Examining Political Mobilization of Online Communities Through E-Petitioning Behavior in *We The People*

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Background: We discuss *We the People (WtP)*, an unprecedented US national experiment in using social media to enable users to propose and solicit support for policy suggestions. Using *WtP*, users generate petitions for actions of the petitioner's choosing and employ other social media to solicit signatures for their proposals; with sufficient signatures, petitioners may obtain a response from the Administration (see https://petitions.whitehouse.gov/).

In the wake of the Sandy Hook shootings on December 14, 2012, President Obama responded to 33 petitions initiating policy proposals. He pledged a national conversation about gun control, fueled by the single largest petition to appear on *WtP*, which advocated that the country "Immediately address the issue of gun control through the introduction of legislation in Congress" and which gathered over 195,000 signatures in less than a week. We apply Baumgartner and Jones's (1993; True, Jones & Baumgartner, 2006) work on agenda setting and punctuated equilibrium, which suggests that policy issues may lie dormant until some event triggers attention from the the public. E-petitioning may play a role in this process by enabling a process of definition and mobilization that can move issues to the forefront of policy attention, unless countered by "negative feedback." We focus on 21 petitions initiated during this week *in opposition* to gun control, which we view as mobilized efforts to maintain stability and equilibrium in a policy system threatening to change.

Objective: While e-petitioning is common, few studies address this data (but see Hale, Margetts, & Yasseri, 2013 on Britain; Jungherr & Jurgen, 2010 on Germany). This paper aims to reveal patterns of petition co-signing that are indicative of mobilized opposition to gun control.

Methods: Using market basket analysis and social network analysis on petition and coded signature data publicly available on the *WtP* website (see https://petitions.whitehouse.gov/developers), we analyzed 21 oppositional petitions, which attracted over 120,000 distinct signatures. It was evident that individual signers had signed more than one petition. Table 1 and 2 in the Appendix presents title and signature counts for each petition; market basket analysis and social network analysis are described in the Appendix.

Results: We sorted the 21 petitions into thematic clusters, finding three: support law-abiding gun owners; invest in mental health care; and guard our schools; The undirected graphs that result from our methodology are shown in the appendix. The structure of these graphs gave rise to a few early conclusions:

At the largest confidence value (50%), the seven petitions in the cluster "Support law-abiding gun owners" were highly connected on the basis of common signers and constituted a "frequent itemset"; petitions in the other two categories are not highly connected. That is, individuals signing a petition in this itemset were more likely to sign others in the set, but not petitions in the other two clusters. With confidence lowered to 30% and 10%, additional associations begin to appear between the first itemset and others. The significance of these associations will be presented in an expanded version of this document.

We also constructed a social network (an undirected graph) where each node represents a person who signed at least seven of the 21 petitions and an edge between the nodes indicates that the two corresponding people co-signed at least seven petitions. The graph had 2285 nodes and 487,336 edges. We computed three different centrality measures for each node of this network. For each centrality measure, we also obtained the list of 500 nodes with the best value for that measure. We observed that 416 nodes appeared in all three lists, suggesting that the set of highly central nodes in the network is roughly the same regardless of which centrality measure is considered. We also noticed that the nodes of the graph can be partitioned into four communities with respective sizes 844, 531, 461, and 449. By considering the sets of petitions favored by these communities at various levels of support, we noticed further evidence of mobilized opposition to change in gun control policies. Additional details regarding these results will be presented in a longer version of this paper.

Conclusions and Future Work: Community detection techniques and social network analysis were used to to determine if groups of individuals sign similar anti-gun control petitions, thus suggesting the creation of "communities" whose actions are similarly aligned in opposition to gun control. We plan to run a similar analysis on the remaining 12 pro-gun control petitions.

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Appendix

Table 1: 21 Anti-gun Control Law and “Other” or Alternative Policy Petitions

Petition ID	**Anti Gun-Control Petitions (Support Law Abiding Gun Owners)/Title**	**Creation Date and Time**	**Signature Count**
982	Place Security Guards in Schools Nationwide: The Safe & Sound Schools Initiative	Dec. 14, 2012 23:35:59	2943
987	No more gun control.	Dec. 15, 2012 2:36:09	3406
990	Not punish the tens of millions of law-abiding gun owners with ineffective and unconstitutional assault weapons/bans	Dec. 15, 2012 11:41:58	8227
996	Ensure the 2nd Amendment cant be infringed in anyway limiting citizens ability to defend against tyrannical governemnts	Dec. 16, 2012 1:55:43	9063
1006	We ask President Obama to support law abiding gun owners in this time of tragedy.	Dec. 16, 2012 20:27:15	53677
1009	Dissolve any petitions on an Assault Weapons Ban as unconstitutional under amendment II of the Constitution	Dec. 17, 2012 5:48:55	9070
Petition ID	**Invest in Mental Health Care Petitions/Title**	**Creation Date and Time**	**Signature Count**
975	Make Mental Health a National Emergency	Dec. 14, 2012 18:52:03	10235
981	Address the shortcomings of the current mental health system to prevent at-risk people from becoming violent offenders.	Dec. 14, 2012 21:55:40	9896
983	Stop crime before it starts by funding mental health facilities instead of prisons.	Dec. 14, 2012 0:19:45	6046
984	Launch a federal investigation in to the relationship between school shootings and psychiatric drugs	Dec. 15, 2012 1:16:55	6334
1003	Build a federally-funded mental healthcare system in the United States that offers	Dec. 16, 2012 14:39:13	11747

