WHY DID THEY MARCH?
NETWORKS, BELIEFS, AND POLICY CHANGE

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Abstract. One of the ongoing puzzles of political economy is political protest. Unlike voting, however, what needs to be explained is not large turnout, but how small numbers can sometimes have a large impact. We develop a computational (signaling) model where individuals are privately informed yet also communicate with their 'neighbors,' or friends. Properties of this communication, or social network can give rise to different levels of information aggregation. Different amounts of information can lead to different aggregate turnout. Hence, both the leader's and individuals' beliefs about the structure of the social network can have policy implications.

Introduction

One of the ongoing puzzles of political economy is political protest. However, unlike voting, what needs to be explained is not large turnout, but how *small numbers* can sometimes resonate with the government and have a large impact.

As several authors have noted, major policy changes have been preceded by political action of a few (relative to the population), such as demonstrations, petitions or even violent riots [20]. Some of the more notable ones include the New York rent strikes or the Vietnam War protests, [23] [12] [14].

For researchers of social movements, a theory of participation in collective behavior has been problematic. Arguments put forth historically range from "attitudinal fit" with the movement to sociological arguments involving political opportunity structures [21] [16]. Other rational choice arguments, initially put addressed by Downs and later

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elaborated by Olson, suggest that self-interested individuals would not have the incentives to engage in collective action. However, more recent work suggests that this is not always the case.

With signaling considerations, it can be shown that it may be rational for the individual to engage in political action, and that such actions have an impact on policy decisions. In previous work by Lohmann, political actions convey information to the political leader who then decides whether to act on the basis of the size of the protest movement [13].

For example, assume the leader observes 20 percent of the population protesting. In Lohmann's model, if costs are positive, only a minority of the citizens may actively protest. Whereas a large number who are in favor of a policy change may not engage in active protest just because the cost they would incur would be too high. In particular, from the leader's prior beliefs about individuals' policy preferences, he would expect to observe a certain number of protesters at a rally. In her model, if the observed turnout is above this expected amount, the leader is very well motivated – and moreover, by her logic, justified – to change the policy. However, Lohmann's model is agnostic as to *which* people turn out at a rally. So to the leader, it does not matter if this 20 percent comes from a very well organized union, or if it is composed of grandmothers and businessmen.

In this paper, we propose a different model. We do not assume the political leader knows the individual costs of engaging in political action. Moreover, we do not assume that people make their decisions in a vacuum. As Carole Uhlaner has stressed, individuals make their political decisions with reference to social groups in which they are embedded. The group may be as small as a family or as large as a trade union. Others have also demonstrated the influence of belonging to a group. For instance, Snow, Zurcher and Ekland-Olson survey nine studies of movement participation. In eight of the nine cases, a large majority of the participants had precious connections with those previously involved [6].[1]

A formal way to model the effects of being embedded into groups is social network theory. Network analysis allows to specify the impact of group structure on individual decision making. In particular, group structure influences information transmission, hence it influences the individual's ability to coordinate. We want to argue that group structure is crucial in the decision to engage in political protest.

In our model, the political leader is assumed to have prior beliefs about the odds that an individual disagrees with a current policy. The leader has no knowledge of individual preferences or costs; nor does he have any exact knowledge of the network. Furthermore, in our model the decision to engage in political protest is determined by three variables: personal preference, costs and the information about the preferences of one's neighbors. For example, a low cost pro-change individual may only need one or two pro-change neighbors to engage in political protest. Another individual with a similar preference but with high cost will need information that a much higher number of neighbors share his preferences in order to engage in political protest. We thus embed the cost variable into the decision rule. A low cost individual will need very little information about his neighbors in order to act, whereas a high cost individual will use a more cautious rule (i.e., he will need to know that a much larger number of neighbors share his preferences).

If we go back to our previous example of the politician observing only twenty percent of the population protesting, the politician's knowledge of the network structure will influence his response. As we shall make clear in the rest of the paper, in our model a small turnout has a greater chance of producing a political response than in Lohmann's model.The network structure can be very informative if the individuals that actively protest belong to different, unconnected networks. Then even a small number engaging in political action could be the tip of an iceberg. There is an obvious difference between

[1]The interesting lone exception was Hare Krishna, which specifically looked for socially isolated individuals.[6]

the protest of a group of union members and that of a group of disgruntled citizens that do not belong to any formal, or informal organization.

Rather than explicitly modeling organizations and specific group structures, we shall focus on one property of any social structure: its density.[2] We shall also explore a variety of individual behavioral rules, combine them with different network densities and simulate the turnout results. Note that simulations – as opposed to a formal analytical model – are needed to make the complexity of combining various networks with several behavioral rules tractable.

The simulation results show the specific ways in which networks may matter to a politician. In particular, our simulations show that a situation in which turnout is less than 50 percent, but more than 50 percent of the population is in favor of a policy change, occurs more frequently in low density networks than in high density networks. A savvy politician, who knows (by assumption) the density of a network, may thus take action to change the status quo since his knowledge of the network may drastically decrease his probability of making a mistake. Whereas many models of political action may discount the protest of a few, our model shows under which conditions the few matter most.

Rational Choice

For rational choice theorists, political participation has been traditionally plagued by several problems. Downs contended that people may be rationally uninformed about complex policy issues [9]. In fact, they may rationally choose to disregard information if the cost of gathering it outweighs its benefits. Hence, rational political participation will only allow the leader to infer the policy preferences of a few. While Downs' hypothesis seems reasonable for expert or complex knowledge that is costly to obtain, it is less plausible for types of knowledge that are byproducts of practical experience. Through daily life an individual could easily obtain information about the consequences of a

[2]Density is the extent of interlinking between agents, usually expressed as the ratio of the number of existing links to the number of possible links [24].

policy, or policies, on his or her well-being, whether this policy is local or national (taxes, abortion, etc.).

A second problem, originally presented by Olson, is that political participation is subject to a free-rider problem, in that self-interested individuals do not have the incentives to engage in costly collective action. Specifically, the individuals that want action to be taken realize that if enough others perform the action and they abstain, they get a free-ride, i.e., incur the benefits without being subject the costs. In her "costly signaling" model, Lohmann circumvents Olson's free-rider problem by showing that in equilibrium there can exist rational, self-interested individuals that have incentives to engage in costly political action [13].

Similarly, in the voting literature, rational choice researchers are often concerned with the decreasing probability of being pivotal in an election [19]. Given this, it is often the case that the costs outweigh the expected benefits of turning out to vote. McKelvey and Patty proved that in large electorates there exists a global equilibrium at the social optimum [17].[3] Expected turnout is strictly positive for some positive costs of taking action.

Besides being compatible with a narrow cost-benefit analysis, political action may provide other, less quantifiable benefits to individuals. There is a growing amount of experimental evidence that people engage in pro-social behavior even at a cost to themselves. Several models have been provided to explain how people derive positive utility from reciprocating trust, sharing fairly, and even donating generously to perfect strangers [3]. Similarly, political participation may be motivated by reasons as diverse as a desire to express one's opinion, to imitate one's friends or conform to what is done by one's reference group. We assume that there is a combination of factors at work. Namely, in our model we assume that people believe that their actions are informative

[3]This result, which holds in multi-candidate contests, requires voters to have privately observed payoff disturbances associated with each action. These disturbances are candidate-specific. Or, in other words, the individual gets some random utility for voting for some specific candidate. As the authors point out, "any probit or logit analysis of voting behavior where the dependent variable is the party vote implicity makes this assumption [17]."

for the political leader, but they also experience group pressure and may desire to conform to the reference group's opinion.

From a real world perspective, individuals that wish to protest, say at a public rally, still face an issue of coordination, i.e., where to meet for the rally or at what time. Some do not even know that there is an option to protest. Information, and the flow of it, is obviously crucial for coordination purposes.

Some analytic work has been done to show that coordination is "easier" in denser networks [5]. The density of a network clearly impacts the ability of individuals to share and transmit information.

We will show that this seemingly obvious intuition could have major consequences for the political leader. In particular, we allow individuals to communicate with their neighbors about the state of the world. Instead of an "I'll go if you go" message, people send messages like "I'm in favor of the policy change" or "I like the policy as it is." Hence individuals gather a neighborhood-based straw poll, on which to base their decision whether to engage in political action.

Groups and Organizations

It is well known that major political changes have been often enacted by political action engaged by relatively few individuals. Such individuals certainly possessed a greater than average ability to coordinate their actions. It has been empirically demonstrated that individuals' ability to communicate with each other can have a major impact on their ability to coordinate or organize political action.

The women's suffrage movement was made possible by a large network of women's clubs, organizations and professional associations [8]. The success of the Civil Rights movement of in 1960's relied greatly on preexisting social networks. For example, black church leaders played a key role in their ability to mobilize their congregations to partake in economic boycotts and join in public rallies and meetings [4]. The flow of information obtained through social interaction has been perceived as crucial by all the parties involved.

Indeed, there are cases of administrative action to block, or limit, social interaction in order to stifle potential political action. Berkeley administration's decision to limit organizing and fund-raising on the main campus area is an example [4].

It is also a common tactic of political activists to transform, or piggyback political groups on preexisting social groups. For example, early organizers of the farmers' unions in the 1800's organized meetings to promote friendship and recreational events, as well as a trading post for information on prices, farming practices and politics. Organizers emphasized that families came and good music was provided. Those interested in attending were told to bring friends or neighbors. [4]

Social relationships may help a group's ability to to coordinate or organize, but they may also suppress it. Southern white men and women active in the civil rights movement where torn between their personal ideals and the social norms of their families and friends. It was common for these individuals' families to be ashamed of the protesters' actions. They tried to make the protesters feel guilty, even accusing them of hurting the family business and making it more difficult for them to do their jobs. [4]

Do different networks matter? The Mississippi Freedom Summer

One of the main points put forth in this paper is that different social networks lead to different outcomes. While there is a substantial amount of literature to indicate that organizations play an important role in social movements, one might ask if the same is true for different social networks – not just membership in an organization. In this section we provide an illustrative example based on a case study originally presented by Doug McAdam on participation in the 1964 Freedom Summer project [15].

This project brought northern volunteers, comprised mostly of college students, to Mississippi for all or part of the summer of 1964. While in Mississippi, participants were expected to do things such as register black voters or staff freedom schools. This venture was obviously very costly and risky for the participants. Not only did they give up their summer and were expected to be financially independent, but they also faced the possibility of physical harm. As soon as it began, three project members were kidnapped and killed by a group of segregationists.

Admittedly, there are methodological problems in generalizing from case studies. This study does help to alleviate some of these issues. If one would like to examine the influence of individual beliefs or structural aspects of the group, subjects should be studied before any involvement. Many case studies can only examine individuals after the movement has started. In order to partake in the Mississippi Freedom Summer project, volunteers had to fill out detailed applications, which requested information on organizational affiliations, extracurricular activities, reasons for volunteering, etc.

There were a total of 1068 applications: 239 withdrew, 55 were rejected, 720 participated and 54 were left unknown. This study has the advantage that while even though those that applied might not be representative of the population as a whole, we can examine both those that went and those that did not. Therefore, the application process does not completely alleviate the methodological concern, it does help.

The applications required individuals to list at least ten other people with whom he or she would like to keep in touch with over the summer. Typically, after people listed their family, professors and local politicians, they listed their friends. Therefore, McAdams was able to get a rough idea of the social networks of people who participated and the networks of those who withdrew.

