Tweeting Politics: Exploring Behavioral Patterns and Partisan Stands on Social Media

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Social media has become the most prevalent platforms for public discussions today in America. While it reflects the soaring partisan antipathy, there are concerns that online discourses may have exaggerated the level of polarization. We explore the 2018 Twitter survey data to explore associations between the users' real-life social conditions, online behavioral patterns, and partisan stands. Our analysis find that Twitter users are not inherently separated or clustering based on real-life social trust, but Trump's presidency radicalizes the public sphere and catalyzes the formation of clear-cut cleavages.

social media | social trust | partisanship | polarization | neural network

Partisan antipathy is tormenting the American public and restructuring the way people think and feel about social cleavages, leading to political polarization and democratic backsliding. Group identification along neat partisan divisions in opinions towards social problems is one of the prevailing contributors to the anger and resentment in today's public sphere (1). The increasingly radical and polarizing discourse on social media provides the most evident manifestation. However, it remains questionable whether the opinions on virtual platforms reflect personalities and political stands of the real users. Being offensive online bears fewer costs than in real life, and therefore the platforms themselves may have taken a part in exaggerating the existing antipathy. This study targets not only the Twitter users' attitudes toward social problems but also their tweeting habits. By exploring the relations between the users' real-life social networks or political stands and their behavioral patterns online, we attempt to provides implications on whether and how the interplay of structural socioeconomic factors and personal agency, such as Trump, on social media facilitates political polarization.

Literature Review and Theoretical Framework

A plethora of literature have point to the potential dangers of polarization resulted from oversimplified group identifications. The lack of cross-cutting cleavages undermines the defense against violations of democratic principles, as it "raises the stakes of elections" and the priority of partisan interests (2), whereas, by theory, the democratic mechanism functions well only if the stakes are not extremely large, namely within the limits of the institution's capacity of absorbing political conflicts (3). Some have also discussed the possible reasons for partisan antipathy. On one hand, Przeworski lists many institutional and social factors of the rising stake itself, including economic stagnation, increasing inequality, and breakdown of class compromise based on moderate wage and taxation demands (3). On the other hand, Levitsky and Ziblatt stress irresponsible agency of political elites, who failed to carry out the democratic "gatekeeping" to shut demagogues outside. Democratic institutions themselves cannot safeguard its their own norms and principles without the establishment's active protection (4).

Both approaches provide precious insights, yet structuralist or voluntarist explanations alone are insufficient to get the full picture. Social cleavages exist at all historical periods, and we need explanations for why particularly the 2010s saw cross-cutting divisions of social groups turned into dichotomy of two groups along the partisan line. The theory of "gatekeeping" emphasizes the importance of holding the last line of defence, yet in a scenario of democratic backsliding, what we are equally interested is still how voters are radicalized and mobilized to consciously or unconsciously tear down the democratic principles. It is thus essential to look into the interplay between partisan agencies and existing structural divisions in the public sphere, and social media is one of the most crucial and prevalent platforms today in America.

Our research explores whether Twitter, as today's representative virtual arena for political discussions, tends to exaggerate or distort the patterns of division in the American political society and catalyze the neat bipartisan division. There have been evidence exhibiting the positive effect of higher exposure to social media on increasing political polarization (5). The hypothetical mechanism is that those with low level of social trust and community attachment, namely those who feel "left behind" in Przeworski's theory (3), tend to more frequently participate in online communities as the substitutes for real-life associations and create more radical or offensive contents during public debates. In fact, according to prior analysis by Pew Research Center, about 97 percent of tweets about national politics were created by the most active 10 percent of users, while most of the tweets are created by those who strongly approve or disapprove of President Trump, and the discourse may radicalize the entire public sphere (6).

Materials and Methods

Data. The 2018 Twitter survey data targeted non-institutionalized adults age 18 and older living in the United States who use Twitter. Ipsos invited adults who have a twitter account to take this survey and the final number of qualified cases is 3,293. In addition to the survey variables, the dataset also contains respondents' demographic profile information such as age, educational level, race, household income, marital status, housing type, employment status, etc. The main survey questions can be categorized into two types: the first type of questions concerns users' social habits of using Twitter to build their online networks and the second type involves users' views and attitudes towards their ideological identity and a range of political topics.

