The future of complex networks:

statistics, algorithms and causality

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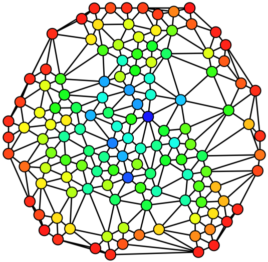
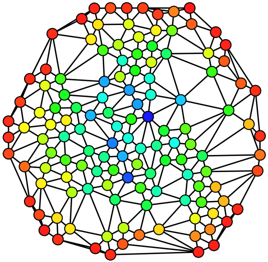
October 11, 2017
National Academies: Leveraging Advances in Social Network Thinking for National Security



- Networks are everywhere

Image source: Wikimedia



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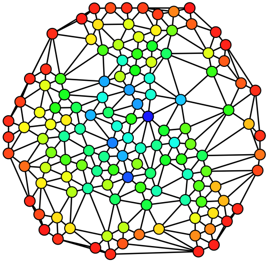

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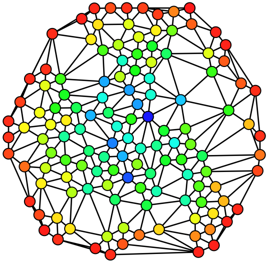

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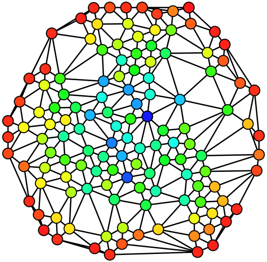

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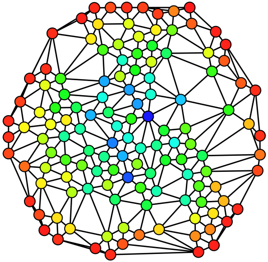

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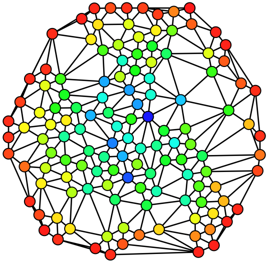

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Address **statistical**, **engineering** and **substantive** problems

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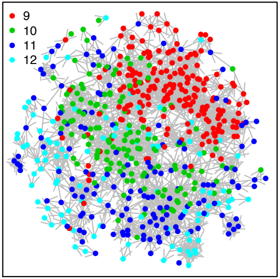
Statistical and substantive

- Datasets: PROSPER, NSCR, AddHealth



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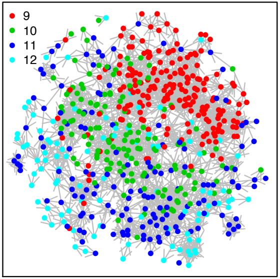

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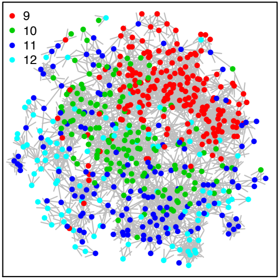
- Literature: ERGM, latent variable models



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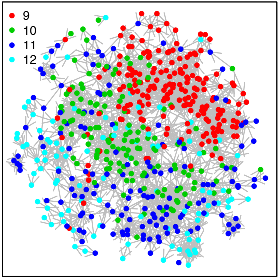

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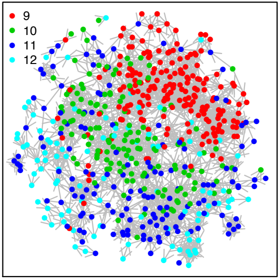
  - Censored observations



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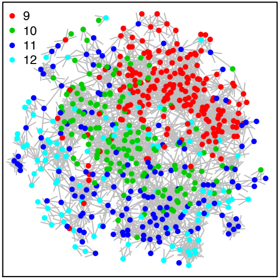
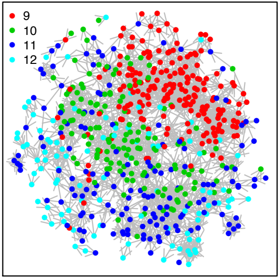


Hoff, Fosdick, Volfovsky and Stovel (2013) introduces a likelihood that accommodates the ranked and censored nature of data from Fixed Rank Nomination (FRN) surveys and allows for estimation of regression effects.

Difficulties that come up

- Communities are frequently based on more than one attribute.



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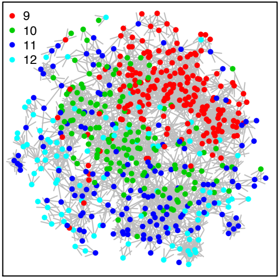

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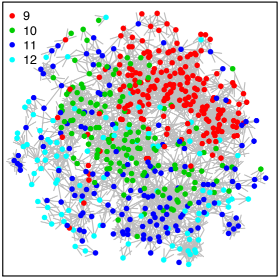

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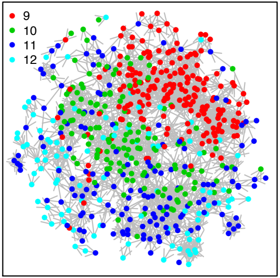

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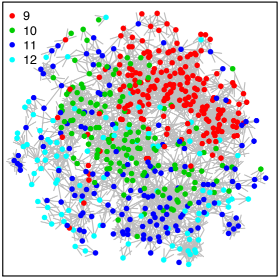