Interestingly, participants listed many more other participants and known activists than those that withdrew. If we aggregate strong and weak links, 22.8 percent of participants listed other participants, whereas only 11.6 percent of withdrawals listed names of those that actually went to Mississippi. Moreover, 5.4 percent of participants listed names of those who withdrew, while 6.4 of the people who withdrew listed others that withdrew. Even more suggestive is the fact that of the 202 strong ties to other applicants listed by participants, only 25 were of withdrawals. This yields a withdrawal rate of over 12 percent versus the rate of 25 percent in the overall study. [15]

The Mississippi Freedom Summer was a venture that put volunteers in a very risky situation. In this case, applicants that withdrew before the project started, listed

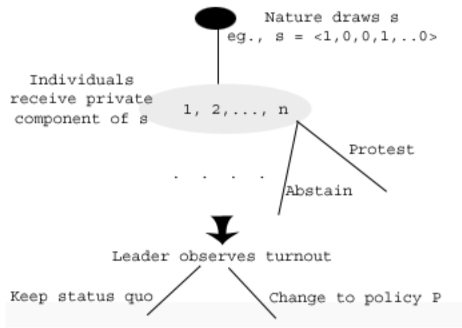

FIGURE 1. General Game Structure

individuals from a different circle of friends. Moreover, a strong predictor as to if they continued with the project were their friends *before* going to Mississippi. [15] McAdams' research is certainly suggestive of different social networks leading to different outcomes.

The Model

In this section we will present our model. Though our model is similar to Lohmann's in some respects, it differs substantially. The sequential structure of the game is the similar. We add, however, neighborhood-based communication to allow for group influence, relax the typical rational inference assumptions imposed on the citizens and do not use a spatial model. Moreover, our model is not a spacial model, so individuals do not have ideal points in some policy space.

The structure of the game may be found in figure 1. Let there be n total citizens, indexed by $i = 1, 2, \ldots, n$. The political leader has two options: he may either not change the policy and keep it at the status quo, or he may change it to a fixed and exogenous policy, P.

Initially, nature draws a state of the world, s. Technically, this is an n-dimensional vector of 1's and 0's. More specifically, it represents each individual's policy preference. However, with a small abuse of notation, we denote with s_p the proportion of those in favor of a policy change and refer to this as the type probability, or the probability of being the type that wants policy change.

Information about s is distributed across society. Each individual i, receives a private binary signal, σ, which should correspond to the i^{th} entry in the vector s. The signal i receives is a noisy indication of his true policy preferences. This represents the agent having (a sometimes incorrect) knowledge of how a policy might affect him. Thus an agent may strongly prefer a policy that will ultimately harm him.

After receiving the signal, each member of the society talks with her friends, or neighbors, about her friends' attitudes towards the proposed policy. Given this additional information, agents decide whether or not to turn out at a protest. In this model, we use an alternative method to model how individuals decide to turn out.

People are often modeled as Bayesian statisticians when they make inferences. This assumption often has questionable empirical validity [10]. Yet, how people aggregate information is of the upmost concern to the leader, because it maps directly into their decision to turnout. Some work in psychology, however, suggests that people are not quite perfect Bayesians in that they are systematically biased in their inferences.

In this paper, we will relax the assumption that citizens are Bayesians. Rather, we will introduce different behavioral decision rules to model how people aggregate information and conform to social pressures. We will discuss these rules in more detail in the following section. Individual turnout can be thought of as a mapping $t : b \times \mathcal{N} \times \sigma \to \mathcal{A}$, where $b \in \mathcal{B}$ is the behavioral rule, $\mathcal{N}$ is the neighborhood of friends, σ is the signal the individual received and the action set available to each citizen is $\mathcal{A} = \{\text{Turn out at protest}, \text{Abstain}\}$. The cost of taking political action, as well as the psychological influences are embedded of others into the behavioral rule. A citizen's signal and his social connections then get mapped, together with the behavioral rule, into his choice of political participation.[4] This participation (or lack thereof) is a signal to inform the leader about an individual's preferences.

[4]A more standard rational choice model in which there is no participation cost would assume that individuals follow their signal (taking into account the prior probabilities) independent of group influence. If instead we were to use a spacial model similar to Lohmann, the decision to turn out would not depend only on the signal received, but also on cost and policy preferences.

The political leader wants to make a decision that a majority of the population prefers. Therefore, a leader who is fully informed about s would choose the policy preferred by a majority of citizens. The leader, however, is uninformed about the realization of s; whereas, in the aggregate, the population is very informed.

In our model, the leader attempts to infer what a majority of people prefer, given he observes only aggregate turnout. Total aggregate turnout, T, is a function of the behavioral rule,[5] b, density, d, and the policy preferences, σ. In essence, the leader calculates the conditional expectation of the state of nature: $E(s|T)$.[6]

We assume that the leader is Bayesian in his inferences and takes an individual's turnout as a sincere action. Or in other words, he attempts to infer what a majority of people want, given his prior knowledge and the observed turnout. His preferences are simply to do what a majority of the society prefers.[7]

Simulations

In the previous section, we outlined our model. Rather than impose strong rationality assumptions on the agents, we are examining decision mechanisms which more empirically supported. These alternative mechanisms, however, can become analytically unwieldy. Therefore we use a computational simulation to analyze the effect of social structure on turnout.

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[5]For all simulations we present in the rest of the paper, we assume that all agents use the same behavioral rule.

[6]An alternative version of this would be a case in which the leader knows the behavioral rule and the network density, $E(s|b, d, T)$. Other interesting cases exist. For example, when the leader does not know the psychology leading to a decision involving, and in essence has beliefs $P(s, b|d, T)$ that then influence his expectation of s. Other cases exist, such as when he does not know the network density, $P(s, d|b, T)$, or both the network and the behavioral rule $P(s, b, d, |T)$. It could even be more valuable to the leader to know a different property of the social network. For instance, another property such as degree centrality, rather than density, could be more important in small groups. Such an analysis, unfortunately, goes beyond the scope of the current project.

[7]Perhaps the leader may wish to be more cautious in the number of type-I or type-II errors he makes. This would an interesting extension, but goes beyond the scope of the current work.

In the following simulations, we appeal to findings from psychology on how people aggregate information and conform to social pressures. We have grouped our analysis into two different families of 'behavioral rules.'

In the 1950's, the psychologist Solomon Asch conducted experiments on social conformity. He found that a significant proportion of subjects conform to social pressures, i.e., by also stating the obviously wrong response if everyone else did.[8] Asch found little influence of group size. Subjects conformed in groups of three or four as readily as in larger groups. However, if subjects had another group member express disagreement, then they were more likely to give their true answer [1].[9] Therefore, in our first family of behavioral rules, we only impose that the agent needs a minimal number of allies to support his decision to protest. Exactly how many others is an indication of how cautious the rule is, i.e., someone using a more cautious rule would require more people to support his view before he would take action.

A more cautious rule would be indicative of higher costs involved in taking political action. For example, a low cost pro-change individual may only need one or two pro-change neighbors to engage in political protest. Another individual with a similar preference but with a higher cost will need information that more neighbors share his preferences, in order for him to engage in political protest. We thus embed the cost variable into the decision rule.

Since this rule includes costs and gives an absolute threshold needed for action, it might appear familiar to readers accustomed to cut point models. In a cut point model, essentially there is a threshold and observations above that threshold dictate action. The same logic is used in this rule. For example, if the individual is following a rule which requires two allies, then any number of supporters above two, will move the citizen to turn out and protest.

[8] In Asch's original results, only about $\frac{1}{3}$ of the subjects conformed. However, this is still quite a few considering how obviously wrong the response given by the other group members.

[9] Interesting, this effect was strongest when the other group member disagreed with both the stated and true response. In this paper, choices are dichotomous, so any disagreement with the group implies agreement with the individual.

In terms of aggregate turnout, note the difference between small and large groups. In small groups, because each individual needs an absolute number of people and there are fewer people in the group, one would expect a lower turn out. In a large group, there are simply more people, and as such the odds that there are more in agreement with the individual are greater. Therefore in large groups, one would expect higher turnout, or more precisely turn out more observationally equivalent to sincere turn out.

In our second family of behavioral rules, we turn to a different psychological phenomenon. Numerous studies from Behavioral Decision Research, suggest that people suffer from availability biases and do not integrate information appropriately [10]. Additionally, people may over emphasize their own opinion [11]. In this family of behavioral rules, we impose that agents think that their neighbors, or friends, are representative of the population as a whole. The agents, however, give their own opinion additional weight (up to two to three times as much as what they would give a neighbor). Moreover, agents conform easily to their reference group, so they go with whatever a large proportion of that group does.

Notice that requiring a proportion of the group is very different than the number required in the first rule. In this rule, instead of requiring an absolute number of people to support his opinion, the individual has a threshold for turning out. This threshold can be considered to be a proxy for the cost the individual faces for taking political action. A low cost individual will turn out if a simple majority of his neighbors declare that they do not support the current policy. On the other hand, a high cost individual would be more cautious and require a larger proportion of his neighbors supporting his opinion.

For this family of decision rules, aggregate turnout should look quite different. For small groups, a few number of people may be decisive. Specifically, because an individual conforms to the reference group and does what a certain "majority" states, fewer people are needed to define that "majority." Whereas in large groups, more people are simply needed. Therefore one would expect a flip in observed behavior in large groups, along the lines of an informational cascade. Specifically, from almost no turnout to a massive turnout. This is because up until a point, everyone is conforming to the "majority's" opinion but as soon as enough people voice disagreement with the policy, many more members of the group will follow suite and turn out.

At first glance, a high threshold, say $\frac{2}{3}$, might seem unrealistic. However, work by Davis and others suggests that it might not be so far off [7]. Psychologists researching jury decision making have found empirical support for the need of a high threshold before individuals switch their opinion. In particular, if there is a two-to-one division of the group against the individual, then the individual tends to be swayed and switch his or her position [7].

Method

Mathematica simulations were ran on groups of 500.[10] Agents were connected via a random graph. The independent variables are density and type probability.[11] We varied expected density of the graph from .005 to .15, in .005 increments.[12] This amounts to each agent, on average, communicating with 2-3 to 75 different agents.

All agents received an independent signal about their policy preferences. This signal was accurate 95% of the time. In other words if the true state of the world was such that the agent would correctly prefer a policy change, then $\sigma = 1$, 95% of the time. Similarly, if the agent would correctly prefer the status quo, then $\sigma = 0$, 95% of the time.[13] We varied the type probability from .02 to .98, in .02 increments. Agents truthfully reported their signal to their neighbors, and accurately heard all signals sent to them.

[10] Larger group sizes were also ran, but did not qualitatively differ.

[11] Recall that type probability is the probability of being the type that wants policy change.

[12] We say expected density because the random graph did not necessarily have that *exact* density; it does only in expectation, or on average. At each density setting we ran 35 independent trials. Therefore we are inherently appealing to a law of large numbers argument.

[13] We say "correctly" prefer, since an agent may wrongly believe a policy is good for him, hence prefer it to another.

Agents then aggregated the information sent to them. As previously mentioned, we ran different 'families' of information aggregation rules. All agents used the same aggregation rule during each simulation session.

The first group of behavioral rules, which we will call *Minimal Ally* (MA), had three variations. Specifically, if an agent is against the policy, i.e., he received the protest signal, then the agent only needs X other agents to support his 'belief' that the policy is wrong to induce him to turnout at a protest. We ran the simulation, with $X = 1$, $X = 2$ and $X = 3$. So in the case where $X = 2$, the individual would essentially ask all of his connections and if at least two of them agreed with his opinion that the policy was wrong, then he would turn out and protest.

The second group of rules, called *Non-Bayesian Threshold* (NBT), also had several variations. In each case, the agent inferred what a majority of the population wanted only sampling his neighbors. He then went with what most of the group thought was correct. We ran different thresholds as to what determines "most" of the group: from simple majority (50%) to a two-to-one split (66%). The agent, however, potentially over-weighted his own opinion. We ran three cases: $1x$ (no over-weighting), $2x$ and $3x$. Specifically, he could double or triple count his own signal. This over counting represents a strength of confidence in his opinion.

There are two main aspects of interpreting political protest: actual number of people taking action, and how that aggregate statistic is related to the number of people against the policy. Therefore under the different behavioral rules, we have two dependent variables: total turnout and "lost" protesters. The latter indicates those people who are against the policy but did not turn out, Total number against - Total who turnout. Typically people think about the former. Total turnout, however, does not help answer the puzzle of protest: how small numbers can sometimes have a large impact. Our second dependent variable gives an indication of how little representative the openly expressed disagreement (aggregate turnout) is. We are interested in this measure primarily because of its key role in the interpretation of a protest. If a leader or citizen of a country wishes to make some inference about a population's policy preferences, he or she must be concerned with how aggregate turnout can be systematically misrepresentative.

