Modeling Political Information Transmission as a Game of Telephone

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POLITICAL INFORMATION TRANSMISSION

Abstract

Many individuals learn about politics from other people instead of directly from the media. While this could be a good way to reduce information costs, highly controlled lab experiments reveal that the information exchanged can be biased. These important lab experiments are so controlled, however, that they ignore the complexities of language inherent in real-world information transmission. In an effort to improve our understanding of how political information changes as it propagates from the media to one person to another, I conduct a novel online experiment in which I track information diffusion through individuals in communication chains. I then use content analysis to examine how the information is actually changing, finding that the amount of political information communicated decreases as the number of people in the chain increases. Furthermore, the information is increasingly distorted as the length of the chain increases.

Keywords: information transmission, political communication, socially supplied information, experiments

Supplementary material for this article is available in the appendix in the online edition. Replication files are available at the JOP Data Archive on Dataverse (http://thedata.harvard.edu/dvn/dv/jop). This study was conducted in compliance with relevant laws and was deemed exempt by the University of California, San Diego Institutional Review Board. Support for this research was provided by National Science Foundation grant SES-1423788.
How does information change as it flows from the media to person to person? A long line of research suggests that many individuals turn to others for political information instead of turning to the media [Katz, 1957; Katz and Lazarsfeld, 1955]. The idea is that individuals can form opinions and ultimately make rational voting decisions using information from others who are more knowledgeable than they are and who share their preferences instead of spending time doing the research themselves (Downs, 1957). While turning to others can reduce information costs, there is evidence from lab experiments that socially supplied information can be biased in favor of the information sender’s preferences (Ahn, Huckfeldt and Ryan, 2014). These highly controlled experiments have allowed us to explore the conditions under which individuals send biased information to others and how that biased information impacts learning and vote choice. However, most of these experiments involve individuals communicating numeric messages that represent preferences in a spatial model, which does not fully capture the complexities of language inherent in information transmission in the real world.

Research outside of political science has pushed beyond numeric information transmission, using content analysis of conversations to examine how information changes as it flows from one person to the next. Specifically, Moussaïd, Brighton and Gaissmaier (2015) find that social information transmission about a controversial antibacterial agent results in less—and less accurate—information being communicated. It is important to examine whether this pattern exists in the communication of political information because of the impact that socially supplied political information can have on individuals’ opinions and voting behavior. In addition, the strong influence of partisanship (Campbell et al., 1960; Bullock et al., 2015) and motivated reasoning (Taber and Lodge, 2006) on how we interpret political information distinguishes the communication of political information from the public health information previously explored.

In this paper, I build on these two important bodies of work by bridging them together to provide a fuller understanding of how political information changes as it flows
from the media, to person, to person. I expand on the important lab experimental work in the political context (Ahn, Huckfeldt and Ryan, 2014) by introducing an experimental design that allows individuals to communicate more than numbers. By modeling information transmission as a game of telephone, we can track changes in content from one person to the next. This paper alone cannot answer all of the important questions about the normative implications of social information transmission, but future studies can utilize variations from this core design to improve our substantive knowledge of information transmission.

Method

Modeled after the research design employed by Moussaïd, Brighton and Gaissmaier (2015), I examine how political information changes as it is passed from person to person using experimental diffusion chains. A diffusion chain consists of three unique participants that attempt to inform one another about the 2016 presidential candidates. The first participant (P1) read an article about the 2016 candidates as if he or she was trying to learn about the candidates. After reading the article, the next screen prompted the participants to write a message to people with whom they have previously discussed politics, elections, or current events, telling them about the 2016 presidential candidates. The next participant (P2) then read P1’s message about the candidates and was asked to write a message under the same instructions. P2’s message was then given to a third participant, P3, to read, and P3 was asked to write a message under the same instructions. All participants were blind to any characteristics about the people from whom they received messages and to whom they sent messages. This provides for a baseline

1I selected a New York Times article that listed the presidential candidates for each party and sorted the candidates into “running,” “probably not,” and “not running” and included three pieces of information about each candidate. The article was updated the day before I collected the data. The full survey instrument is available in the online appendix.
test of information diffusion, net of strategic communication or discounted interpretation conditional on individual characteristics.

The data were collected in three stages on July 28, 2015 on Amazon’s Mechanical Turk (MTurk). Approximately 150 individuals participated in each position of the diffusion chain. P1 participants wrote a message after reading the previously described news article. Each P2 individual was randomly assigned to read a message written by a Republican or a Democrat in P1, and P3 individuals were randomly assigned to read a message written by a Republican or Democrat in P2 before writing their own messages. Participants were not explicitly informed of the message’s author’s partisanship.