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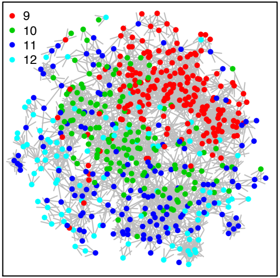
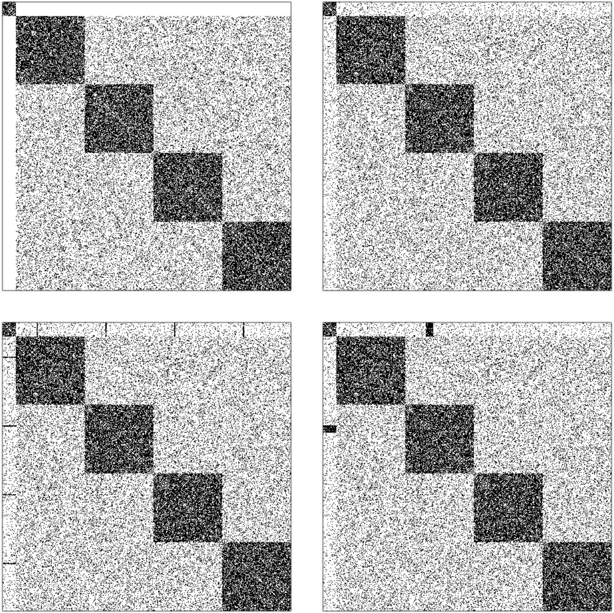
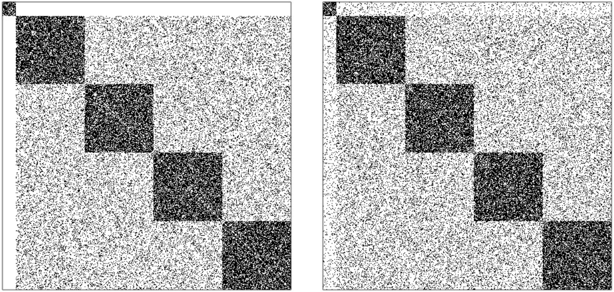


Need new tools to understand

Specific problems: detection

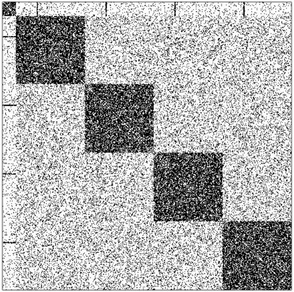


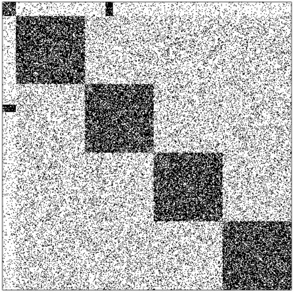
Easy



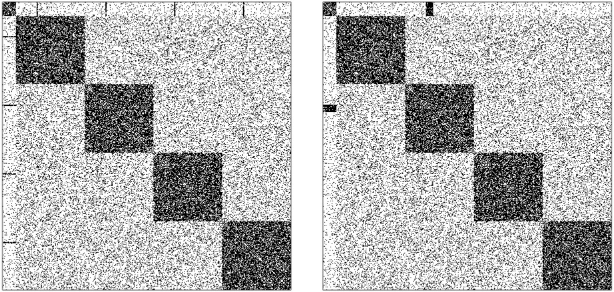
We have fast machinery to do this well
(Spectral methods and guarantees for the stochastic blockmodel)

Hard



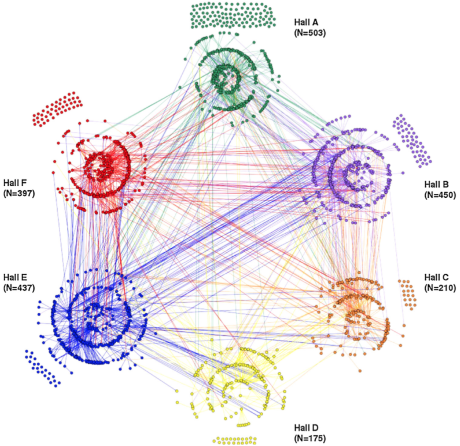


Hard



Looks like multiple or overlapping memberships
We need to build fast machinery to do this

Specific problems: disease spread



- Want to study efficacy of isolation as treatment for influenza-like illness.

Image source: Figure 9 of "Design and methods of a social network isolation study for reducing respiratory infection transmission: The eX-FLU cluster randomized trial" by Aiello et al.

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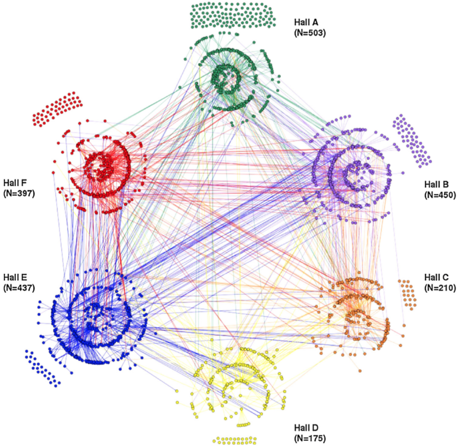

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- Interested in spread, duration of illness, etc.

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Experimental design with networks

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- Basse and Airoldi (2017) describe optimal design for the treatment effect under homophily.
- Jagadeesan, Pillai and Volfovsky (2017) provide a new graph-based randomization technique for estimating direct effects with arbitrary interference and homophily.

How do we put everything together?

Problems that should be addressed together

- Substantive network based goals:
  - Find someone
  - Learn something about a group
  - Get people (or computers) to do something
- Observed networks are full of uncertainty (statistical problem)
- Available models are too computationally expensive (engineering problem)

Thank you!

Website: `https://volfovsky.github.io/`

- Hoff, Fosdick, Volfovsky and Stovel. Likelihoods for fixed rank nomination networks (2013). Network Science 1 (03), 253-277.
- Jagadeesan, Pillai and Volfovsky. Designs for estimating the treatment effect in networks with interference (2017). arXiv:1705.08524.