Results

The different behavioral information aggregation rules we examined were intended to capture different psychological phenomena. As expected, they produced very different results. In each simulation, we ran 35 sessions at each density and type probability setting. For ease of presentation, the graphs presented here plot only the average over these 35 sessions.

We have divided our result analysis into five different parts. First we will present the formal limiting results one would expect to see. Then we will examine the total turnout produced in each situation. Next we examine the number of "lost" protesters, or the difference in the number of those that turn out and the number who privately disagree with the policy. This measure gives an indication of how little representative the expressed disagreement (aggregate turnout) truly is. We are interested in this variable primarily because of its key role in the interpretation of a protest. By a similar token we examine the value of information of knowing the density of a network. More precisely, we examine the regions in which knowledge of the network density is very important for inference. Finally, we discuss the challenges the leader faces in inferring the true state of the world, and how possible errors are reduced dramatically given he knows the correct network density.

Limiting Results

With the rules we are examining, let us denote total turnout in the Minimal Ally condition, T_{MA}, and similarly, T_{NBT} for the second family of rules. Let us denote expected density with d, and recall that the proportion of individuals that disagree with the policy is denoted, s_p.

Perhaps it is illuminating to contrast what would happen in these rules verses what would happen if people do *not* make their decisions with respect to others. Consider the case in which people who disagreed with the policy turned out and those who agree with the policy stayed home. Note, this is one of the equilibrium Lohmann examines. Precisely it is the zero cost, fully revealing (separating) equilibrium. This case in our model, would translate into everyone who receives a indication that they are against the policy (a signal), turning out at a protest. For a simple figure, see 2.

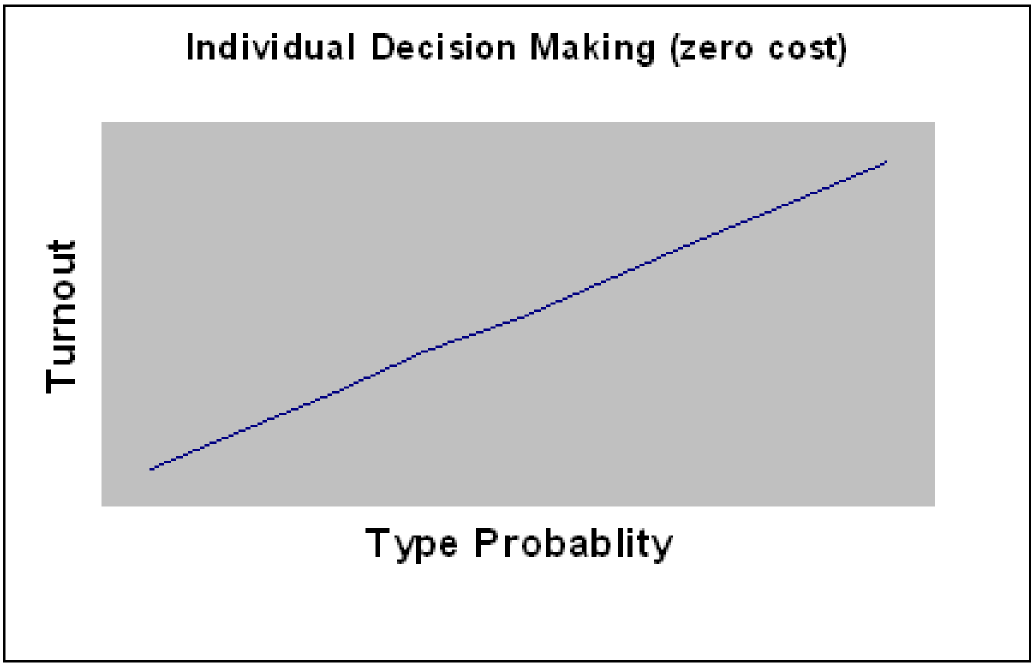

FIGURE 2. Total turnout with zero cost and no group.

Similarly, the limiting results of our decision rules thankfully agree with one's intuition. As the proportion of individuals that disagree with the policy goes to one, $s_p \rightarrow 1$, then everyone turns out, $T_M A \rightarrow N$ and $T_N BT \rightarrow N$. Similarly, when $s_p \rightarrow 0$ or no one wants policy change, then $T_M A \rightarrow 0$ and $T_N BT \rightarrow 0$. The exception is the dual limit of the Minimal Ally rule. It does not make sense at zero because it requires an absolute number of other people, therefore $\lim_{s_p \rightarrow 1, d \rightarrow 0} T_M A = 0$. This is not the case with the proportional rule, because each person is aggregating their signal with others; if there are no others then it corresponds to the zero cost case above.

What are perhaps more interesting are the limits when the expected density of the network goes to 1, $d \rightarrow 1$. The Minimal Ally condition corresponds to the zero cost sincere turn out case, 2. The second family of rules, does differ substantially. Rather than a straight line, a step function should be observed. When $d = 1$, then everyone is communicating with everyone else in the society. In which case, because everyone has the same threshold τ, $T_N BT = 0$ for $s_p < \tau$ and $T_N BT = N$ for $s_p > \tau$.

Total Turnout

Total turnout for the first family of rules may be found in figures 3, 4 and 5. With the exception of very low density values, the variations on this rule produce very similar results. The total turnout from requiring one other partner correlated .9935 with the total turnout produced when two others were needed. When two other individuals were needed to support one's opinion that a policy change is needed, total turnout correlated .9937 with the total turnout in the case in which three others were needed.

Figure 3 is a graph of the total turnout under the case in which only one other person was needed to support the decision to turn out; similarly, figure 4 is the case for two others needed and figure 5 for three others needed. Essentially we see an effect of density only in very sparse, or low density, networks.

This effect of density is amplified by needing more people to support the individual's opinion before he or she acts. For instance, only needing one other individual (figure 3) produces more turnout in a sparse network than needing three other individuals (figure 5). This again, is not extremely surprising: this rule requires an absolute number of others, and in very sparse (or low density) networks there are fewer people.[14]

In our second family of rules, we have very different aggregate behavior. Interestingly, we observe behavior which is reminiscent of informational cascades. In a lower threshold setting, for instance 50%, the threshold acts somewhat like a tipping point. Specifically, we observe almost no action up to a level close to the threshold, and then a massive switch in behavior. The graph found in figure 6 displays the case when there is a 50% threshold, and no one over weighs, or over counts, his or her signal.

[14]For a graph of 500 with .005 expected density, each individual has on average 2.5 connections.

Across the different weighting conditions, we see slightly more of an informational cascade, or a quicker jump. Figures 7 and 8 show the total turnout when there is a 50% threshold with double and triple over weighting, respectively. Therefore, transitions happen faster the more one over weighs his own signal.

In all conditions, we see an effect of density on turnout. In a denser network, we observe no one turning out until the type probability is close to the threshold. So, in a dense network when 30% of the population is against the policy, no one would know from observing turnout – because zero people turn out. Therefore in a dense network when a few people do start to turnout, a few could be very meaningful: protest could catch fire and take off. In a less dense network, turnout seems to be more gradual and when there is no over weighting, turnout is almost linear (at the extreme).

Again, results of total turnout were very similar among the different weighting schemes. In the 50% threshold case, no overweighting correlated .997 with double weighting, and it correlated .9924 with triple counting. With different thresholds, results were slightly different, but overall quite similar. The total turnout when there was a 50% threshold and no overweighting correlated .9684 with the 66% threshold no overweighting case.

There was, however, more of a difference between the two families of rules. The 50% no overweighting threshold rule correlated .9311 with the first variation in the Minimal Ally family (only one other need), and .9053 with the third variation (three others needed).

Difference in Turnout

Our second measure of interest is the difference between the observed turnout and the number of individuals that that disagree with the policy, i.e, those that received the $\sigma = 1$ signal. We are interested in this measure primarily because of its key role in the interpretation of a protest. If a leader or citizen of a country wishes to make some inference about a populations's policy preferences, he or she must be concerned with how aggregate turnout can be systematically misrepresentative.

Again, within the rules, results were very similar. For ease of presentation, let "actual" be the total number of individuals who received the $\sigma = 1$ (pro-policy change) signal, and let "observed" be the total number of individuals who then took political action. We will term the difference between actual and observed as the "lost" number of protesters.

In the Minimal Ally family of rules, the difference between actual turnout and observed turnout ended up being similar across the different treatments. When only one other individual was needed to support a policy disagreement, the lost number of protesters correlated .9503 with the lost number of protesters resulting when two others were needed; and .8727 with the case in which three were needed.

The second family of rules also produced similar results. In the 50% threshold case, the difference between actual and observed in the no over weighting condition correlated .9863 with the double-weight condition, and .9646 with the triple-weight condition. Using different thresholds, the lost number of protesters was still somewhat similar: the 50% no overweighting condition correlated .857 with the 66% no overweighting condition.

The two families of rules, however, differed substantially. In the Minimal Ally family in which only one other person was needed, the lost number of protesters correlated .1132 with non-Bayesian threshold 50% no overweighting condition; and even less so, .0777, with the number of lost protesters resulting when there was a 66% threshold and no one over weighed his or her signal.

For graphs of the difference between observed and actual, refer to figures 10, 11 and 12. The first graph is the difference between the actual number against the policy and the number observed, i.e., the lost number of protesters in the Minimal Ally condition when only one other was needed. Figures 11 and 12 display the difference between actual and observed in the non-Bayesian threshold model when the threshold is 50% (no overweighting) and 66% (no overweighting), respectively.

Value of Information

While it would be nice to examine the value of knowing the density, it is not possible in our setting. We cannot determine how much a leader is willing to pay for knowledge of network density, because we have not imposed any utility scale on the leader, just preferences. However, we want to know when network density is important for a leader's inference. The partial derivative, $\frac{\partial \frac{\partial T}{\partial S}}{\partial D}$, gives an idea of how density may matter. Here, T denotes the total turnout, s_p the type probability and D the network density.

Namely, it gives an indication of how the slope is changing as we move along the Density axis. For example if we look at figure 8, as we move along the Density axis becomes much steeper for values in the middle of the type probability. A steep slope indicates that a slight increase in type probability results in very large increase in turnout. Areas in which the value of the partial derivative is high (in absolute value), would indicate a strong role for network density. Alternatively, one may think of this as giving an indication of how robust turnout is, given small changes in the initial conditions.

We estimated this ratio using data averaged over thirty five trials.[15] Figure 13 indicates the estimated absolute value of this derivative in the Minimal Ally condition when three others were needed. As one may see, there is only a (slight) influence of network density when the network is very sparse (everyone spoke to only a few other people).

The influence of network density on the rate of change in turnout can be seen more when using a threshold rule. Figure 14 depicts the ratio when the threshold was 50% and there was no overweighting. As we mentioned earlier, the total turnout we observe under this rule has almost no turnout up to a point where the type probability is close to the 50% of group members dissenting threshold, and then a massive switch in behavior. This massive change can be seen with the large absolute value of the derivative around the area in the type probability. Moreover, we observe an influence of network density.

[15]Recall that, for each value of Density and Type Probability, we ran 35 trials. Correlation analysis was performed on the full data set. The graphs, however, only show the averaged results.

In a graph where people on average communicate with 75 people (.15 expected density) we observe a knife-edged result. With a low density, however, this flip in behavior is less immediate.

Interestingly, this influence of density intensifies with the more overweighting that occurs. When an agent weighs his signal more (i.e., when he double or triple counts his signal), there is a larger role of density on changes in turnout. For example, under the non-Bayesian 60% threshold when there is no overweighting, the areas in which the partial derivative is large (in absolute value) are tightly grouped around the 60% type probability. Whereas in the non-Bayesian 60% threshold when individuals triple counted their signal there is a larger (absolute) value of the partial derivative across more of the type probability area when density is low.

conclusion

Leader's Inferences

The question of how a leader infers the state of the world from only observing turnout is nontrivial. We will assume that the leader takes turnout as sincere action. This implies that those in favor of a policy change turn out, and those that favor the status quo do not. This is similar to the fully revealing zero cost equilibrium found in Lohmann's model.[16] The intuitions behind the positive cost equilibria found in her model still carry over. Though, since we are not using a spacial model with a common prior on the ideal point distribution, we can not say how much turnout would shift away from the median citizen. A high threshold, however, would indicate a more cautious individual that is facing a higher cost. In such as setting, we would expect to see less turnout. Therefore while we simplify the leader's inference procedure, the influence of groups and group structure can still be seen.