From the survey data, we selected subsets of variables that form a "social trust question space" and a "political activity question space" to explore relations and patterns in Twitter users' views on and behavior with respect to trust and politics. The first question space includes survey questions such as whether most people can be trusted, how attached people are to their local community, and how much they trust their members of congress. On the other hand, the second question space, which is further subdivided into three subspaces, consists of survey questions on political participation and opinions on political issues, including views on fairness and approval or disapproval of the president. The full list of variables included in the social trust question space are in Table 1 while the variables in the political activity question space are in Tables 2, 3, and 4.

For our analysis on partisan antipathy, we constructed a measure of antipathy based on the survey questions on whether respondents view people in the opposing party as feeling different about politics but sharing many other values and goals (i.e., sympathetic) or as feeling different about politics and not sharing many other values and goals (i.e., antipathetic). To complement our analysis of differences among users based on their online behavior, we also created a variable on the frequency of Twitter usage based on whether they use the social media platform at least once a week (i.e., frequent) or once a month or less (i.e., non-frequent).

Analysis Using an Unsupervised Learning Approach. We applied unsupervised machine learning methods on our question spaces to examine interesting associations and natural groupings in relation to political affiliation, partisan antipathy, and online behavior.

We built self-organizing maps on our question spaces to find patterns of grouping among observations along the themes of social trust and political activity. The grid size for each SOM is chosen such that there is an adequate number of observations in each neuron and to avoid overfitting. Hyperparameters are tuned using a grid search. Specifically, hyperparameters that result in the lowest quantization error–the mean distance of the elements from their best matching unit–are chosen for the best model.

After identifying the best models for each question space, we examine whether observations grouped in the same neurons are similar and whether there is a pattern among adjacent neurons in terms of certain factors which we layer onto the resulting map. For SOM results that appear to have a natural grouping, we identify distinct clusters using the k-means algorithm. Applying this clustering algorithm allows us to see whether there are clear separations in the map.

As another type of artificial neural network used for dimension reduction, we also fit vanilla autoencoders on our question spaces. Our autoencoders have a single hidden layer with only two nodes. The result is a projection of the input features for each question space onto a two-dimensional space using the first two deep features. The same factors we previously layered onto our resulting map from the SOM are used to color the observations in our resulting projection space from fitting the autoencoder. With this approach we can examine groupings and separations among observations in the projections space based on the specified factors.

Exploratory Results: Association Rules Mining

Associations rules mining identify some interesting relations between the variables. We find relatively strong associations rules from higher social trust and higher attachment to local community to lower level of partisan antipathy or polarization, which indicates that those who have higher confidence in their surrounding social circle and in the greater American society in general are more likely to acknowledge the pervasive existence of shared values between different groups and different people 1. However, there are no associations between low level of trust and high level of antipathy.

We also find that those never tweet about political issues or do not use Twitter frequently are likely to be less polarized or radicalized 2. However, once again we are not able to find significant associations regarding Twitter usage that lead to high level of antipathy. It seems that the debates and opinions on Twitter may have exaggerated the severity of division in political values existing in actual politics. Yet we cannot falsify the rival explanation that those with low frequency of Twitter usage may simply be apathetic towards political or public discussions entirely.

```
    lhs                           rhs                   support confidence  coverage     lift count
[1] {high trust,
     never tweet,
     unfair society}           => {low polarization} 0.1311358  0.6245734 0.2099606 1.297978   366
[2] {high trust,
     mixed politics followed,
     never tweet}              => {low polarization} 0.1608742  0.6201657 0.2594052 1.288818   449
[3] {high trust,
     never tweet,
     social assistance}        => {low polarization} 0.1372268  0.6177419 0.2221426 1.283781   383
[4] {high trust,
     mixed politics followed,
     other affiliations}       => {low polarization} 0.1099964  0.6055227 0.1816553 1.258387   307
[5] {high attachment,
     high trust,
     never tweet}              => {low polarization} 0.1375851  0.6018809 0.2285919 1.250819   384
```