**Dependent Variable Measurement**

This study includes two dependent variables: the amount of information communicated and the distortion of that information. I measure both using a coding scheme developed by Moussaïd, Brighton and Gaissmaier (2015). First, I measure the amount of information in each message by coding for "units of information." A unit is defined as a statement that conveys a single, identifiable piece of information. For example, Table 1 shows the messages written in one diffusion chain, with the units of information

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2 Please see the online appendix for a discussion about features of MTurk that are uniquely suited for this study.

3 This analysis only examines partisans. Messages written by Independents were not passed on to the next stage. Independents who leaned toward one party were coded as partisans and were included in the analyses. As a result of dropping messages written by Independents, some messages were received by more than one participant at the next stage. The results presented reflect the *unique* messages or chains written and received by Republicans or Democrats. A preliminary analysis including Independents is presented in the appendix. Future work should take care to closely examine Independents as they could be the group most susceptible to bias introduced by partisans in socially transmitted messages.
identified below. Two independent coders coded these messages blind to the chain position and in a randomized order. The coders were blind to the purpose, hypotheses, and design of the study, and converged on similar amounts of information (Krippendorf’s alpha=0.65; correlation coefficient=.86; intraclass correlation coefficient=.85).

Second, I measure information distortion by using the distortion coding scheme developed by Moussaïd, Brighton and Gaissmaier (2015). This coding scheme considers a unit of information to be distorted based on the following non-mutually exclusive characteristics: (1) a numerical value has changed or disappeared, (2) a qualitative indication of volume, frequency, or probability has changed or disappeared, (3) an element has moved from a specific to more general class of information, (4) a previously inexistent element has been added, and (5) content is obviously wrong.

<table>
<thead>
<tr>
<th>Units of Information</th>
<th>P1</th>
<th>P2</th>
<th>P3</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. There are a handful of people running for the Democratic presidential nomination.</td>
<td>There are a lot more Republican candidates than democrats- many of which will run out of funding or are unknown. The democrats are focusing on a few strong candidates while the republicans have many options.</td>
<td>There are many more Republican candidates on the presidential race. Many of those running are unknowns or will drop out of the race. Democrats are focusing on a few candidates.</td>
<td></td>
</tr>
<tr>
<td>2. There is a much larger number of people running for the Republican nomination.</td>
<td>Many will run out of funding.</td>
<td>Many are unknown.</td>
<td></td>
</tr>
<tr>
<td>3. Many will drop out for lack of funding.</td>
<td>Many are unknown.</td>
<td>Many will drop out of the race.</td>
<td></td>
</tr>
<tr>
<td>4. Many will drop out for lack of recognition.</td>
<td>The democrats are focusing on a few strong candidates.</td>
<td>Democrats are focusing on a few candidates.</td>
<td></td>
</tr>
<tr>
<td>5. A few more names on either side will be added to the mix.</td>
<td>Republicans have many options.</td>
<td></td>
<td></td>
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</table>

Two objective, independent coders coded these data. They were not blind to each message’s position in the chain in this case because they needed to be able to evaluate whether distortions occurred relative to the previous message. All statistical relationships

4Detailed information about the coding scheme, including the training materials presented to the coders is available in the online appendix.

5See the appendix for examples of distortions in each of these categories.
and patterns hold for both coders, though the specific quantities, such as the mean number of distortions, fluctuate slightly.\(^6\) I created a total distortion score for each participant by summing the number of distortions in each of the five categories.\(^7\)

**The Amount of Information Transmitted Declines**

I first examine the *units of information* in each position. As shown in Figure 1a there were fewer units of information in each position down the diffusion chain. A \(t\)-test indicates that there are significantly fewer units of information in the third position than the first position \( (p < .05, CI = [0.02, 2.83]) \), so by the end of the three-person chain, there is significantly less information being transmitted. The people at position 1 only passed on about 3% of the information from the article to the next person.\(^8\) Figure 1b shows that the distribution of units of information is roughly the same for each position in the chain, aside from subtle shifts to the left for P2 and P3 relative to P1.\(^9\)

\(^6\) The two coders did not have sufficiently high levels of inter-coder reliability. The results presented in the paper reflect the average of the two coders, but results from each coder independently are included in the appendix.

\(^7\) Under this coding scheme it is possible that accurate information gets coded as a distortion. For instance, if P1 introduces content that is obviously wrong (Category 5), but P2 corrects that information, P2’s correction is still coded as a distortion because he or she has added a previously nonexistent element (Category 4). However, a very small percentage of all distortions in the study were Category 5 (obviously inaccurate content), and this content was not corrected by subsequent participants in the chain.

\(^8\) The same pattern is evident comparing the number of words in the messages as a noisy proxy for units of information. There were significantly more words in the messages in position 1 than position 3 \( (p < .05, CI = [0.80, 18.77]) \).