Petition ID	Guard Our Schools Petitions/Title	Creation Date and Time	Signature Count
	treatment, education, and advocacy.		
Petition ID	**Guard Our Schools Petitions/Title**	**Creation Date and Time**	**Signature Count**
980	A gun in every classroom. Arm every teacher and principal to defend themselves and their students during an attack.	Dec. 14, 2012 21:14:38	8955
982	Place Security Guards in Schools Nationwide: The Safe & Sound Schools Initiative	Dec. 14, 2012 23:35:59	2943
985	Have armed security at all schools across the nation who are ex military from combat MOSs or combat	Dec. 15, 2012 1:34:49	4256
1008	Hire military veterans as armed resource officers in all public schools throughout America.	Dec. 17, 2012 3:50:12	2219
1013	Allow individual School Districts and/or schools the ability to train staff to be School Marshalls.	Dec. 17, 2012 17:17:56	1964
1025	Employ competent veterans as armed security guards for America's schools	Dec. 17, 2012 19:18:28	2518
1043	Place police officers and metal detectors in all of our schools.	Dec. 17, 2012 14:17:16	667

Market Basket Analysis: A Brief Overview

The primary goal of market basket analysis is to identify patterns concerning co-occurrences of objects. The basic idea can be readily understood through a simple example. Consider a super market where each transaction (or market basket) consists of a set of items bought by a customer. By collecting and analyzing transactions that occur over a period of time, managers can identify sets of items that are frequently bought together by customers. Such sets of items can be placed in adjacent shelves to make it more convenient for customers to shop at the store.

A few definitions are needed to precisely describe the notion of frequent co-occurrence of objects in the context of supermarket data. Any set of items is called an itemset. As mentioned above, each transaction consists of a set of items bought by a customer. The support of an itemset S is the fraction of transactions which include all the items in S; that is, the support for S is the ratio of the number of transactions that include all the items in S to the total number of transactions. Any itemset whose support exceeds a chosen support level is called a frequent itemset. Thus, frequent itemsets represent sets of items that are bought together often by customers.

In addition to frequent itemsets, analysis of market basket data can also reveal other patterns related to co-occurrences. For example, for some items x, y and z, a large fraction of customers who buy items x and y may also buy z. Such patterns are captured through an association rule which is usually shown as {x,y} ---> {z}. The importance of an association rule is specified using a measure called confidence. Formally, the confidence of the association rule {x,y} ---> {z} is the ratio of the number of transactions that contain all the items x, y and z to the number of transactions that contain the two items x and y. (Formally, confidence gives the conditional probability that customer's basket contains item z given that it contains both x and y.) Thus, association rules with large confidence values also provide insights regarding co-occurrences.

We used market basket analysis on the data collected for the 21 anti gun control petitions. In our case, each person who signed at least one of the 21 petitions represents a market basket and the subset of the 21 petitions signed by the person represents the items in that basket. Thus, our data set for market basket analysis consists of more than 121,000 baskets, with each basket containing at most 21 items. A number of algorithms are known for identifying frequent itemsets and association rules (Tan et al. 2006). We used the algorithm discussed in (Han et al. 2000) for identifying frequent itemsets since a public domain software tool based on this algorithm is available. We generated association rules and their confidence values using a software tool available at orange.biolab.si.

Social Network Analysis: A Brief Overview

Large-scale networks are ubiquitous in modern society; examples include the Internet, friendship networks (such as Facebook), professional networks (such as LinkedIn), social media networks such as Twitter, etc. Social network analysis provides methods to understand the roles of participants and the nature of interactions among the participants in such networks. These methods have been applied to study behaviors in various networked systems such as computer communication networks, biological networks, economic networks, terrorist networks, etc. (Newmann 2010).

The notion of centrality, introduced by (Freeman 1979), is commonly used to characterize the level of importance of a participant in a social network. Freeman's seminal paper and a number of subsequent papers have identified a variety of centrality measures for social networks (Newmann 2010). Examples include degree centrality, closeness centrality, betweenness centrality and eigenvector centrality. Precise definitions of these and other measures can be found in (Easley & Kleinberg 2010, Freeman 1979, Newmann 2010). For our purposes, it suffices to know that a larger value of centrality measure indicates that the corresponding participant plays a more important role in determining the behavior of the network.