Fig. 1. Social Trust and Antipathy Associational Rules

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    lhs                        rhs                   support confidence  coverage     lift count
[1] {healthcare concern,
     never tweet,
     other affiliations}    => {low polarization} 0.1092798  0.5980392 0.1827302 1.242835   305
[2] {drug concern,
     never tweet,
     other affiliations}    => {low polarization} 0.1049803  0.5967413 0.1759226 1.240138   293
[3] {college cost concern,
     never tweet,
     other affiliations}    => {low polarization} 0.1028305  0.5954357 0.1726980 1.237424   287
[4] {never tweet,
     other affiliations}    => {low polarization} 0.1142960  0.5863971 0.1949122 1.218640   319
[5] {never tweet,
     not xenophobic}        => {low polarization} 0.1644572  0.5802781 0.2834110 1.205924   459
```

Fig. 2. Twitter Usage and Antipathy Associational Rules

There are few relations between partisan affiliation and online behaviors, yet the different attitudes toward Trump associate with some intriguing different outcomes in online discourse. Trump supporters tend to believe that people are too easily offended today, whereas Trump adversaries tend to argue that people need to be more cautious about their language and do not be offensive. The associations with social problems generally follow the expected pattern. For example, Trump adversaries tend to focus on issues such as treatment of immigrants, racism, healthcare, and climate change, whereas Trump supporters are apathetic towards these topics. In terms of political trust, each partisan faction associates with both high level and low level of trust in the congress, probably depending on the perspective of the specific respondent. Based on associational rules mining, we find that those with lower level of partisan antipathy tend to converge in patterns of social trust and online activism, whereas the radicals are diverse. To better observe the clusters and divisions across multiple variables, it is necessary to employ dimension reduction methods for clustering and visualization.

Results and Discussions: Neural Network-based Machine Learning

Social Trust. The Pew Research Center defines social trust simply as "faith in people." Depending on a multitude of factors such as race and income, levels of trust can vary among the population (7). In this study, we examined how social trust differs across various groups of Twitter users based on their political views through applying unsupervised learning methods. Studies have also shown that online communities can aid in building social trust through bridging social capital (Nah and Chung 2012 (8); Norris 2002 (9); Williams 2006 (10)). Hence, we analyze whether there are differences in social trust between frequent and non-frequent users of Twitter.

We first built a Self-Organizing Map on our social trust question space, which consists of the variables in Table 1. With the tuned model, we colored the observations based on respondents' party affiliation, political antipathy, whether or not they support Trump, and how often they use Twitter to examine patterns in these variables that may be associated with individuals' views on social trust. The resulting maps colored according to the four factors are shown in Figure 3. The empty neurons indicate that there are no respondents matching the pattern of responses for those neurons.

Table 1. Social Trust Question Space

Variables	Meaning
SOCTRUST2	whether most people can be trusted
COMATTACH	how attached people are to their local communities
GSSTRUST2	whether most people would try to be fair
GSSTRUST3	whether most of the time people try to be fair
TRUSTCONGa	how much of the time people believe members of Congress care about the people they represent
TRUSTCONGb	how much of the time people believe members of Congress do a good job promoting laws and policies that serve the public interest
TURSTCONGc	how much of the time people believe members of Congress handle the resources available to them in a responsible way
TRUSTCONGd	how much of the time people believe members of Congress make public statements that provide fair and accurate information
TRUSTCONGe	how much of the time people believe members of Congress admit mistakes and take responsibility for them

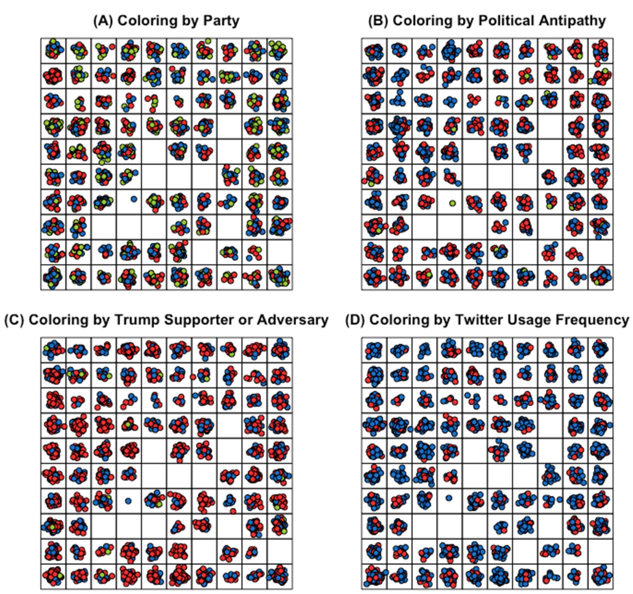

Fig. 3. Social Trust Self-Organizing Map

