Identifying the Motivations of Political Donors using Donation and Social Media Data

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Code and data available at: github.com/Rdahlke/political_donor_motivations

Abstract

Recent elections have shown that online, small-dollar donors can impact political campaigns. Much reporting pointed to campaigns' digital communications as a method for cultivating these donors. My research asks: What motivates political donors in Wisconsin state-legislative elections? My analysis finds a link between candidates discussing certain issues online and donations from specific donor communities. This research contributes to the field of ideological estimation and the ability to find connections between online political activity and traditional political actions, such as making a political donation.

Keywords: networks, statistical analysis of texts, preference measurement

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It is well-documented that the prevalence of online, small-dollar donors to political campaigns was one of the major stories of the 2016 election cycle (Foran, 2016; Prokop, 2016; Sherfinski, 2017; Stein & Cherkis, 2017; Vogel, 2016). I hypothesized that this change in the culture of political contributions would mean that at least some political donors at all levels of government would be attracted to political campaigns based on the issues that those campaigns talked about on social media. I created a unique methodology that built upon previous scholarly research into the motivations of political donors by quantifying political ideology and predicting the issues that political donors care about.

Past research has used political donation information to predict the ideology of donors (Bonica, 2014). But that analysis is limited to predicting ideology in a left-right continuum. I attempt to layer on elite social media data from the candidates receiving political contributions to identify the specific issues that motivate political donors. The output of this study shows that there is a distinct intersection between candidates' online communication and political donors.

Literature Review

Political Donations

Academics have long studied the motivations of political donors. There are two predominant explanations for why donors contribute to campaigns: to gain access to candidates, to empower the candidates that are best for their personal interests, or to support candidates who champion specific policies.

The bulk of academic inquiry into political donors and their motivations has focused on access-oriented donors such as large-dollar donors with business interests or political action committees (PACs). Predominant views of political donations hold that campaign contributions are chiefly investments in a political marketplace “where a return on that investment is expected” (Ansolabehere, de Figueiredo, & Snyder Jr., 2003). Special interests groups have been found to frequently donate to incumbent candidates even if their ideologies do not perfectly align because those groups want to try to attain access to incumbents who are likely to be reelected for a long period of time and attain powerful leadership positions or higher office (Hall, 2014).

Historically, political scientists have seen donors as being primarily access-oriented. But while donors may contribute to candidates in both parties, they generally seek to maximize the odds of their preferred party winning, even when making contributions to candidates in their non-preferred party (Brunell, 2005). Overall, case study observations, the opinions of participants and observers, inferences from indirect quantitative analysis, and direct computational analysis have been used as evidence that points to access as an important motivation for campaign contributions. (Langbein, 1986).

More recent studies offer a new paradigm that contributions should be thought less of as investments and more as political consumption (Ansolabehere, de Figueiredo, & Snyder Jr., 2003). Even individual corporate executives who make contributions that are “often best understood as purchases of ‘good will’ whose returns, while positive in expectation, are contingent and rare (Gordon, Hafer, & Landa, 2007). On the other hand, another study found that 11 percent of CEOs in 2000 who retired by 2011 ended up obtaining political positions—apparent evidence of quid pro quo (Coates IV, 2012). Also, PAC contributions should not be equated to individual donors. “Individuals consistently rank ideological concerns as highly important when deciding where to give” (Barber, 2016).

These ways of seeing political donors was fundamentally changed with the watershed moment of the *Citizens United v. FEC* supreme court ruling. This case ended longstanding campaign finance law limiting political contributions and enabled increased corporate spending to PACs (Kang, 2011). Whether one was personally for or against the ruling, legal and academic researchers largely agreed that it would dramatically change how campaigns were funded and operated (Briffault, 2010; Coates IV, 2012; Epstein, 2011; Gerken, 2014; Hasen, 2011; Kang, 2011). However, there was a subset of academics who questioned whether the change in campaign finance law would actually have a large practical impact (La Raja & Schaffner, 2014).

