Considering Interference in Field Experiments

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Abstract

We plan to write a paper about how interference hypotheses can and should be used to analyze the results of field experiments in which there is a high probability that subjects interacted between the administration of treatment and the observation of outcomes.

1 Introduction

Networks are integral parts of human interaction and hence social science research. If one unit in a network gets treated, the effect may trickle down throughout network. The currently established framework for causal inference relies on SUTVA (Stable Unit Treatment Value Assumprion). It assumes that whether or not one person/unit/node is treated, does not affect any other unit. However, SUTVA breaks down in a network setting. It is therefore imperative to take the interference structure into account. Rather, in policy planning or designing marketing campaigns, a researcher may be interested in studying the propogation of treatment effect itself.

In field experiments on social groups, interference may be substantial. In this project we intend to study intererence models for randomized experiments coducted on social networks and causal inference basis this.

To understand, explain and predict social phenomena, social scientists typically look to individual actors' attributes to explain their behavior (e.g., an increase in an individual's wealth will result in a decrease in that individual's support for government spending on social welfare), or to attributes of the macro context (e.g., an increase in the unemployment rate will lead an individual's support for the party of the president to decrease). However, these two conceptual approaches to explaining individual behavior leave out a potentially powerful class of social dynamics – interpersonal influence. That is, the behavior of one individual may depend upon the behavior of one or more others (e.g., a person may decide to vote due to their friends claiming to have voted (**?**)). Inferences regarding influence involve the analysis of individual behaviors and the behaviors of those adjacent or nearby in some contact network. However, as in most settings, it is generally not possible to identify the causal effects that map onto the process of social influence in observational data CITE SHALIZI. As such, we need experimental methods to identify causal influence effects.

1.1 tasks

- Points about why it is interesting to study propagation. (BD)
- Outline of the paper (SP)

2 Background

Review of relevant methodological work and substance.

2.1 tasks

- Paragraph on each category of papers that serve as relevant background (SP)
  - Interference models (diffusion, propagation) (SP–Review)
  - Experiments on networks (applications) (SP–Review)
  - Approaches to inference or estimation with propagation (SP–Review)
  - Potential outcomes framework (SP – find papers & Review)
  - Review of political networks (SP–Review)
  - Review of field experiments (SP–Review)
    - (**??????**)

3 Research Design

We plan to re-analzye data from past field experimental studies to understand how conclusions regarding direct effects and interference effects depend upon

3.1 tasks

- Develop a list of alternative propagation models to evaluate. (SP)

4 Analysis

- Replicating results from the Nickerson paper

The first table contains results of balance test for pre-treatment covariates in the analysis. The p-values are calculates using simple logit regressions. This table shows that there is covariate balance across treatment conditions

	Treatment	Control	p-value
Republican	40%	40%	1
Constituent support for spending	40.8%	41.3%	0.8
Constituent support for health care	54.2%	52.7%	0.34
Bush vote-share 04	51.3%	49.3%	0.59
Member vote-share 06	60.6%	61.2%	0.86
Running for re-election	91.4%	88.6%	0.69
Running unopposed	59.4%	58.1%	0.92
Supported prior health care bill	54.3%	51.4%	0.81

Table 1: Table 1: Randomization checks

The next two tables present regression results. We are modeling the likelihood of voting in favor of SB 24. In the first regression, we study whether the treatment effects differ substantively across districts where support for the governor's spending proposals was low and ones where it was not. This is our key independent variable. Each regression uses a Probit model with standard errors clustered on the 35 matched pairs on which the randomization was based. We use the Zelig program/package in R to incorporate clustered standard errors into the model. The original analysis was performed in STATA. We notice that our estimates are the same as those in the original paper and standard errors are very close as well.

In the second regression, we also control for whether the legislator was a Republican and the 2004 Presidential election results for the given district.

- Present original results from studies that we replicate: Coppock

	Coefficients	SEs
Constant	0.76	0.33
Treatment	0.16	0.49
Low support for spending	0.70	0.60
Low support*Treatment	-1.49	0.76

Table 2: Table 2A: Regression results without controls

	Coefficients	SEs
Constant	-0.16	1.65
Treatment	-0.07	0.70
Low support for spending	1.50	0.83
Low support*Treatment	-1.86	1.04
Republican legislator	-1.61	0.68
2004 Democratic two-party presidential vote share	4.06	2.78

The Coppock (2014) paper builds upon the New Mexico Legislator experiment conducted by Butler and Nickerson (2011). The next two figures replicate analysis from the original paper, as shown in the Coppock (2014) paper. Figure 1 below replicates the result under the assumption that indrect effecrs are exactly zero. X-axis represents the proposed values for direct treatment effect, Y-axis represents simulated p-values and the colouring is according to the p-values.