We simplify the the inference to almost the simplest case: if a leader observes twenty percent of the population protesting, then he infers that twenty percent is against the

[16]The partially revealing equilibria that she examines do not directly carry over because we are not working in a spacial framework. Specifically, because we are not working with ideal points, we can not talk about cut point strategies that determine her boundaries $\widetilde{s}_1$ and $\widetilde{s}_0$.

population. I.e., individuals are completely sincere and protest is perfectly informative. Given this is the case, the leader has a simple cut point strategy. If the leader observes over fifty percent of the population protesting and calling for a policy change, he changes the policy.

Given the leader uses such a strategy, one may ask how often does the leader make type-I (false negative) and type-II (false positive) errors. Or in other words, how often does the leader incorrectly infer that a major of the population prefers the status quo, when in fact they want a policy change (false negative). Or how often the leader infers that a majority wants a policy change, but in actuality the populations prefers the status quo (false positive).

In the simulations we ran, these errors were most likely to occur in low density networks. A graph displaying the frequency of false negatives may be found in figure 18. In this graph, we see that these errors occur most often (across all rules) when individuals only speak to a few other people. Moreover, it occurs most often when the citizens are using a very cautious (high cost) rule, such as needing three others to support their opinion. Whereas, the false positive errors occurred most frequently when individuals were using a lower threshold rule such as the 50% threshold. For a graph of the frequency of false positives, refer to figure 17.

These results indicate that these errors occur most frequently at lower densities. Moreover, if the leader knew the density was higher, for example .10, or that people on average spoke to fifty people before making a protest decision, he would be much less likely to make an inference that was contrary to the public opinion.

False positive and false negative errors are a function of the leader's strategy. However, if a leader were to incorporate intensity of preference (for instance in a spacial model), then he should be concerned with how often the aggregate turnout is being under or over representative. For instance, in our behavioral rule which required two other people to support one's opinion, 42.7% of the time the total turnout was less than the number of people who wanted policy change. For a full summery statistics broken apart by rule, refer to figure 16.

Discussion

We began by questioning the puzzle of political protest. Namely, how can (relatively) small turnout have a large impact? Previous scholars have sometimes considered political protest as only composed of angry mobs and inherently irrational. Lohmann presents a rational choice model that suggests that it could be rational for individuals to take political action. In her model, political protest is viewed as a signaling mechanism that allows members of the society to inform the political leadership. The costs involved with protesting may give an indication of why a few may have an impact. While we share Lohmann's spirit that protest may be a rational choice meant to inform the government, we do not assume that people make there decisions in a vacuum. We rely on the research that suggests that individuals make political decisions with reference to social groups in which they are embedded. Furthermore, there may be certain properties of the group structure which may be analyzed in a rigorous fashion. Specifically, we formally incorporate insights from behavioral research in a computational analysis.

Let us return to our example of the leader observing 20 percent of the population protesting. Previous models exclude reference as to the composition of this 20 percent. Current rational choice models are games in which observation of protest turnout above a given threshold indicates that policy change is rational, whether this turnout comes from a labor union or parent-teacher association members.

The model we present here is also a threshold model, yet we attempt to address the effects groups may have on individual decision making. It is difficult to discuss the specific details of being embedded into groups in a formal model. Contemporary work in social network theory allows one to talk generally about properties of group structures and how these structures may influence behavior. The model we present here is simplistic yet makes a logical point: groups matter. Moreover, beliefs about how groups organize can influence how one interprets political action.

In our simulation, we examined several different behavioral rules. These rules were an attempt at capturing different psychological phenomena. The first family of rules, *Minimal Ally*, were inspired by the psychological work on social conformity. In these rules, individuals needed others in their reference group to support their policy disagreement. How many others needed serve as a proxy for the cost of taking political action. Requiring more people indicates a setting where people are more cautious about participating, or in other words, the costs for taking action are greater.

The results from this family of rules indicate that in more cautious settings, sparse (or low density) networks may under represent the total population than denser ones. Therefore if one were to observe low total turnout and know that the group was fairly close knit (dense), the research on social conformity would indicate that turnout would be sincere for those strongly opposed to the policy. Whereas, if we observe a fair amount of turnout and the network is sparse, there could be many more individuals also against the policy.

The second family of rules produced slightly more surprising results. These rules were inspired by numerous studies in Behavioral Decision Research. It has been shown that people are not Bayesian in their inferences. Additionally, people may over weigh their own opinion. We imposed that agents think that their neighbors, or friends, are representative of the population as a whole. The agents, however, could give their own opinion additional weight (up to two to three times as much as what they would give a neighbor). We also impose that agents conform at varying degrees to their reference group, so they go with whatever a certain proportion of that group does.

Notice that requiring a proportion of the group is very different than the number required in the first rule. In this rule, instead of requiring an absolute number of people to support her opinion, the individual has a threshold for turning out. In a similar fashion to the previous family of rules, the threshold in this family of rules may be considered a proxy for the cost the individual faces for taking political action. As one might guess, this family of rules produced results very different from the first family.

In cases where there is a lower threshold, or when individuals were experiencing a lower cost, there are results reminiscent of informational cascades. In situations where individuals communicated with many people, almost no one turned out in disagreement – even when 20-30 percent of the population disagreed with the policy. In less dense networks this effect was diminished; so that people were turning out to protest in a proportion that was closer to the actual number of people against a policy. There was, however, almost a tipping point around the threshold in dense networks.

In a setting where people communicated with many other individuals, the change between everyone publicly supporting the policy (by not turning out) to everyone publicly disagreeing with the policy (by turning out) happened very quickly. In groups with a lower density, this cascade was not as pronounced. In particular, in networks with lower density, turnout was more gradual and approximated the actual number better.

While it is an empirical falsity to claim that everyone in the society turns out at a rally, these results might give an indication of the turnout process in smaller, very closely connected groups. I.e., there could exist turnout from individuals that in fact do support the policy but because of group pressures still march at a rally.

In general, our results indicate that different network densities can lead to different turnout, and that knowledge of the network could be important for how a leader interprets aggregate turnout. Our model is a simple one shot game. Therefore, there is no opportunity for any one involved to learn about the network. Arguably, most situations are recurring situations, or they happen again from time to time. In terms of our model, people have the same group of friends or same communication network through time, and it would have not differential impact. Therefore the leader might have the opportunity to learn the network.

In our model, once a leader learns a network structure, he or she would best respond. This might seem problematic; however, not necessarily. There could be one "true" communication structure, but who we communication with might be issue dependent. In other words, there could be issues in which an individual does not speak to some others. For example, some one might not wish to speak to his or her grandmother regarding gay rights. If this is the case, then there could be different communication structures found within the "true" network.

A leader that best responds given knowledge of a social network structure also raises an interesting question for researchers of social movements. Some authors have argued that "Political Opportunity Structures" allow for a social movement's success. However, if there is such a structure, then a leadership's knowledge of it should *decrease* the influence of a large turnout.

In this paper we present a very simple computational model to show a logical point: networks matter and therefore beliefs about networks matter for interpreting protest turnout. There are many areas, however, in which the current work may be extended. Our most questionable assumption is that signals are independent across the population. Or, that the likelihood that my neighbor receives a signal about his policy preferences, is independent of my signal. This seems to be counterintuitive when one considers friendships. People who are friends tend to have the same values and beliefs. For example, one's friends might share the same view on a policy issue such as a tax cut. The independence assumption implicitly says that everyone is the same – friend or not. A future extension of this work would be to relax the independence assumption. Relaxing it might amplify the non-Bayesian inference aspect of individuals. Specifically, agents will be sampling non-randomly and thus think more people in the population agree with their own opinion.

Another fruitful extension would be to relax the random graph assumption. This assumption implicitly states that if an individual has two friends, A and B, the likelihood of A knowing B is the same as A knowing C, where C is some other random individual in the society. This seems a bit odd. Previous work in Balance Theory found in Psychology, suggests that people want to maintain balanced relationships. So that if an individual has a positive relationship to A and a positive relationship to B, then she has a desire to induce a positive relationship between A and B. This suggests that people cluster in their social groups; or in more common terms, they have a circle of friends. Duncan Watts and others have examined network structures that attempt to capture these "small world' phenomenon [25]. A fruitful extension to our model would be to replace the random graph with a "small world" structure.

A similar extension to incorporating small world graphs, would be to replace the random graph with a graph that included more organizational structure. One might think of two graphs that operate on top of one other. This would capture things such as local communities and their leaders, with their leaders then also having a communication structure. This seems to be analogous to the social structures of black churches in the civil rights movement. As Chong points out, the black church leaders played a key role in their ability to mobilize their congregations to partake in economic boycotts and join in public rallies. These leaders organized their communities, but also communicated with other civil rights leaders.

We began by questioning the puzzle of political protest. Namely, how can (relatively) small turnout have a large impact? In the model we presented here, we attempted to address the effects groups may have on individual decision making. These group influences contribute to turnout. Though moreover, a leader's beliefs about a group's structure might influence his interpretation of aggregate turnout. Our model attempts to highlight some conditions under which the few matter the most.