In the shadow of *Citizens United*, the growing role of online, small-dollar donors and their potential role in political campaigns was largely overlooked by both scholars and modern political actors. However, recent political campaigns have brought these donations to the forefront of present-day campaigns (Foran, 2016; Prokop, 2016; Sherfinski, 2017; Stein & Cherkis, 2017; Vogel, 2016).

Despite the lack of research into this particular field, the analysis that does exist on the internet's role in politics provides context for my research. Before the internet was studied as a vessel for fundraising, it was seen more broadly as an agora of public discussion (di Gennaro & Dutton, 2006; Gallego & Cantijoch, 2010; Gil de Zúñiga, Puig-I-Abril, & Rojas, 2009; Valenzuela, Kim, & Gil de Zúñiga, 2011; Vesnic-Alujevic, 2012), a hub of political organizing (Jost, et al., 2018; Cogburn & Espinoza-Vasquez, 2011; Levenshus, 2010), and predictor of offline political capital (Gil de Zúñiga, Jung, & Valenzuela, 2012; Hardina, 2005). The bulk of literature that explicitly focuses on online fundraising comes from the field of nonprofit organizational studies (Hazard, 2003; Karpf, 2010 Marx DSW, 2008; Miller, 2009; Raihani & Smith, 2015).

Although the study of the internet as a medium is relatively new to political science, research suggests that its communication methods are similar to traditional political communication and can be extrapolated to offline characteristics. The differences that are seen in online political communication, like lowered costs and eased barriers to entry, represent a “difference-of-degree” and not a paradigm shifting “difference-in-kind” (Karpf, 2010). Furthermore, there is a strong connection between online channels of communication in the form of social networks and offline connections and building and maintaining social capital from those offline connections (Cranshaw, Toch, Hong, Kittura, & Sadeh, 2010; Ellison, Steinfield, & Lampe, 2006; Liben-Nowell, Novak, Kumar, Raghavan, & Tomkins, 2005; Scellato, Mascolo, Musolesi, & Latora, 2010). And online social networks have been used to study offline-based actions and beliefs like opinion polarization (Lee, Choi, Kim, & Kim, 2014), political polarization (Hanna, et al., 2013), political participation (Lawrence, Sides, & Farrell, 2010) and political discourse (Kushin & Kitchener, 2009). The bottom line is that online actions and behaviors have been found to mirror the offline world and they are frequently extrapolated to explain offline actions and behaviors by other studies in political science and communication. My research builds upon these previous uses of online indicators of offline actions and beliefs to layer in political elites’ online communications to decipher the offline ideologies of non-elite actors.

Measuring Ideology

Fundamentally, my research is a methodology paper that proposes an experimental and novel way to consider the intersections between political donor communities and social media communication. The inspiration for attempting such research draws from previous attempts to uncover ideology and policy preferences of political actors using quantitatively-driven methods.

The debate on the best method to estimate the ideology of the electorate has traditionally broken down into two camps: those who use observational data to make inferences and those who primarily rely upon surveys. Each side has its proponents and detractors. Previous studies found compelling results in the estimation of U.S. states' ideologies by looking at the outcomes of congressional elections, roll call votes of congressional delegations, interest-group ratings for members of Congress, and the partisanship and results of state elections (Berry, Ringquist, Fording, & Hanson, 1998; Holbrook-Provow & Poe, 1987). Meanwhile, survey-based research claimed to be able to make similar ideological estimations of aggregate populations by extrapolating polling data (Brace, Arceneaux, Johnson, & Ulbig, 2004; Wright, Erikson, & McIver, 1985). Eventually, Berry et al. concluded that inferred ideology and survey responses measured two fundamentally different things. They argued that results from action-observed methodologies indicate political mood, whereas surveys are a measurement of self-identified ideology. Unsurprisingly, they maintained that their non-survey method "is more appropriate when studying the impact of public opinion on public policy" because it's based on people's actual actions and not just their reported (but possibly unacted upon) feelings (Berry, Ringquist, Fording, & Hanson, 2007).