\(^9\) The decline in information could be an artifact of the instructions. Participants were not incentivized to write thoroughly, inform, or persuade the person to whom they wrote. Future studies utilizing a similar design could vary the instructions and incentives presented to participants.
The Quality and Precision of the Information Declines

Second, I examine whether the fidelity of information decreases as it propagates through the chain. Ultimately, the additive effect of distortion is more appropriate to evaluate than the number of distortions made at each position because P3 is not only exposed to P2’s distortions, but P2’s distortions of the information already distorted by P1. I therefore, discuss the cumulative distortion of the information across each chain. On average, a participant at P1 made about 65.2 distortions, a participant at P2 made about 9.1 distortions, and a participant at P3 made about 8.2 distortions. Looking at the cumulative distortion indicates that a hypothetical person at P4, getting information from the person at P3, is exposed to information with about 82.6 distortions, which is 26.6% more distorted than the information the person at P2 receives from P1.

Looking into the five types of distortion classified by Moussaïd, Brighton and Gaissmaier (2015), Figure 2 shows the mean proportion of the number of distortions of each type relative to the total number of distortions for each position in the chain. This suggests that individuals at P2 and P3 are more likely to introduce new information than
individuals at P1. Upon reevaluating the messages, it is clear that individuals at P1 have omitted so many details in consolidating the information from the article that there is very little specific information left for individuals at P2 and P3 to generalize, few numeric values to change, and few quantities to describe qualitatively.\footnote{It is important to note the remarkably low levels of wrong information being introduced because it suggests that the changes in information through a diffusion chain might not be problematic. Individuals at the end of a chain are certainly not exposed to the same, as much, or as precise information as those at the start of a chain, but they do not appear to be any more likely to be exposed to blatantly wrong information.}

\[ \text{Proportion of Each Type of Information Distortion} \]

<table>
<thead>
<tr>
<th>Proportion of Distortions</th>
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</thead>
<tbody>
<tr>
<td>New Info Introduced</td>
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<tr>
<td>Qual Description of Quant</td>
</tr>
<tr>
<td>Specific to General</td>
</tr>
<tr>
<td>Numeric Value</td>
</tr>
<tr>
<td>Wrong Info</td>
</tr>
</tbody>
</table>

\[ \text{Proportion of Each Type of Information Distortion} \]

\[ \frac{d_i}{D} \]

where \( d_i \) denotes the number of distortions made of each type \( i \in \{ \text{New information introduced, qualitative description of quantity, specific information generalized, numeric value has changed or disappeared, wrong information introduced} \} \), and \( D \) denotes the total number of distortions.

That changes in qualitative descriptions of quantities and numeric values were the most common distortions in position 1 could suggest that individuals have a difficult time interpreting numbers. This should be evenly distributed between the positions, but it is worth considering the possible role of numeracy in information transmission.
Discussion

This study introduces an experimental paradigm to political science research on information transmission. The substantive results suggest that the *amount* and *quality* of political information declines as it propagates through more people. This suggests that people farther removed from the initial source of information—farther down an information diffusion chain—will not only receive less information, but that information will also be distorted, particularly from the introduction of information external to the initial source and a dramatic loss of specificity.

Although the results of this analysis are interesting, this study is not without its limitations that present opportunities for future research utilizing this design. First, the study involved information about the 2016 presidential candidates, which was a relatively salient topic in July 2015. The salience of the topic poses a potential problem for this analysis: because most of the participants had likely heard something about the candidates, it is possible that they wrote their messages based solely on prior knowledge instead of what they read from the previous person. However, given that individuals rarely discuss political topics that are not salient, it is likely that they have at least *some* information prior to hearing from another person. Future research should build on this by examining how individuals re-aggregate information from multiple sources. Future work could also probe how the topic, affective content, or partisan bias of the news articles influence the transmission process.

Second, a related limitation is that individuals self-select into information diffusion chains in the real world. Individuals might self-select into getting information from only copartisans in reality, yet in this study, participants were blind to all characteristics, including partisanship, of the information senders and receivers. It is reasonable to expect that individuals interpret information differently from a known copartisan than a known non-copartisan. Individuals are also likely to tailor the information they share with others conditional on anticipated agreement or disagreement. The experimental
design in this study does not allow me to assess these interesting dynamics. Instead, this study focuses on capturing a baseline for political information transmission, absent these potentially influential contextual factors. In addition, individuals in the real world choose their position in the chain based on their information-seeking habits. In this study, the person in position 1 could have been the least informed and least politically interested person in the diffusion chain, which is unlikely to occur in reality. While chain position is not randomly assigned in this study, as those who opted into each round of the study could be substantively different, Table 1 in the appendix suggests that the participants in each stage were highly comparable.

In addition to addressing these limitations, future research should push beyond characterizing political information distortion to explore its implications. Perhaps most important, future work should consider whether individuals receiving more distorted information are still able to make rational political decisions. This analysis will help determine the extent to which the characteristics of political information transmission are good or bad for a well-functioning democracy.

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References


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