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Modeling Gun Culture in United States: Demographics, Networks, Ideologies

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The issue of gun control vs. gun rights is a long standing controversy in the United States. On the one hand, the U.S. have one of the highest rates of gun-related deaths among developed OECD countries [2]. On the other hand, gun ownership in the United States is constitutionally protected by the United States Bill of Rights (the first ten amendments of the U.S. constitution). Indeed, gun ownership is widespread: it is estimated that in the U.S. 35% to 42% of the households in the country have at least one gun.[1] There have been numerous attempts at understanding the reason behind this deep ideological divide in the population [3, 1]. Gun control advocates typically blame gun violence on the pervasive presence and availability of guns. Conversely, gun rights supporters usually blame gun violence on other cultural issues such as portrayal of violence in media, lack of family values, or mental health issues [6]. This paper describes our ongoing work to use data from social media, in particular from Twitter, to understand the cultural divides that are behind this controversial issue.

Data. We gather data from Twitter's Streaming API from Oct 1, 2017 to May 1, 2018 using the keywords *gun*, *guns*, and *nra* (National Rifle Association). Out of these, we are able to geolocate to US 1,857,749 users posting 46,943,763 tweets. We build an *endorsement network* by looking at the retweets as the basic signal. We then use METIS [4] to partition the endorsement graph in two groups by optimizing the number of users within 95% confidence interval of either extreme, finding the optimal proportion to be 1.5 to 1, with gun control being the larger side. Upon manual verification of 200 random Twitter profiles, we find the partitioning to be accurate at $\approx$ 98% which indicates an extremely high quality of the labels. We then use these labels to train a text classifier, with the goal of labeling also users which are not represented in the network (i.e., speak about the gun debate but do not retweet). Using a TF-IDF representation for each user, we train a naïve Bayes model, which achieves an accuracy of 99.46% (5-fold cv). All together, we are able to classify the stance of 1.86M users.

Hypotheses. We aim to test several sociological questions. First and foremost, what are the most divisive factors in the gun debate? Second, given the large support for gun control in polls, also confirmed by the distribution of stances in our Twitter dataset, it is curious that legislation towards it has rarely been passed. This raises the question of whether the pro gun control side is more ideologically diverse and thus difficult to mobilize. Our hypothesis is that gun rights supporters are more homogeneous, and thus easier to mobilize. Another hypothesis is inspired by attribution theory [5]. For the gun control side, gun violence is associated with situational factors (gun availability), and therefore are more "socialistic." For the gun rights side instead gun violence is associated with dispositional factors (e.g., mental health), and are thus more "individualistic."

[1] `https://news.gallup.com/poll/1645/Guns.aspx`

Tasks. To test these hypotheses we set up two different modeling tasks: (1) at the state level, modeling two target variables of interest: (*i*) gun laws, and (*ii*) gun sales, and (2) at the user level, modeling participation to the "march for our lives"[2], a student-led demonstration in support of gun control laws held on March 24, 2018. The gun laws variable is encoded by looking at how gun-friendly the laws of each state are. The rating goes from 1 (most strict) to 5 (most friendly), and is obtained by collating different Web resources.[3][4] The gun sales variable is obtained as a proxy from the FBI National Instant Criminal Background Check (NICS) database.[5]

We take into consideration three kinds of predictors: **Demographics:** At the state level, predictors include indicators such as education, health, employment, income, and crime level. For Twitter, we look at account age, activity level, and number of followers and followees. **Networks:** We compute several typical network analysis measures such as size of the giant connected component, density, clustering coefficient, degree assortativity, and Gini index of the degree distribution. **Ideologies:** We use relative size of each side, the entropy of the hashtags in tweets (topic diversity), the diversity of vocabulary, usage of hate speech based on Hatebase, and LIWC features.

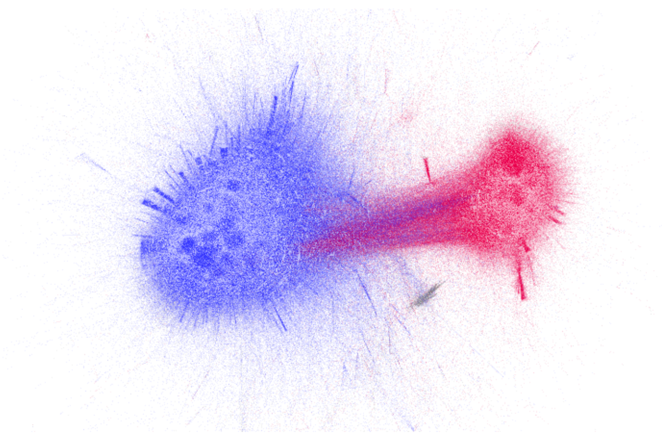

Figure 1: Giant connected component of retweet network, colored by METIS (red: pro gun rights, blue: pro gun control).

Results. Preliminary models built for the state-level prediction task reveal some noteworthy insights. For both gun law ratings and gun sales the number of retweets and the number of edges of the induced subgraph from each side are predictive of the target variable, with the expected sign (negative for the pro-gun-control side, positive for the pro-gun-rights side). Interestingly, the percentage of users with a pro-gun-rights stance within the state is not a good predictor, which indicates that more complex models and features may be needed to capture the link between the offline phenomena and the online world.

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[2] `https://marchforourlives.com`

[3] `https://statelaws.findlaw.com/criminal-laws/gun-control.html`

[4] `https://www.gunstocarry.com/gun-laws-state`

[5] `https://www.fbi.gov/services/cjis/nics`