1. Figures

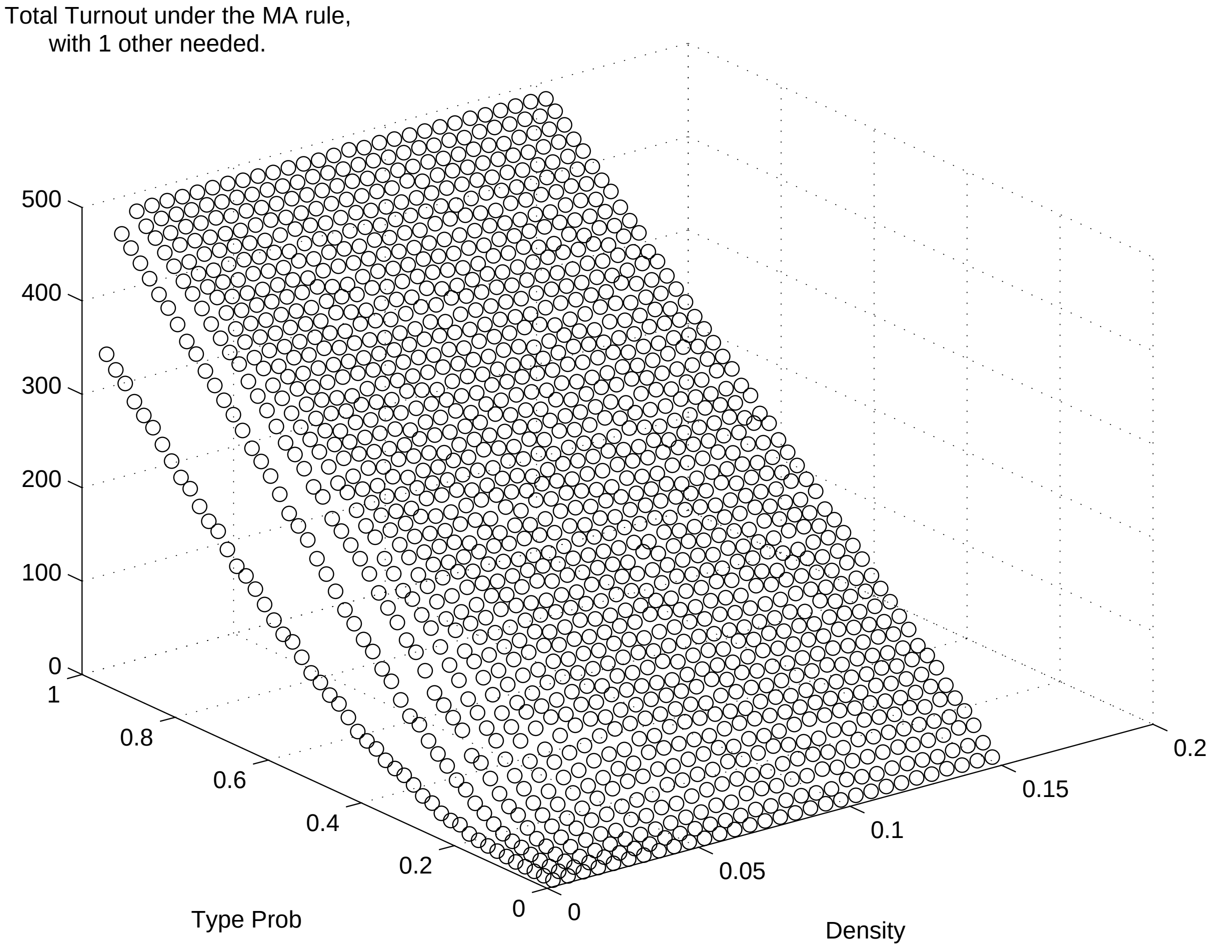

Figure 3. Total turnout using MA. Only needing one person to support signal

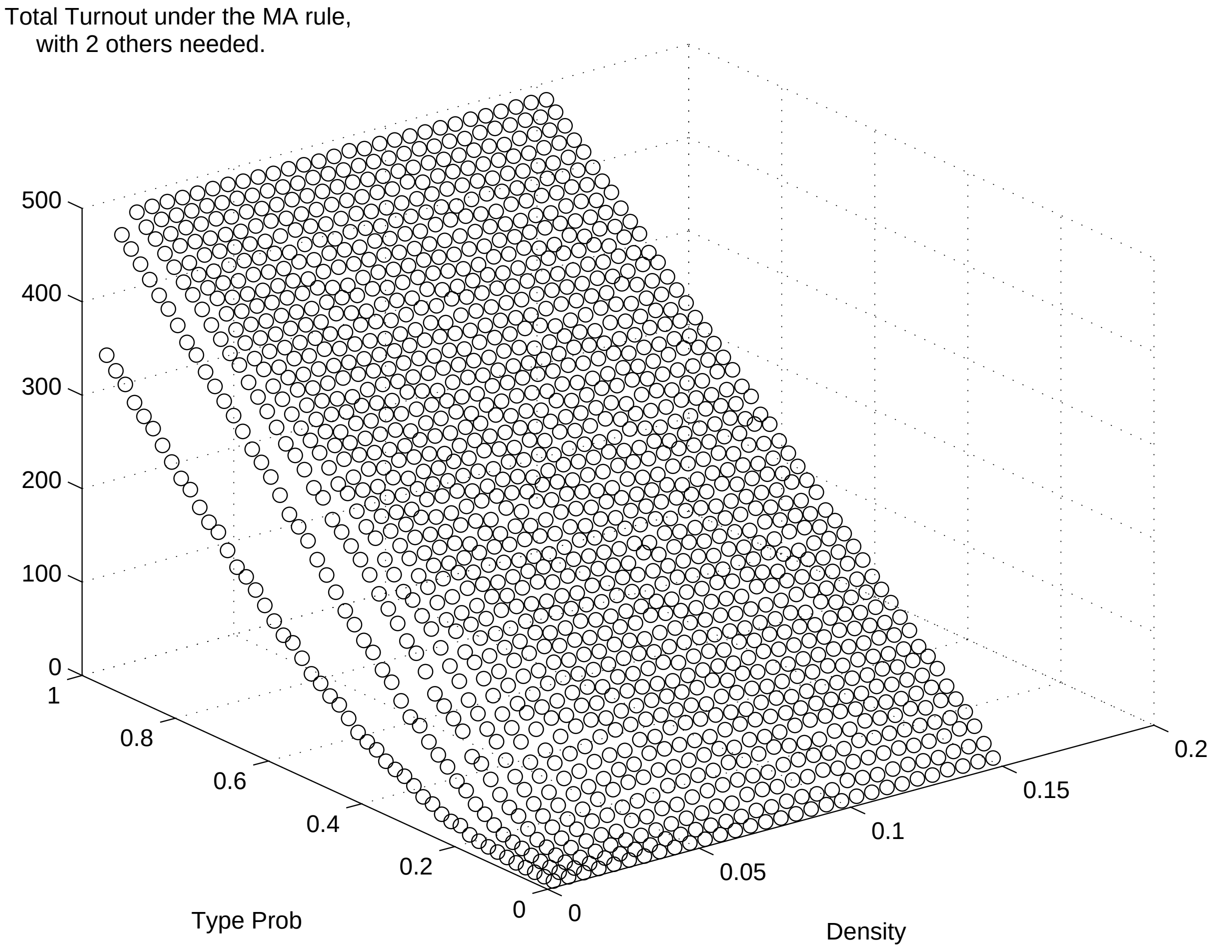

FIGURE 4. Total turnout using MA. Only needing two people to support signal

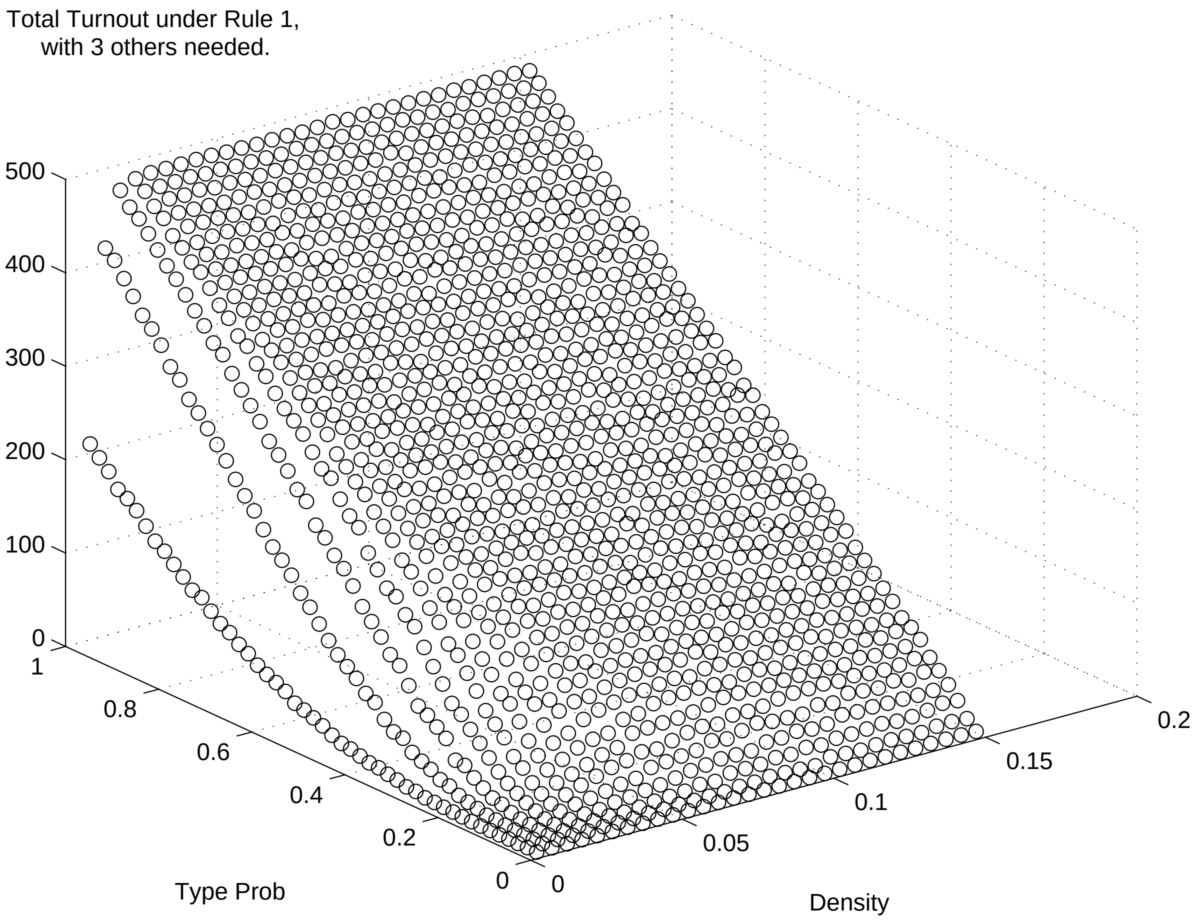

Figure 5. Total turnout using MA. Only needing three people to support signal

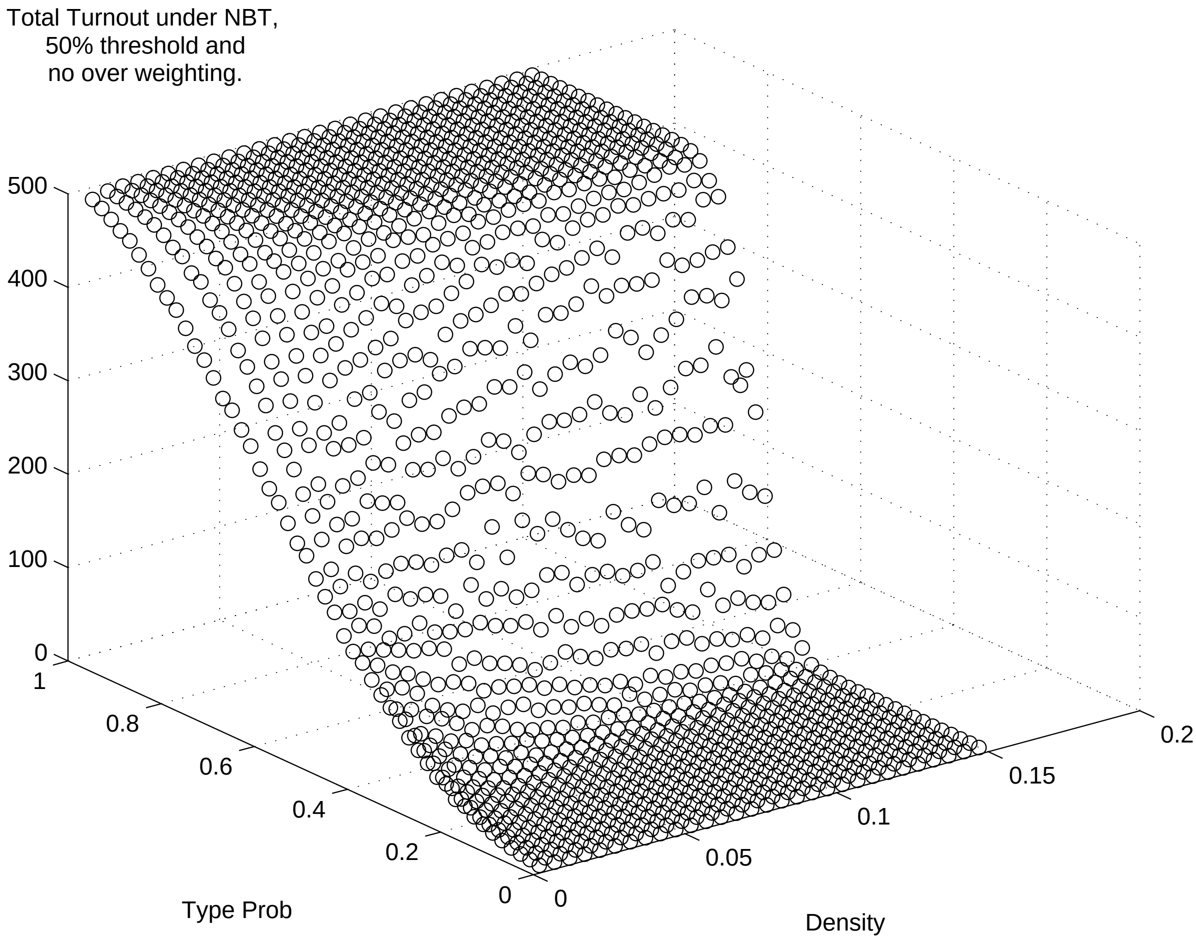

