Modeling interference in networks using experimental data

Causal inference

- Aim is to estimate the effect of treatment (T=1 or 0) on outcome Y
- Donald Rubin’s causal inference model (Potential Outcomes framework) based on counterfactual effects is commonly used
- Stable Unit Treatment Value Assumption:
  - the treatment status of any unit does not affect the potential outcomes of the other units (non-interference)
  - the treatments for all units are comparable (no variation in treatment)

http://www.people.fas.harvard.edu/~plam/teaching/methods/causal/causal_print.pdf

Networks

- The outcome of any unit necessarily affects the outcome of some other units
- SUTVA breaks down
- Studying that effect (interference effect or propagation effect) might itself be of interest
  - Example: How does emailing some of the legislators about an upcoming bill by a grassroots organization affect the vote of those legislators who were not emailed?

Modeling interference

- Interference can be modeled basis links established via a particular type of network e.g. ideological or geographical network
- For an untreated unit, receiving a treatment and its effect depends on the number of neighbors and potentially other external factors
- Fields such as marketing (e.g. spread of advertising campaign) or epidemiology (spread of diseases) have modeled this phenomena

Randomized experiments

- Potential outcomes framework assumes SUTVA and devices methods to ensure that background variables are averages, before calculating expected treatment effects
- Good randomized experiments take care of this aspect
- In field experiments on social groups, interference is substantial

Datasets

1. New Mexico:
   - Studying whether legislator are responsive to public opinion
   - New Mexico’s special legislative session, 2008
   - Treatment: District-specific letters sent to corresponding legislators, indicating the results of an opinion survey
   - Outcome: Voting behavior of legislators (treated and control group)
2. New Hampshire:
   - Estimating the effect of grassroots lobbying on legislators' behavior
   - House of Representative in the state voted on an anti-smoking bill in Spring of 2006
   - Grassroots emailing campaign was undertaken and voting behavior was observed

New Mexico paper (Butler and Nickerson, 2011)

- Treatment given after matching
- Interference was not estimated in this paper. However a follow-up paper by Coppock (2015) estimated the interference effect as well

New Hampshire paper (Bergan, 2009)

- Matched pair design implemented treatment assignment
- Many threats to internal and external validity
- Interference not modeled

Plan ahead

- Building propagation models based on geographical proximity, ideological similarity and co-committee membership
- Ensuring that the data takes care of other factors such as influence from legislators who had already made a decision and interaction between above mentioned factors
- Replicating results from some more papers
- Adapting these propagation models to both datasets and evaluating the effects using permutation testing