Beyond voters' ideology, the ideology of political donors is also an ongoing topic in political science research. Hill and Huber point out that "we know relatively little about the contemporary representativeness of those who donate compared to the larger American electorate" despite money in American politics impacting who runs for office, helping to determine which candidates win elections, and the public fears about the influence of money on the political process (Hill & Huber, 2016).

The most comprehensive study of political donors' ideology is Adam Bonica's "Mapping the Ideological Marketplace" (Bonica, 2014). Bonica used over 100 million contribution records from state and federal elections to create ideological ideal point estimates for every candidate and donor in his data. The comprehensiveness of his data allows him to map virtually any person that has made a political contribution between 1972 and 2012 onto a "common space" with candidates and PACs to make coherent liberal-conservative ideological estimations across a wide variety of political actors.

While not the focus of his paper, he does incorporate donors' policy preferences as a part of his discussion in his findings. He uses the example of the 2012 Republican presidential primary candidates and examines how pro-choice or pro-life their donors were. He estimates their pro-choice/ pro-life level by classifying each contributor based on whether they donated to a pro-life organization or ballot initiative (e.g., Right to Life) or a pro-choice organization or ballot initiative (e.g., NARAL). He then calculated each donors' "pro-life proportions" by dividing their total pro-life contributions by the total of their pro-life and pro-choice contributions. This simplicity works for his ad hoc analysis of pro-life donors in the 2012 Republican presidential primary, but it has some holes when using it to make broad judgements. For example, it does not consider donors who contribute to candidates. Although candidates campaign on many policy issues, it cannot be discounted that donors contribute to campaigns solely based on one issue. In other words, donors could have contributed to candidates solely because they supported that candidate's policy on being pro-life or pro-choice, but that would not have been picked up in Bonica's explanation. My research seeks to fill this research gap of identifying the issues that motivate political donors by using a similar "common space" approach as Bonica but adds network analysis and social media data to determine the issues that political candidates publicly champion to attempt to uncover the policy issues that motivate political donors.

Bonica's methodology has recently been challenged. Hill and Huber compared Bonica's ideology scores to survey data from the 2012 Cooperative Congressional Election Survey (CCES). They concluded that only examining political donations did not do an adequate job of estimating ideology on a spectrum. They conceded that donations could be helpful for sorting people into Democratic and Republican groups but did a poor job of placing donors on an ideological spectrum intraparty. They concluded that this is the case because candidate and donor ideology are only weakly connected, and that even low-dollar donors contribute to competitive campaigns where their donations can have the biggest impact (Hill & Huber, 2016).

Bonica responded by validating his own scores based on direct comparisons of 30 CCES policy items. He stated that, ultimately, his ideology scores are "powerful predictors of policy preferences for a wide range of issues and successfully discriminate within party" (Bonica, 2017).

While my research is most closely related to Bonica's, it is persuaded by Hill and Huber's findings in that it utilizes a community-based approach that does not rely on exact individual placement along a continuum. Placement in my spatial network is only significant in determination of statistical communities. Where Bonica uses this placement to extract ideology on a left-right continuum, I layer on social media data to create policy ideologies of the aggregate communities. Social media data has not widely been used in this fashion. But my findings show that it can be used as an additional variable in the understanding of networks of social connections between elite and non-elite political actors.

Method

To determine if there is a correlation between communities of donors and the policy issues in the online communications of political candidates, I used an original and novel methodology. I took three principle steps: creation of donor community scores, creation of online communication topic scores, and traditional statistical analysis determining if there is a correlation between the donor scores and topic scores.

Donor Scores

To create donors scores, I started with all 92,807 political contributions to candidates for Wisconsin State Senate and State Assembly in 2015 and up to the fall 2016 election. These donations were pulled from the Wisconsin Campaign Finance Information System (Wisconsin Ethics Commission, n.d.). I then removed any contributions made anonymously (currently, contributions under $50 can be given anonymously) or unitemized. This step left 92,284 donations.