FIGURE 6. Total turnout using NBT, 50%. No over weighting

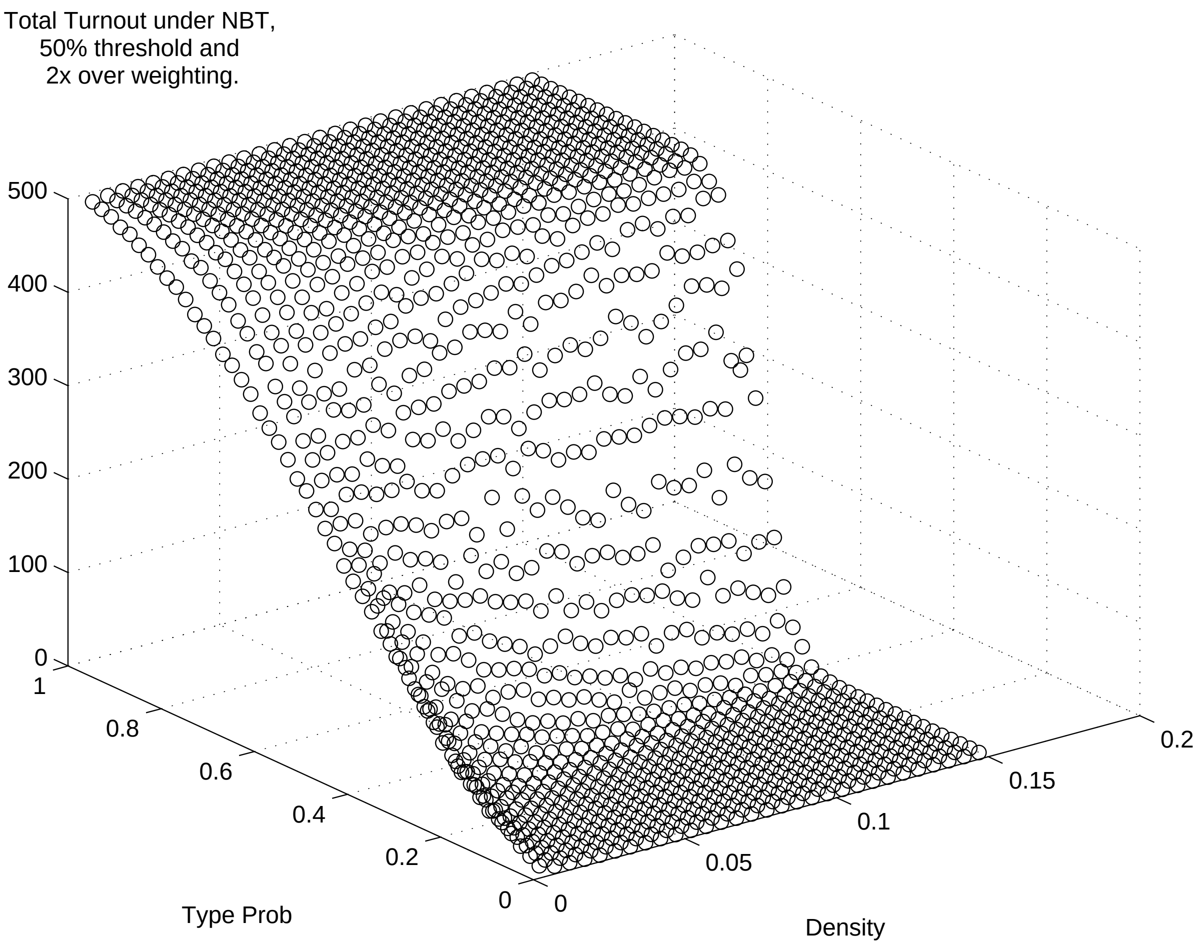

FIGURE 7. Total turnout using NBT, 50%. Double counting own signal

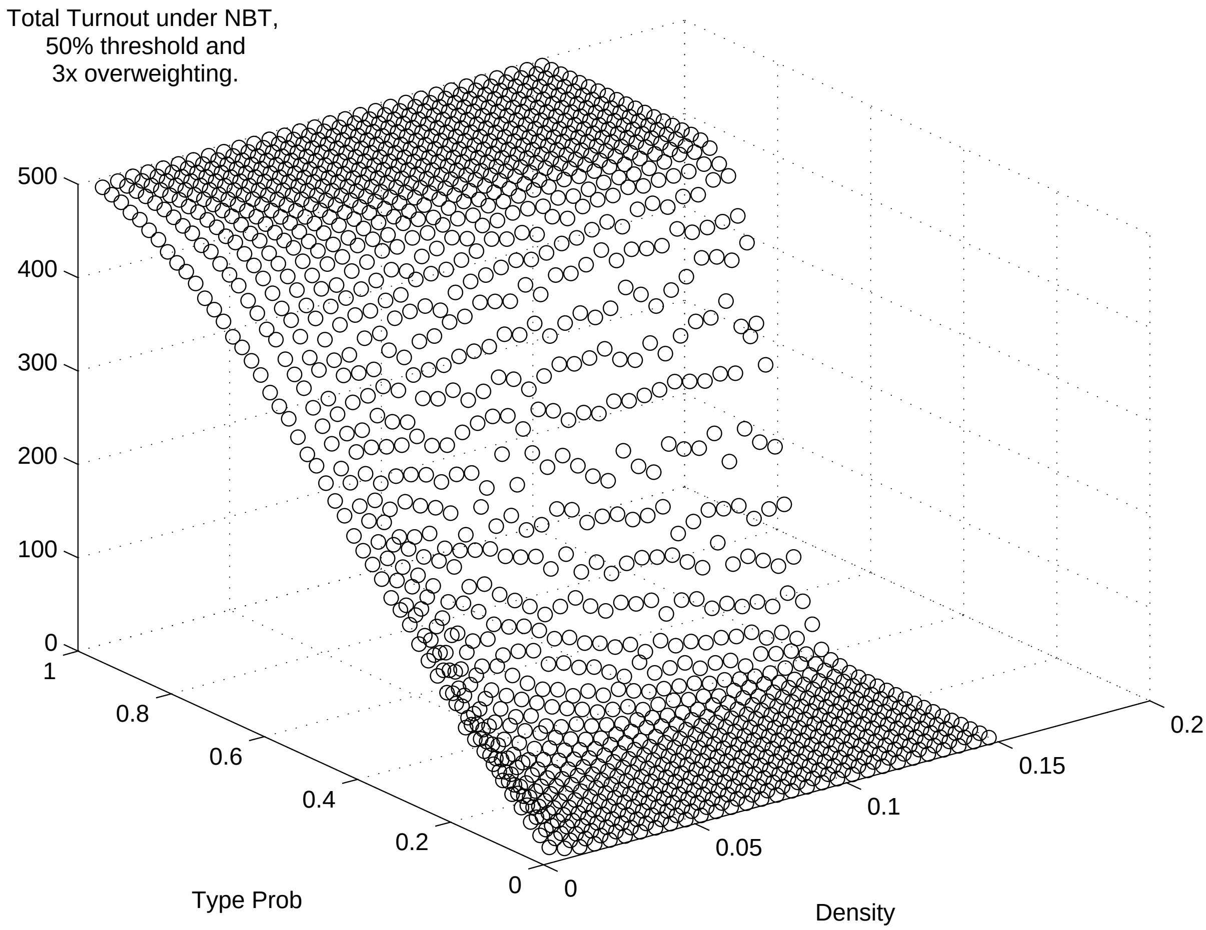

FIGURE 8. Total turnout using NBT, 50%. Triple counting own signal

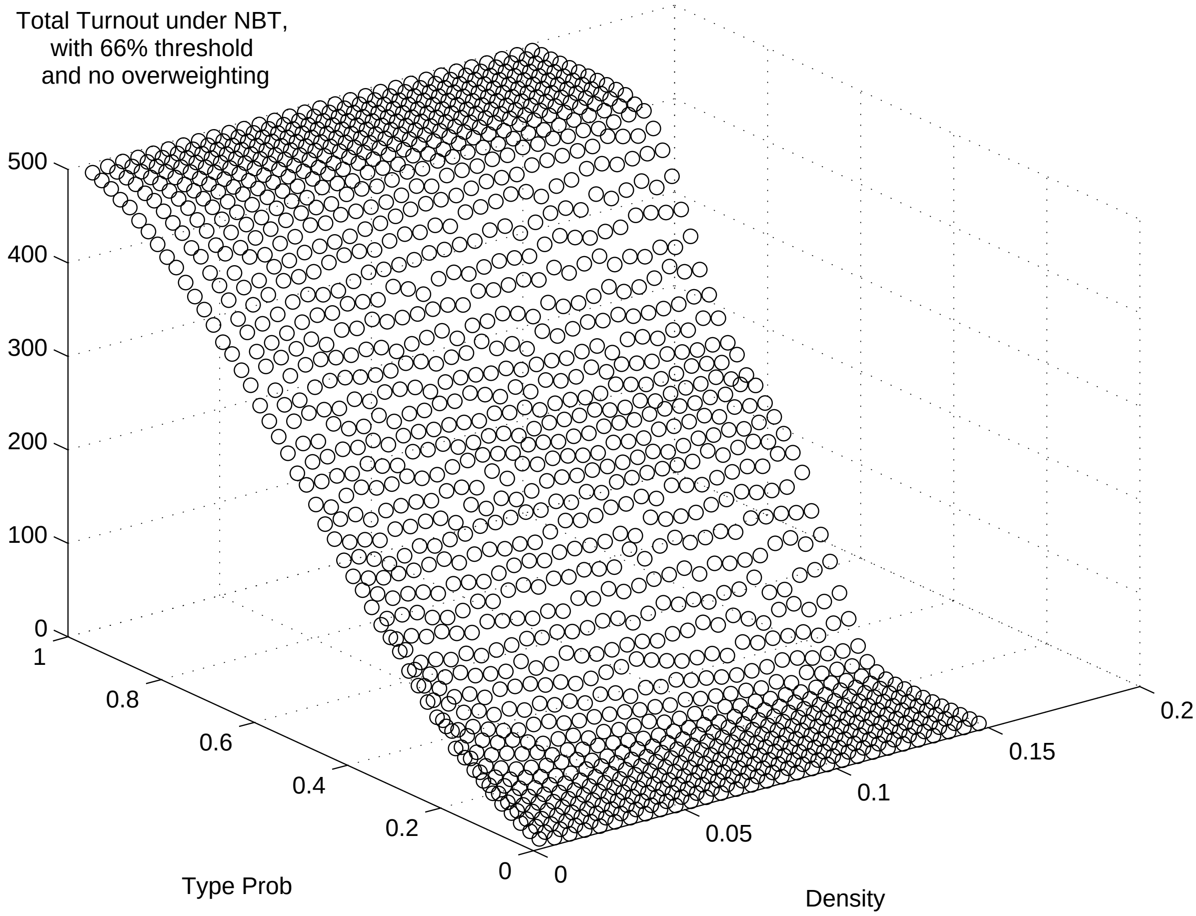

FIGURE 9. Total turnout using NBT, 66% threshold and no over weighting.