Based on how the colored observations are grouped in the map, there appear to be no evident patterns of clustering by party, political antipathy, support for Trump, or frequency of Twitter use. Specifically, in terms of coloring by party (Figure 3, Panel A), the neurons are composed of a mix of Democrats, Republicans, and others. This indicates heterogeneity within parties with respect to trust. That is, respondents have varying levels of social trust regardless of their party affiliation. This result is unsurprising given our relatively broad social trust question space. Differences across parties may be more evident when assessing trust in a more specific context. Based on the Pew Research Center's 2018 survey, partisan differences in levels of trust appear for certain groups. For instance, the military is more favorable for Republicans while professors and journalists are more favorable for Democrats (11).

Likewise, in coloring by partisan antipathy (Figure 3, Panel B), people who view members of the opposing party as sharing the same values and goals are grouped in the same neurons as those who view members of the opposing party as having different values and goals. In this case, it would be reasonable to expect grouping patterns based on the assumption that more sympathetic individuals have higher levels of social trust and more antipathetic individuals have lower levels of social trust. However, our findings show that whether Twitter users are sympathetic or antipathetic towards the opposing party is not connected to their level of social trust.

There are also no grouping patterns that indicate differences in views on social trust by supporters and adversaries of Trump (Figure 3, Panel C). This result can be interpreted much like the findings in terms of party affiliation. The absence of evident patterns suggest that there is also heterogeneity within Trump supporters and adversaries which includes in terms of their levels of social trust.

Similarly, how frequent respondents use Twitter does not appear to be associated with their views on social trust (Figure 3, Panel D). There has been limited literature on the relationship of social media and levels of trust and from the few studies conducted there appears to be some associations. Ismail (2020) found that there are differences in levels of trust according to frequency of social media use (12). Meanwhile, Valenzuela, Park, and Kee (2009) found a positive relationship between intensity of Facebook use and social trust (13). To the best of our knowledge, however, there have been no studies conducted on Twitter users; hence, there is no direct comparison. Nevertheless, our results suggest that unlike previous similar studies, there is no relationship between frequency of Twitter use and levels of social trust.

We observe equivalent results from the vanilla autoencoder fit on the social trust question space. As shown on the projection space based on the first two deep features (Figure 4), there are no distinct grouping patterns with respect to the four factors. The ellipses representing the distributions of different groups clearly overlap in all four plots. Hence, our findings from the autoencoder are consistent with our results from the SOM. The two different approaches both provide evidence that Twitter users' views on social trust are unrelated to their party affiliation, general political stances, and Twitter usage.

Disagreement in Politics. In the 2020 presidential election season, social media platforms, like Twitter, have taken on a heightened role of importance in shaping citizens' political engagement. This real-life case implies that people with different political stands may have notable differences in how they use Twitter, and their use of Twitter and consumption of online information may at the same time make them hold radically different political views towards a wide range of social issues.

To explore the underlying dynamics of users' ideological beliefs and opinions on both politics and everyday life, we focus on two variables representative of people's political stands: (1) stated party affiliation and (2) their attitudes towards Trump's role as President (either support or not support). Figure 5 shows that, among all respondents, there are more Democrats than Republicans, while a considerable number of users claimed themselves as independent or affiliated with