Next, I made the data uniform (removed punctuation, made all names lowercase, etc.) and used OpenRefine (Ham, 2013) to stem names to identify people who might be the same person, but were entered differently. For example, if one campaign reported a contribution from Jim Smith, and another reported a donation from James Smith, both records were changed to be identical (e.g., Jim Smith). To ensure that people who had the same name, but were different people, were not counted as the same individual, I added their zip code to the end of their name to create a unique identifier (e.g., Jim Smith: 01234). I manually checked to see if it would be an issue that multiple people in the same zip code would get stemmed to the same name and found that this was not a concern for the analysis. I then tallied up how many contributions came from each unique identifier. I kept only the donations from people that made more than one contribution. I did this for two main reasons. First, removing these excessive donors allowed for more computational efficiency. Second, I wanted to focus on donors with potentially identifiable policy preferences. It would be difficult to identify the policy issues that motivates donors that gave a single donation because there are so many different reasons that someone could make a donation that has nothing to do with policy. For example, I could donate money to a family member or friend who is running for office. Instances like this one would be much less likely in people who gave multiple contributions and therefore are more engaged in the political donation process. It should be noted, that I kept donations from people who gave multiple times, but only to one candidate. This filtering left me with data on 29,990 donations.

After this data preparation process, I calculated the statistical communities within the donor network using Gephi (Bastian, Heymann, & Mathieu, 2009). In essence, the political donor landscape can be thought of as a network of nodes (donors and politicians) who are connected by edges (political contributions). We can then use modular community detection to identify smaller statistical clusters within the community based on the number of shared connections between nodes (see Figure 1). Specifically, I utilized Newman's modularity—the most widely used modularity detection method (McSweeney, 2009). For example, if nodes A, B, C, and D are all connected to each other, but only share sparse connections to the rest of the network, they are identified as being in a distinct community. To best visualize the network, I used the Yifan Hu layout algorithm (Hu, 2005). This algorithm is force-directed—meaning that it tries to polarize the network away from each other, but nodes are kept more compact when they share more connections. In this application, we see that the network forms two polarized clusters: Democrats and Republicans. For the sake of this analysis, the most important component is noting the statistical cluster that every donor belongs to because my hypothesis rests on these clusters sharing some identifiable common characteristic like donating to candidates who talk about similar policy issues (see Figure 1).

I used these clusters to create donor cluster scores for every candidate. I kept the calculation of these scores simple. However, more sophisticated modeling could be used in the future or if a similar analysis is done at a larger scale. For every candidate, I calculated the percent of their donations that came from each cluster. I then multiplied that number by the percent that the cluster's donations would get the candidate to a "competitive fundraising total." To determine the total amount that a campaign would need to raise to get to a "competitive fundraising total," I took the median contribution total to campaigns in competitive seats. I used Bonneau and Hall's definition that elections in which no candidate won more than 60% of the vote as being competitive (Bonneau & Hall, 2003). In this case, I took the medians of 2016 fundraising totals for seats that were won with less than 60% of the vote in 2014. For State Senate elections that were competitive, the median competitive campaign raised $336,868.93. Competitive State Assembly campaigns had a median of $57,446.74 in contributions. The formula looks like this: ((amount raised from donor cluster / total amount raised x 100) x (amount raised from donor cluster / competitive fundraising total x 100)). For example, say that Jane Doe for Assembly raised $20,000 in total, $10,000 of which came from donors in donor cluster 1. Jane Doe's donor cluster 1 score would be 5.5 (($10,000 / 20,000 x 100) x ($10,000 / 54,449.20 x 100)). I calculated these donor scores in this fashion to balance the potential impact of a single donor community on the campaigns while also considering the scale of the donations. If a single community was responsible for 100% of a candidate's donations, that candidate is strongly connected to that community. However, if that candidate only raised $1,000, that community's impact should be treated less than a candidate who raised $200,000 and received 70% of their contributions from a single community.

Topic Scores

After I calculated donor scores for every candidate, I moved my focus towards creating social media communication topic scores for every candidate based on the issues that they posted about on Twitter and Facebook. I chose to analyze social media data because it the most accessible and quantifiable data that is available on campaigns' communication efforts.