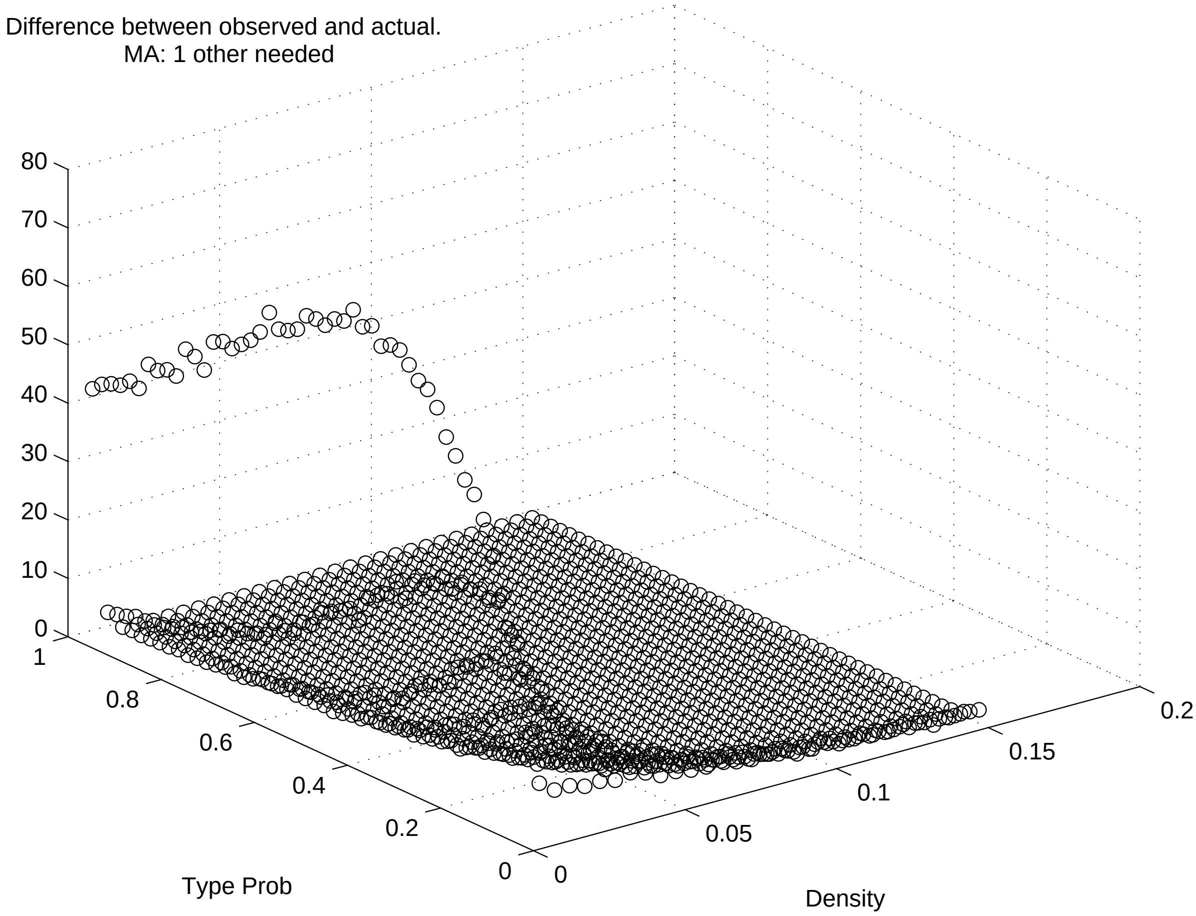

FIGURE 10. Difference between observed turnout and proportion that received signal. MA, only 1 other needed

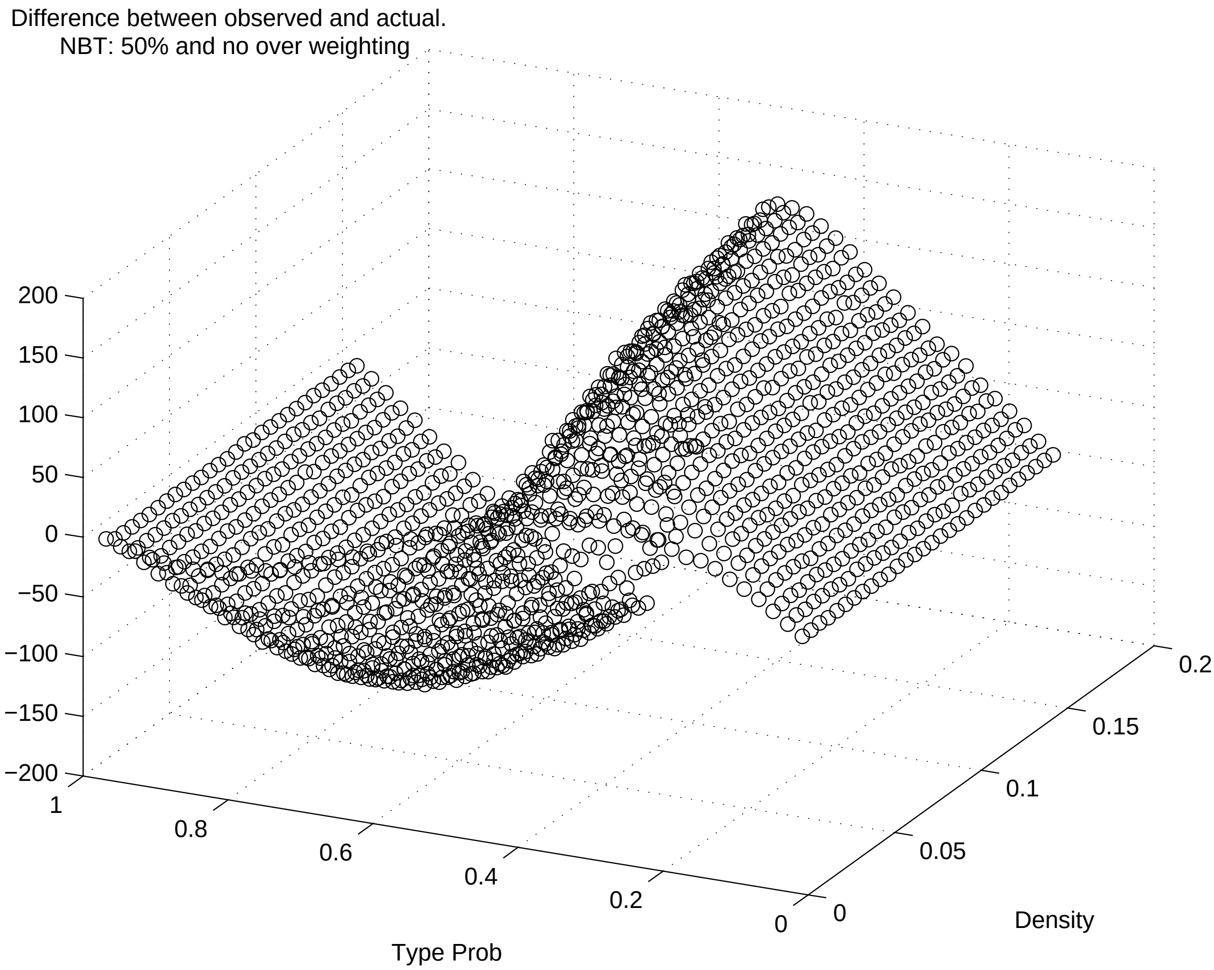

FIGURE 11. Difference between observed turnout and proportion that received signal. NBT, 50% no over weighting.

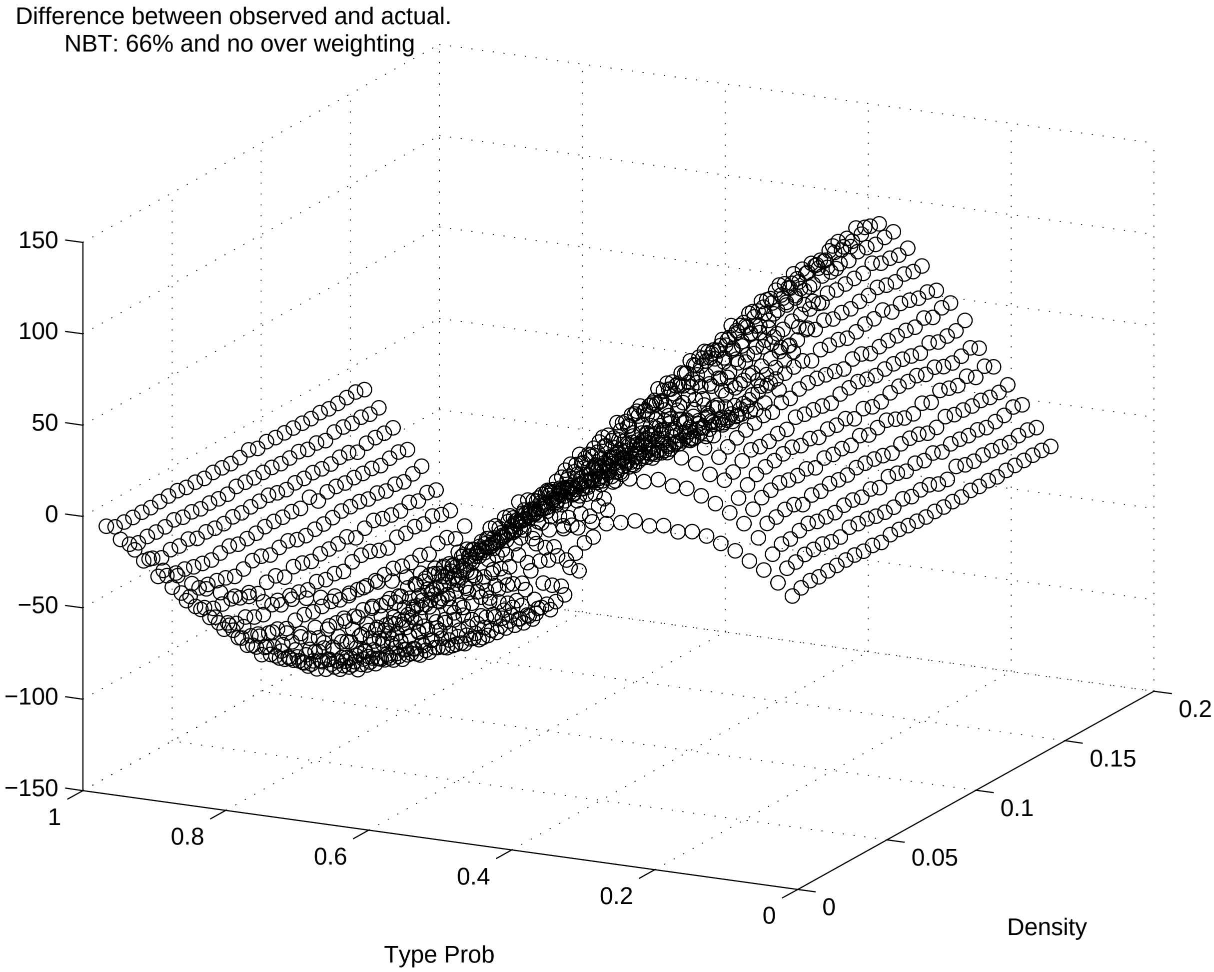

FIGURE 12. Difference between observed turnout and proportion that received signal. NBT, 66% and no over weighting

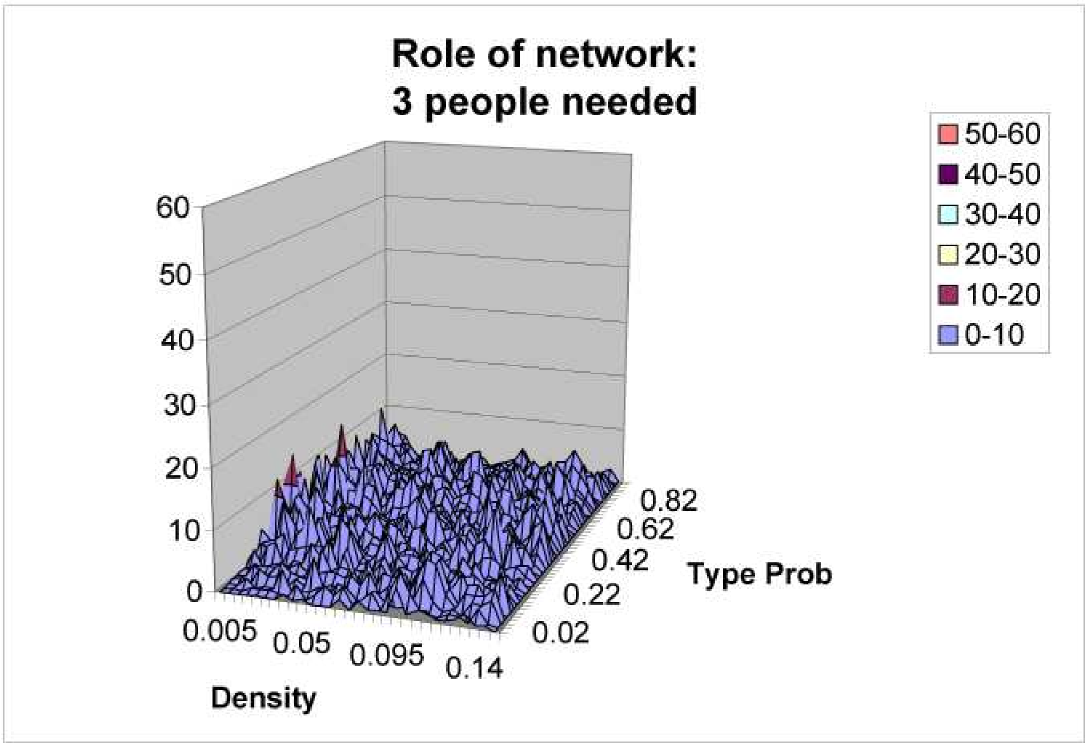

FIGURE 13. Partial Derivative of the MA rule requiring 3 others.