The notion of community (or cluster) is used to identify a group of nodes with similar behavior in a social network. There are several ways to define similarity in behavior and algorithms are available for partitioning the nodes of a social network into communities according to those definitions (Newmann 2010).

The social network constructed in our work was described earlier. The computations of centrality measures were carried out using CINET, an interactive software tool for network analysis, developed by the Network Dynamics and Simulation Science Laboratory (NDSSL) of Virginia Tech. We used a software tool (available from http://perso.uclouvain.be/vincent.blondel/research/louvain.html) for identifying the communities in the network. This tool implements a well known algorithm, called the Louvain Algorithm (Blondel et al. 2008), for finding communities.

Figures 1-3: Graphs 50%, 30% & 10% Confidence Levels

Blue = "invest in mental health care"
Green = "guard our schools"
Red= "support law-abiding gun owners"

Figure 1: 50% Confidence

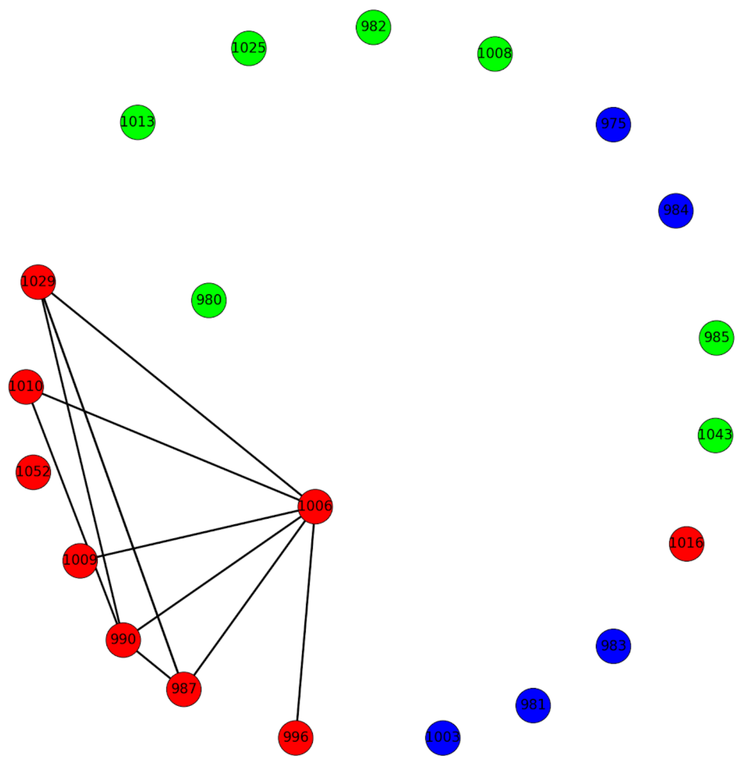

Figure 2: 30% Confidence

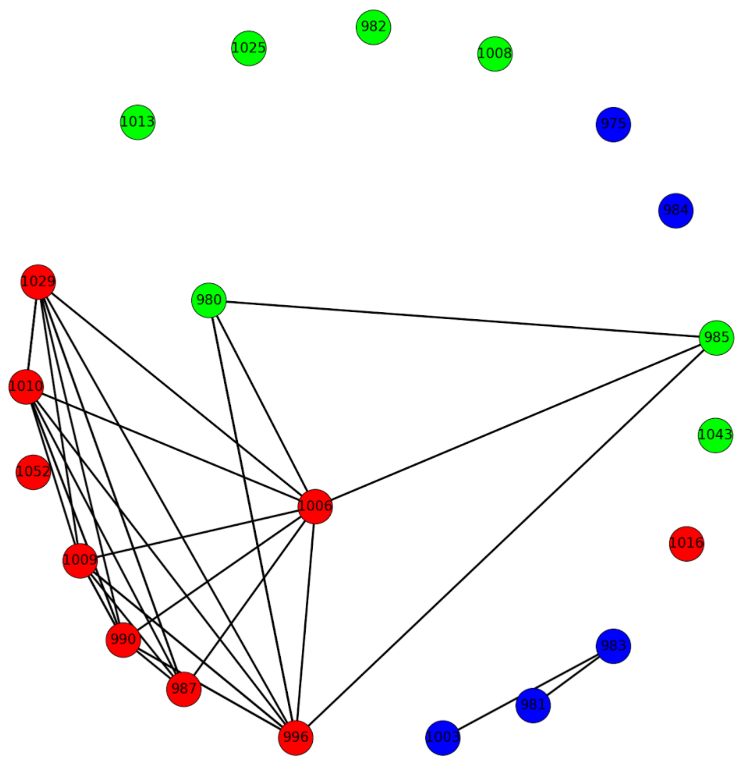

Figure 3: 10% Confidence