First, I manually collected the Twitter handles and Facebook usernames of every candidate running for Wisconsin State Assembly and State Senate. I included both official legislative social media accounts and campaign accounts. Although this might skew the number of posts made by politicians in office (who have both official legislative and campaign accounts), this holistic approach best captures the entirety of a political donors' potential experience with a candidates' online presence. I used this list of accounts to collect all tweets and Facebook posts from these accounts from January 1, 2015 through November 8, 2016 (election day) through the Twitter (Kearney, 2017) and Facebook (Barbera, Piccirlli, Geisler, & van Atteveldt, 2017) APIs. In total, I collected 82,851 posts.

To determine the issues that each candidate talked about on social media, I trained a neural network in R using the quanteda package (Benoit, 2018). To create a training and test set, I hand-coded a randomized 15%—12,428—of the posts (10% for a training set, 5% for test set). I inductively created a codebook based on the topics that were being posted about—the same method employed by previous political science studies (Hershey, 1992). I made sure to differentiate between the view point that the post represented. For example, there was not just one "marijuana" category, instead, there were "pro-marijuana" and "anti-marijuana" categories. After coding all of the posts, I collapsed categories with fewer than 20 posts, or .16% of total posts, into the "other" category. In a perfect world, I could have kept these categories. However, there just weren't enough training posts for the neural network to properly be able to categorize posts in these categories. For the sake of accuracy in the model, I had to put them into the "other" category. I also collapsed categories that fell under similar themes but differed slightly in specific policy. For example, I originally had, "pro-right-to-work" and "anti-union" categories that were combined into a more general "conservative on economic issues" category. I ultimately ended up with 28 categories.

I implemented a supervised latent dirichlet allocation model to train a neural network to classify the posts (Blei & McAuliffe, 2008). As with the selection of any machine learning algorithm, there are pros and cons. Latent dirichlet allocation models are generally used on data sets with fewer topics than my 28. However, it performs best when there is a small number of specific words that make the text document likely to be in a topic—a methodology that works well with short texts like tweets and Facebook posts.

I used my training set to train the model to classify posts based on the classifications I gave the posts in my training set. I then measured the accuracy of my model by running it on my pre-coded test set and comparing whether the model's output matched my hand coding. The model was not extremely accurate but performed admirably with 57.58% accuracy. This number may seem low. However, it is considerably better than if the model just assigned outputs at random (that would have a 3.57% accuracy). In addition, the model seemed to get close, but not quite there on many topics. For example, I classified this post, "Today @JonErpenbach & I unveiled bill that offers veterans immediate mental health care svcs. during VA wait times" as being in the "veterans issues/ King veterans home" category, but the model classified it as "liberal healthcare"—a discrepancy that could be argued either way if done by hand coders. I was concerned that the model's minor discrepancies on individual posts would adversely impact the next step of creating topic scores for each candidate. However, the scores held face validity. For example, Representative David Bowen (D-Milwaukee), a well-known civil-rights activist had a high topic score for "race issues," Representative Melissa Sargent (D-Madison), an advocate of women's health scored a high topic score for "pro-choice/ women's health," and Representative John Nygren (R-Marinette), the main proponent of the Heroin, Opioid Prevention and Education (HOPE) Agenda, and whose daughter has publicly struggled with substance abuse, received a high topic score for "drug abuse and prevention."

While I admit that the model is not perfect, machine learning—especially applied to natural language processing—remains an extremely experimental field, and this method is the best that I could implement. I attempted to closely follow other ground-breaking work in this area (Yano & Smith, 2010) and could be a beneficiary of other ongoing research into text classification from other researchers (Quan, Zhang, Xu, & Hossain, 2015). Hopefully, in the future, a more accurate and easily implementable method for classification will be developed. But for now, my model is accurate enough when taken in aggregate to continue my analysis.