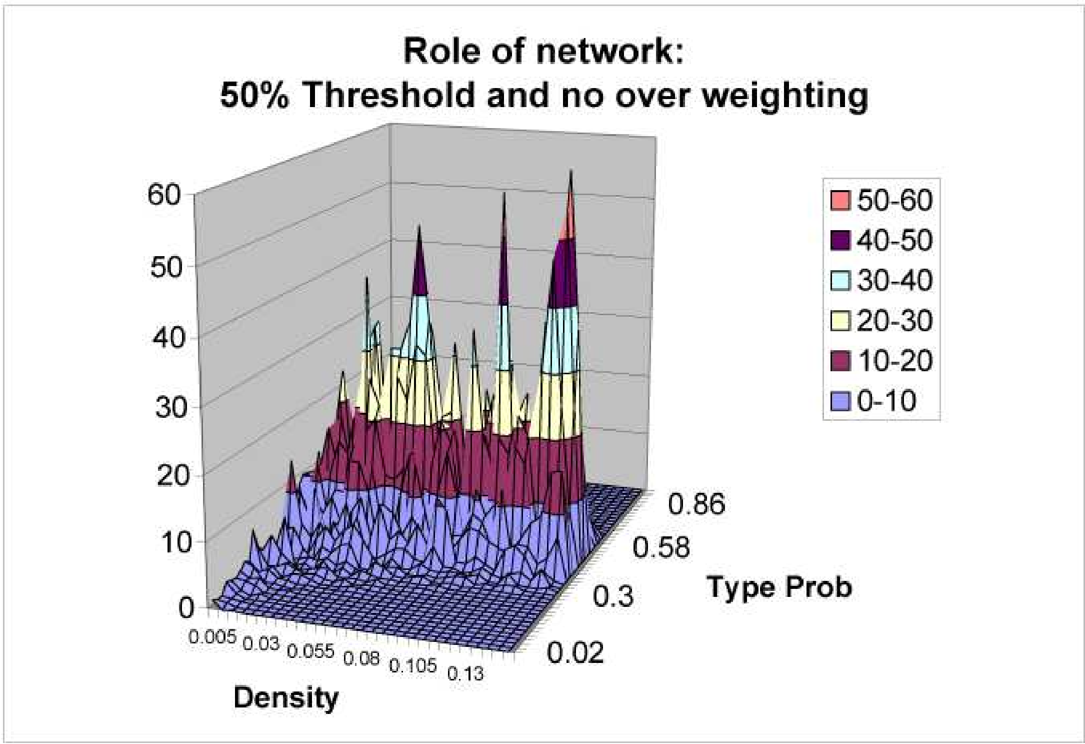

FIGURE 14. Partial Derivative of the NBT, 50% threshold and no over weighting

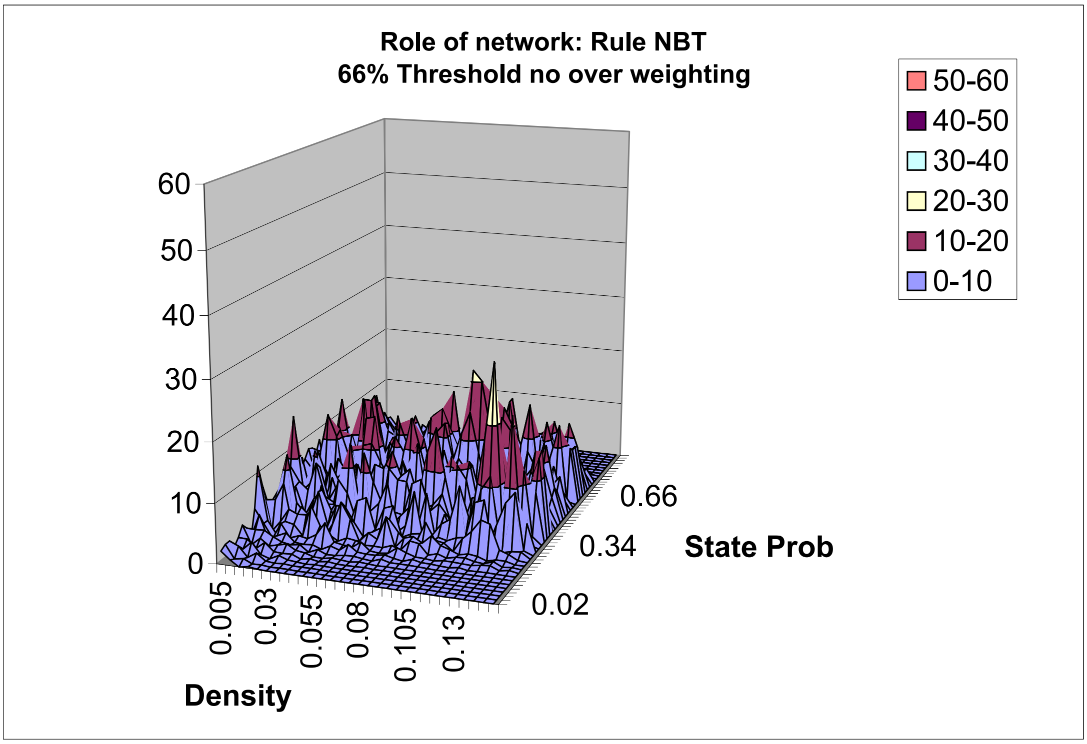

Figure 15. Partial Derivative of the NBT, 66% threshold and no over weighting

State .02-.98	MA1	MA2	MA3	NBT50 N	NBT50 2x	NBT50 3x	NBT55 N	NBT55 2X	NBT55 3X	NBT60 N	NBT60 2X	NBT60 3X	NBT66 N	NBT66 2X	NBT66 3X
Number of times number at turnout was less than 250 (<50% of population), but more than 250 (> 50%) were against the policy	9	28	46	29	0	0	83	50	34	164	124	98	0	6	5
(percent)	0.006	0.019	0.031	0.020	0.000	0.000	0.056	0.034	0.023	0.112	0.084	0.067	0.000	0.004	0.003
Number of times number at turnout was greater than 250 (>50% of population), but less than 250 (< 50%) were against the policy	0	0	0	0	11	29	0	4	11	0	0	3	0	15	15
(percent)	0.000	0.000	0.000	0.000	0.007	0.020	0.000	0.003	0.007	0.000	0.000	0.002	0.000	0.010	0.010
Number of times number at turnout was less than number of people actually against a policy	529	627	724	768	705	663	843	783	731	946	884	833	729	678	632
(percent)	0.360	0.427	0.493	0.522	0.480	0.451	0.573	0.533	0.497	0.644	0.601	0.567	0.496	0.461	0.430
Number of times number at turnout was greater than number of people actually against a policy	0	0	0	702	765	807	627	687	739	524	586	637	740	792	838
(percent)	0.000	0.000	0.000	0.478	0.520	0.549	0.427	0.467	0.503	0.356	0.399	0.433	0.503	0.539	0.570
total sessions 1470															

FIGURE 16. Summery statistics for the full range of type probabilities.

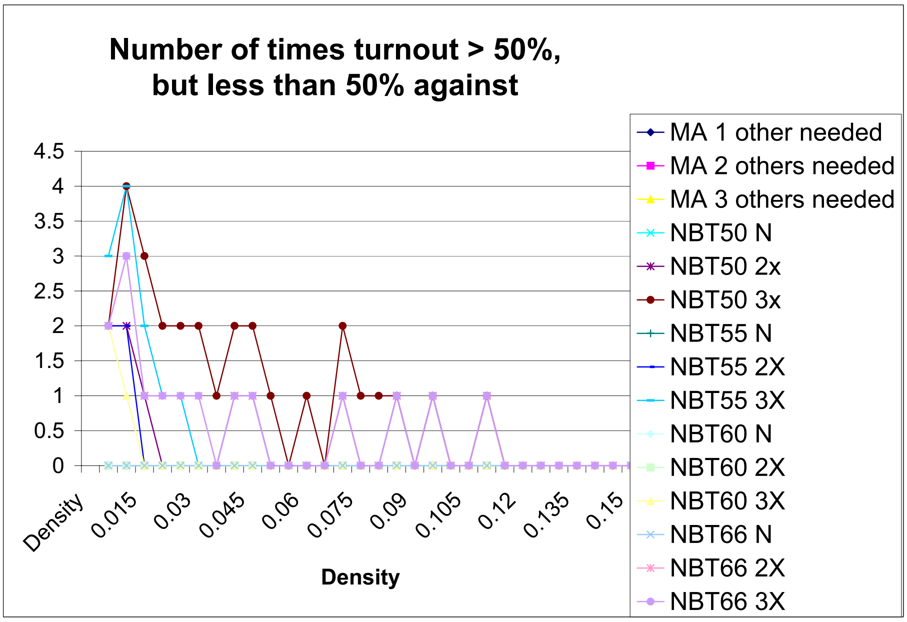

Figure 17. Number of false positive errors

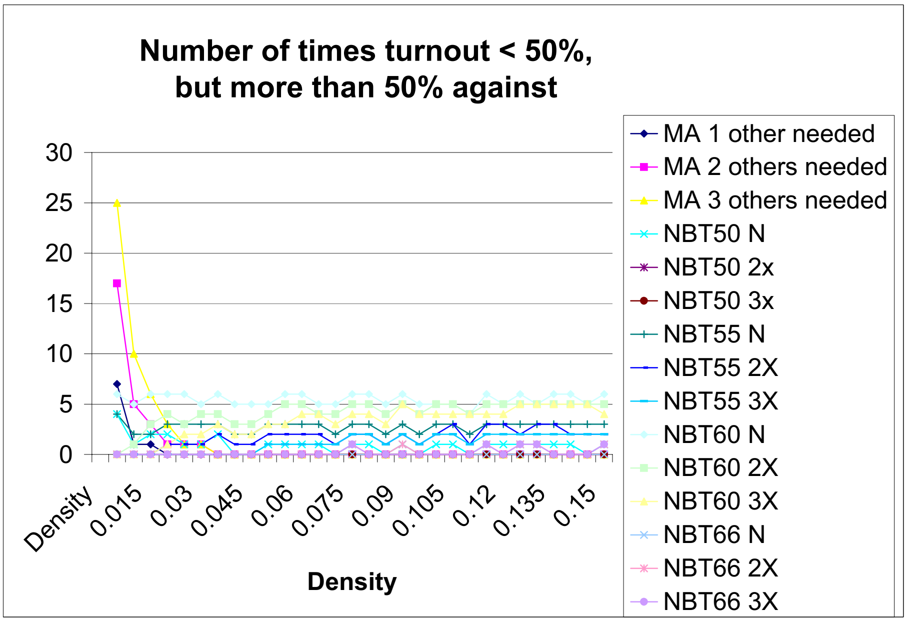

FIGURE 18. Number of false negative errors

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