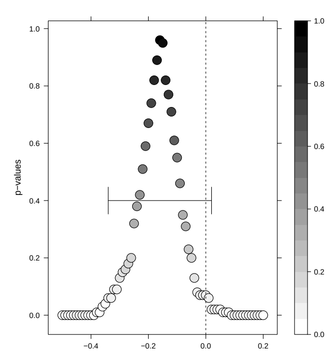

Figure 1: Figure 1

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Table 3: Regression results with controls

Figure 2 shows the heterogeneous effects of treatment. X-axis represents hypothesized effects in higher-support districts as against the hypothesized effects in lower-support districts on Y-axis. Once again, the colour scale indicates the p-value for each pair of hypotheses. Darker region indicates a higher p-value. We observe maximum p-value at effect values (0.05, -0.37) in higher-support and lower-support regions respectively.

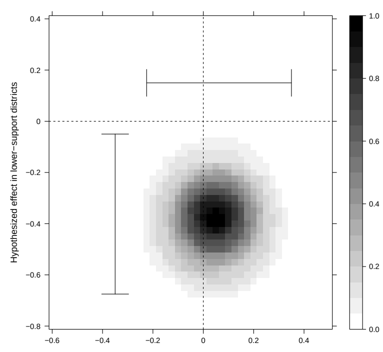


Figure 2: Figure 1

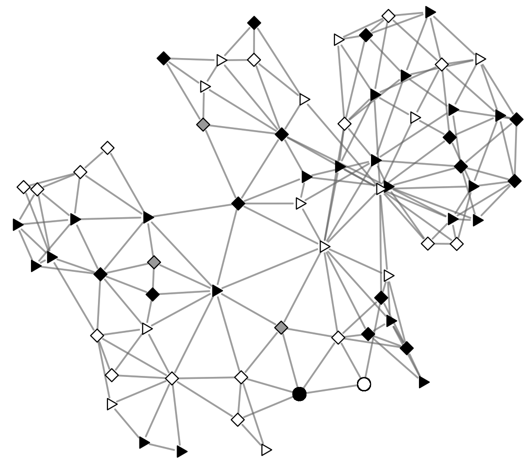
- Present results when we assume some form of interference
- Explore how alternative assumptions regarding interference change results

4.1 tasks

- Replicate Bergan. (SP)
- Find other network data for the New Mexico legislature. (BD)
- Find other network data for the New Hampshire legislature (BD)[1]
- Geography and ideology data for New Hampshire (BD)
- Produce cosponsorship, ideology and geography estimates for both Bergan and Nickerson (SP & BD)
- For at least two spreading models (SP & BD)
- Replicate Nyhan (SP)

[1] For the Legislative Finance Committee, there was no comprehensive list online, so we looked for all members who attended at least one meeting, according to meeting minutes. The Interim Committee memberships are available here http://www.nmlegis.gov/lcs/misc/Biennial%20Report%202006-2008%20FOR%20WEB.pdf

Geographic Network



Ideological Network (top 5%)

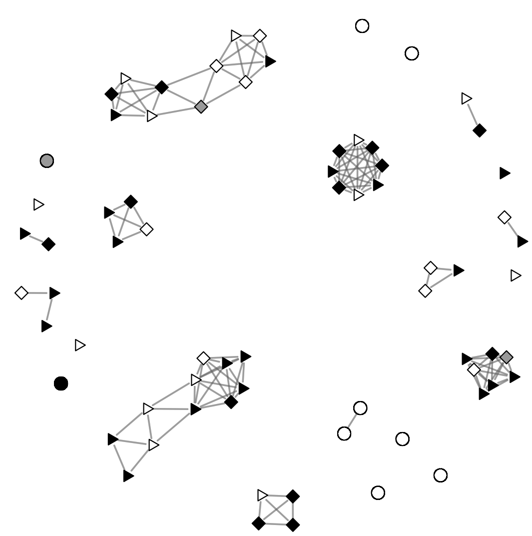


Figure 3: Colors denote outcome: black means voted with district, gray means abstained, white means voted against. Shape denotes treatment status. Triangles are treated. Squares are adjacent to treated. Circles are isolated from treatment

References