I calculated topic scores in a nearly identical manner to the donor scores. I took the percent of a candidate's posts that were classified as belonging to each topic and multiplied it by the number of posts on each topic divided by the "competitive post total" (the median number of posts made the competitive campaigns) of 210. The formula is: ((posts about topic A / total posts x 100) x (posts about topic A / competitive post total x 100)). For example, if Jane Doe made 100 posts about topic A out of 200 total posts, her topic A score would be 7.6 ((100 / 200 x 100) x (100 / 148.5 x 100)). Again, this simple method was employed to balance how much a campaign focuses on a single topic versus scale. If a single topic makes up only a small percent of a candidate's posts, but that candidate posts so much that the raw number is greater than other campaign's total posts, that candidate's topic score should be reflected as being high.

Statistical Analysis

Next, I statistically analyzed to see if there was a correlation between any of the donor and topic scores. First, I calculated a correlation coefficient for every combination of donor and topic scores. Next, I calculated the statistical significance of the combinations by first calculating their p-values and converted those to an adjusted p-value. I opted to convert the p-values to adjusted p-values because I wanted to control for a false discovery rate since I was computing a large number of—364—p-values. I then overlaid the statistically significant donor groups and topic combinations (those with a p-value < .05) (see Figure 2).

Results

My analysis set out to uncover the issues that motivate communities of political donors who contribute to campaigns at a state level. Because of the way that the internet has transformed political fundraising, I expected that candidates' ability to engage individuals on the internet. would mean that donors would coalesce into communities by contributing to candidates who are champions of specific policies.

Taken by itself, I have found statistically compelling evidence that there is a correlation between the amount of money raised by campaigns from various donor groups and specific policy issues that those candidates discuss on social media. The clusters with significant relationships fall into two categories: single-issue clusters and clusters with multiple correlated topics.

A few of the donor groups have significant relationships with a single issue. For example, Cluster 1 has a significant relationship with criminal justice reform. Cluster 2 has a strong correlation between campaigns receiving contributions from this cluster and campaigns talking about bipartisan issues in healthcare. Cluster 3 is comprised of donors who primarily contributed to Democrats and their donations are correlated with campaigns that discussed the environment and climate change. And donations from Cluster 11 is correlated to campaigns talking about pro-LGBTQ+ issues.

Other groups have significant relationships with multiple policies. Potentially, these donors represent “base” donors who are not single-issue donors. Donations from Cluster 0 were correlated with candidates talking about pro-life issues, conservative education, conservative economic issues, and criminal justice/ police. Cluster 6 was correlated with liberal voting (access to voting), the environment and climate change, liberal education, liberal economic issues, and campaign finance reform/ corruption/ open government. Cluster 10 was strongly correlated with pro-choice/ women’s health along with significant correlations to liberal voting, pro-marijuana, pro-LGBTQ+, veterans issues, liberal healthcare, pro-gun control, anti-gerrymandering, liberal.

Discussion

The role the internet played in the 2016 presidential election was the impetus for this research and its attempt to use social media data to infer the issues that political donors care about. This research was able to identify statistically significant correlations between donor clusters and candidates talking about specific topics on social media. Future research should consider other potential explanations for the statistical creation of donor networks such as geography or competitiveness of campaigns.

Practically, this research could inform the strategy of political campaigns. Both local candidates could quickly understand the issues that their campaigns may wish to prioritize, but state-wide or even national campaigns could better understand the policy issues that could attract political donors.

Overall, this paper contributes to the burgeoning field of ideological estimation. It provides novel methodology that successfully finds a correlation between specific donors contributing to campaigns and campaigns discussing various policy issues. Future work should consider geography as competitiveness of campaigns as a potential explanation for political donor behavior.

