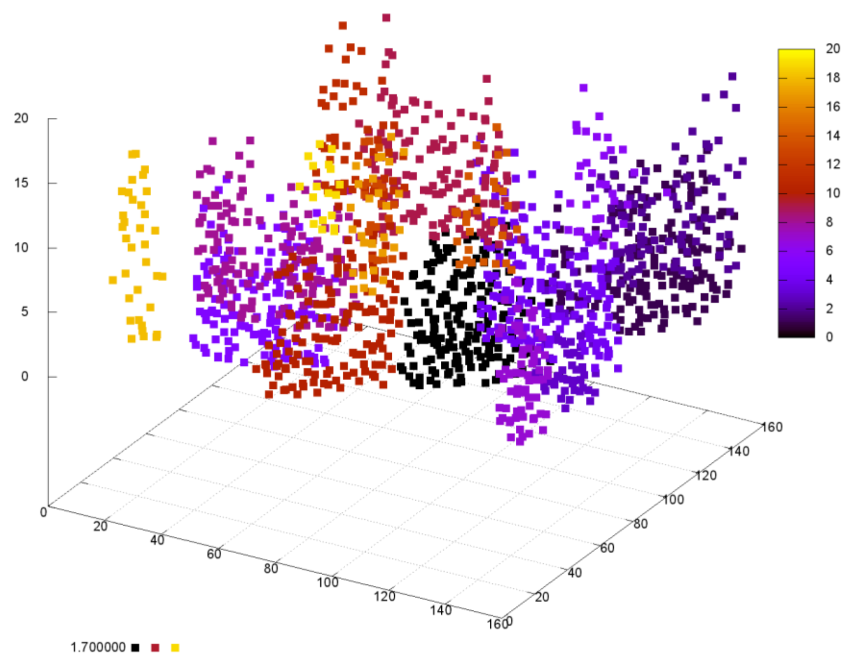


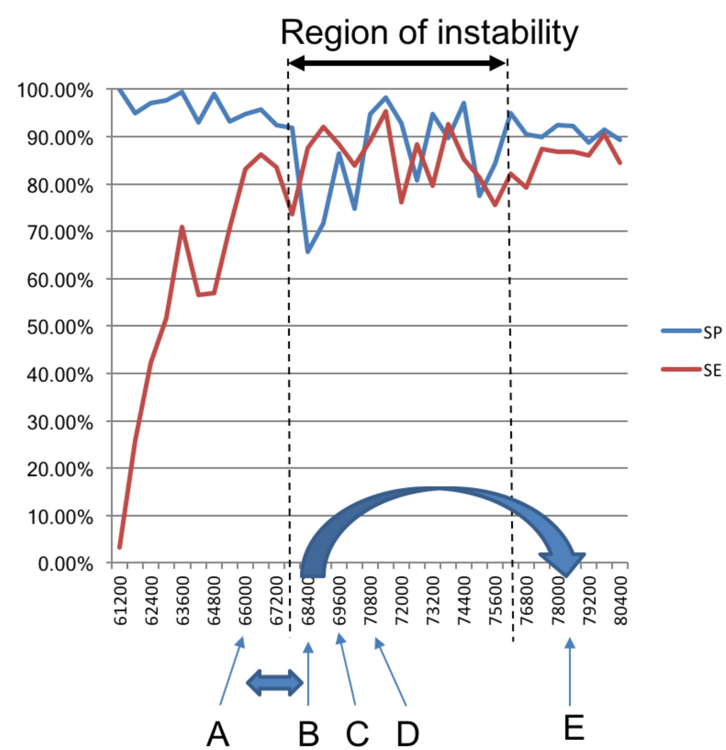
Joint work with M. Halappanavar, A. Sathanur, H. Lu

Community Detection

- Application benchmarks

Capturing biofilm community dynamics





Joint work with R. Marculescu, C. Lo and H. Lu

Challenges

- Generative models
  - Contact probability in time
  - Application context
- Benchmarks
- Persistence properties and metrics
- Scalability
- Visualization
- Real world applications

Selected References

Measures and algorithms on temporal networks:

Kempe, D., Kleinberg, J. and Kumar, A., 2000, May. Connectivity and inference problems for temporal networks. In *Proceedings of the thirty-second annual ACM symposium on Theory of computing* (pp. 504-513). ACM.

Nicosia, V., Tang, J., Musolesi, M., Russo, G., Mascolo, C. and Latora, V., 2012. Components in time-varying graphs. *Chaos: An interdisciplinary journal of nonlinear science*, *22*(2), p.023101.

Pan, R.K. and Saramäki, J., 2011. Path lengths, correlations, and centrality in temporal networks. *Physical Review E*, *84*(1), p.016105.

Moody, J., 2002. The importance of relationship timing for diffusion. *Social Forces*, *81*(1), pp.25-56.

Kim, H. and Anderson, R., 2012. Temporal node centrality in complex networks. *Physical Review E*, *85*(2), p.026107.

Clauset, A. and Eagle, N., 2012. Persistence and periodicity in a dynamic proximity network. *arXiv preprint arXiv:1211.7343*.

Tang, J., Scellato, S., Musolesi, M., Mascolo, C. and Latora, V., 2010. Small-world behavior in time-varying graphs. *Physical Review E*, *81*(5), p.055101.

Mucha, P.J., Richardson, T., Macon, K., Porter, M.A. and Onnela, J.P., 2010. Community structure in time-dependent, multiscale, and multiplex networks. *science*, *328*(5980), pp.876-878.

Berger-Wolf, T., Tantipathananandh, C. and Kempe, D., 2010. Dynamic community identification. In *Link Mining: Models, Algorithms, and Applications* (pp. 307-336). Springer New York.

Lu, H., Halappanavar, M. and Kalyanaraman, A., 2015. Parallel heuristics for scalable community detection. *Parallel Computing*, *47*, pp.19-37.

Review articles on temporal networks and related topics:

Holme, P. and Saramäki, J., 2012. Temporal networks. *Physics reports*, *519*(3), pp.97-125.

Casteigts, A., Flocchini, P., Quattrociocchi, W. and Santoro, N., 2012. Time-varying graphs and dynamic networks. *International Journal of Parallel, Emergent and Distributed Systems*, *27*(5), pp.387-408.

Aggarwal, C.C., 2011. An introduction to social network data analytics. In *Social network data analytics* (pp. 1-15). Springer US.