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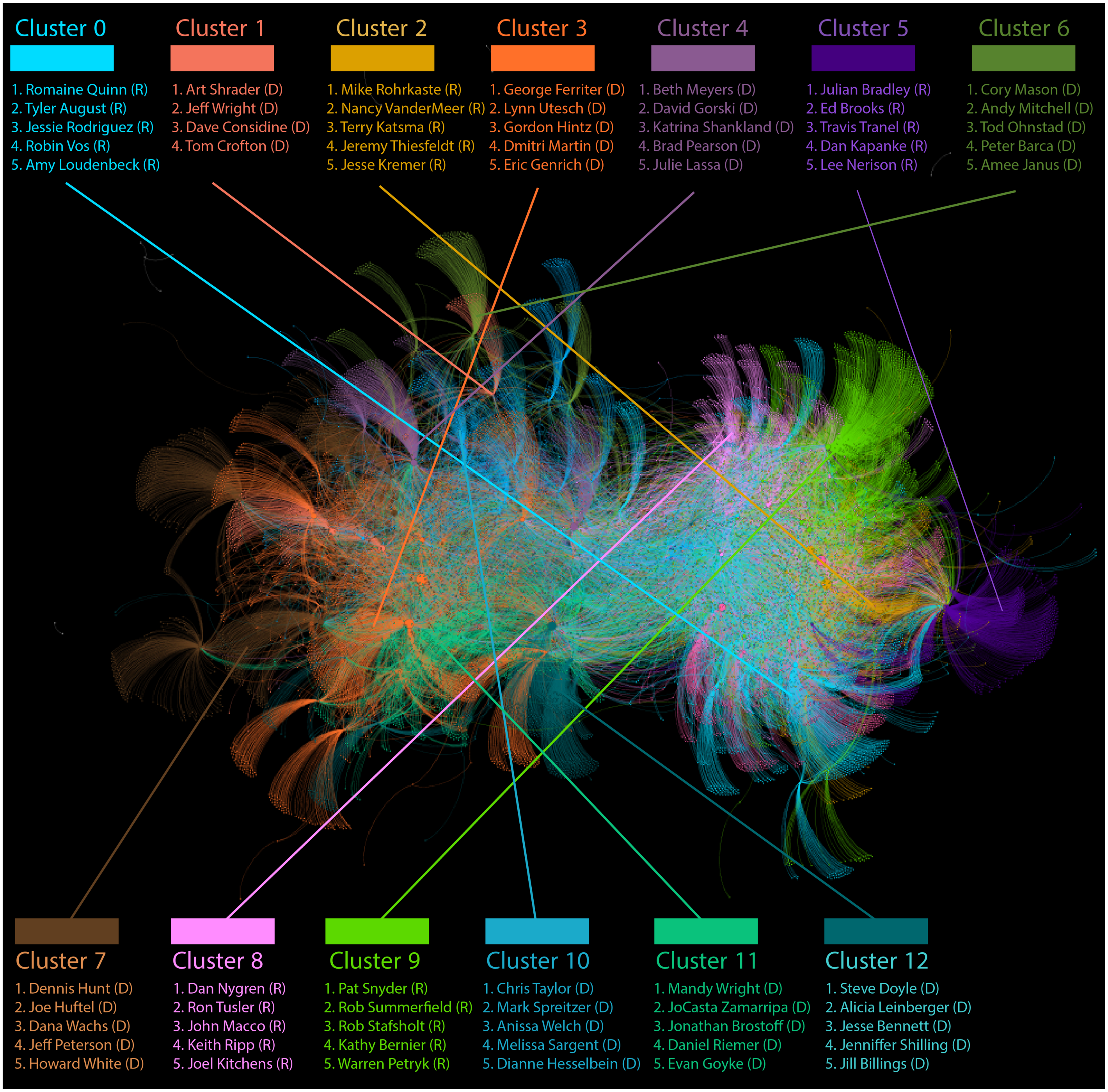

Figure 1. Network of candidates and political donors to Wisconsin State Senate and State Assembly campaigns in 2016. Every node (dot) is a candidate or donor, every edge (line) connecting dots represents a donation. The nodes and edges are colored by their statistical community. Labeled are the cluster that the specific color represents. Also listed are the top five candidates with the highest donor scores that community.

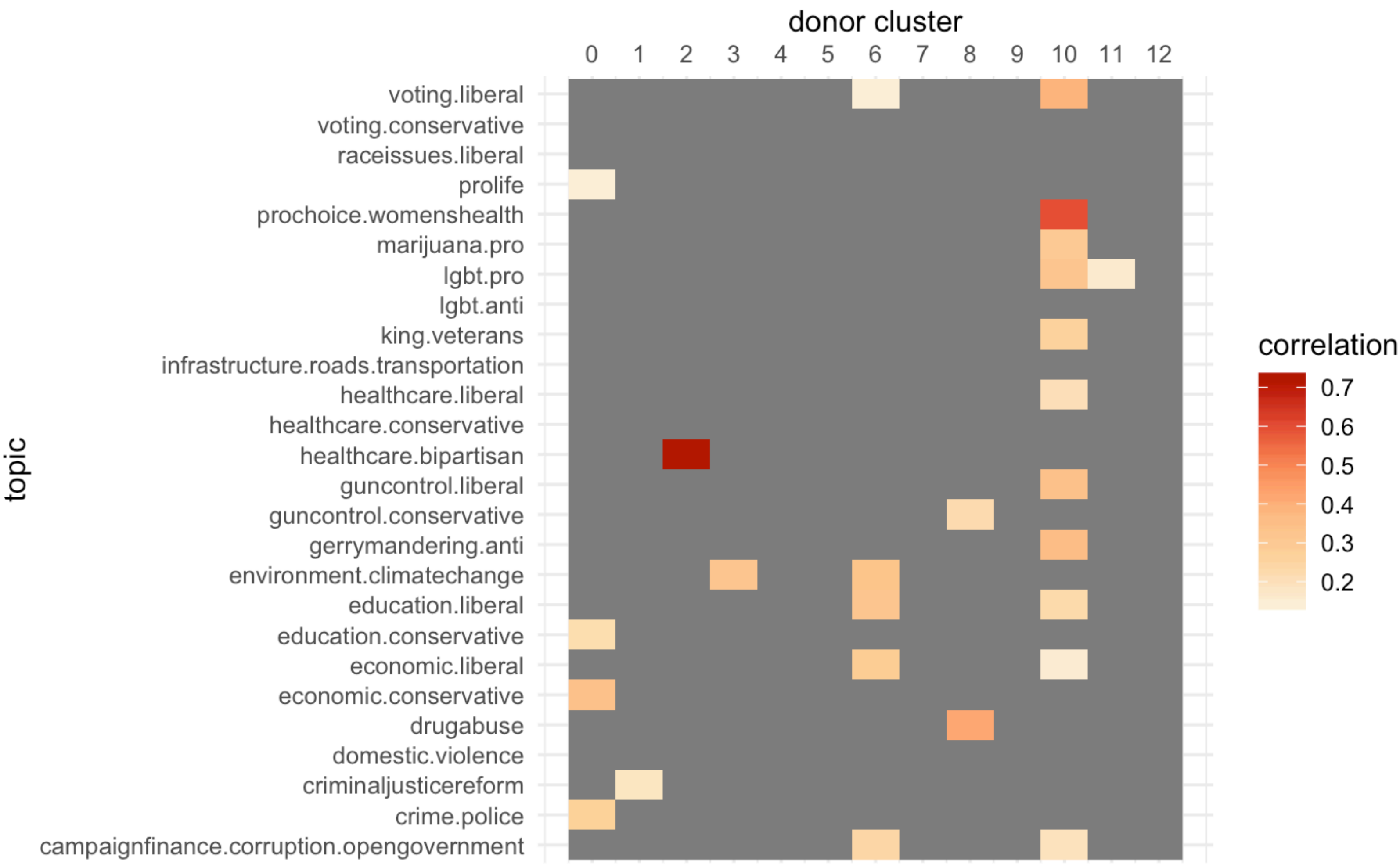

Figure 2. Heat map of correlation coefficients between candidates' contributions from donor clusters and talking about specific policy issues. The darker the color, the greater the correlation. Statistically insignificant measures have been removed.

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