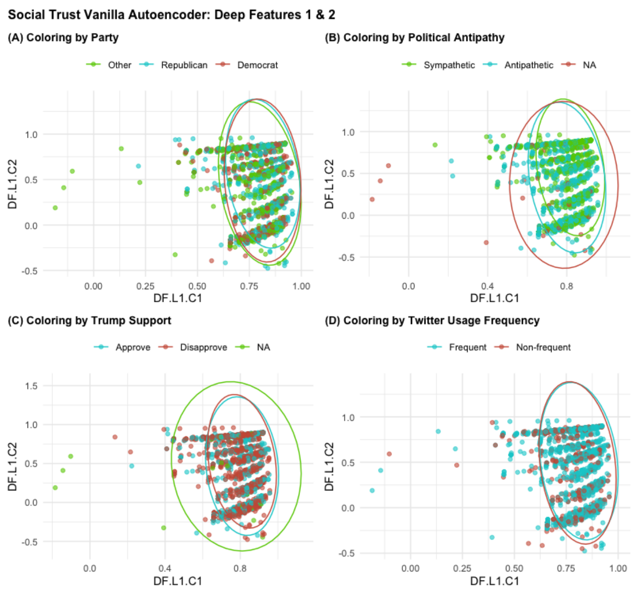

Fig. 4. Social Trust Vanilla Autoencoder Projection

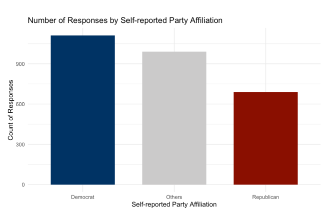

Fig. 5. Party Affiliation

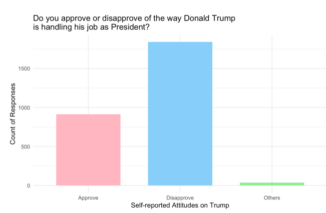

Fig. 6. Attitudes towards Trump

other minor parties. Not surprisingly, if we look at their self-reported attitudes towards Trump, there are nearly one time more respondents who disapprove of the way Trump is handling his job as President (as shown in figure 6). One may ask whether people's attitudes towards Trump are determined entirely by their party affiliation. Figure 7 indicates that very few Democrats approve of Trump' job, whereas around 25% of Republicans actually disapprove of the way he behave as President. Hereby, a sizeable number of Republicans are not Trump supporters. Whether people support Trump may become an emerging indicator to describe their ideological thinking.

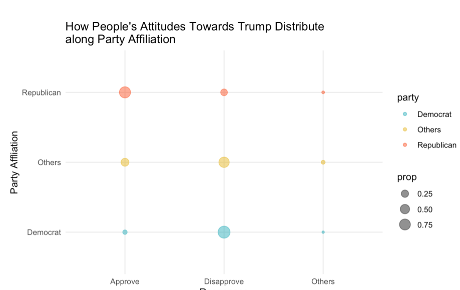

Fig. 7. Party & Trump

First of all, we are interested in which types of users are most drawn to tweet about national politics in the first place. In Figure 8, those with intense negative views of Trump are among the most prolific political tweeters. There are two implications from both the plot and the basic statistics (6). First, the share of U.S. adults on Twitter who strongly disapprove of Trump (55%) is 7 percentage points higher than the share of the general public that holds this view (48%). Second, strong disapprovers of Trump make up 55% of all U.S. adults on Twitter, but their frequency of tweeting about national politics results in them generating 72% of all the tweets about this topic from U.S. adults.

How partisans view each other? How users' tweeting habits interact with the partisan antipathy, which signifies the level of division and animosity among partisans towards the members of different opposing party? According to Figure 9, comparable shares of who frequently and who seldom use Twitter express partisan antipathy. However, users who more frequently tweet politics claim greater partisan disagreements that extend beyond politics to basic facts (see Figure 10). That is to say, partisans who tweet about national political issues tend to have colder views of the opposing political party relative to other users who are less politically active on the site.

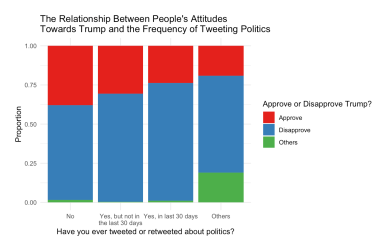

Fig. 8. Tweeting Politics

So far from the descriptive analysis, we get a brief sense of how most twitter users view national politics. In the following three subsections, we will investigate whether users' party affiliation and attitudes towards Trump generate grouping effects on their political views of different social issues, employing both SOM and autoencoder models.

.1. Equality & Diversity of Communities. The first question space concerns people's views on equality and diversity of the community and/or society. Seven survey questions are included in this space, as shown in Table 2, each one indicating whether people treat different special groups equally and fairly. Before studying the underlying pattern using unsupervised techniques, we first draw a bubble plot to see if there is an obvious partisan difference in people's views on equality and diversity (see Figure 11). We can observe that the partisan difference does exist in this question space, where Democrats and Republicans are separating each other a little bit.

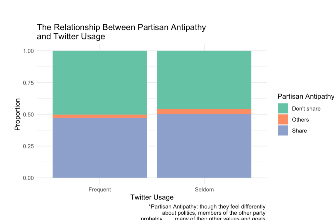

Fig. 9. Usage & Partisan Antipathy

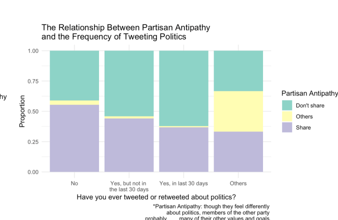

Fig. 10. Politics & Partisan Antipathy

Then, we construct a self-organized map (SOM) and color it by people's attitudes towards Trump. We use the z-score standardized version of the responses for all seven questions. By iteratively running the grid-search function, we manage to find the best combination of hyperparameters at the minimal mean distance to the closest nodes. Meanwhile, we also build a shallow autoencoder, colored by people's attitudes towards Trump. The results of the SOM and autoencoder models are displayed in Figure 12, showing a clear separation in the projection space along attitudes towards Trump. The white dots in the SOM output are those avoided to respond. When comparing these two outputs, the SOM model provides a better division, capturing a great difference between people who approve and disapprove of Trump. Therefore, we reach a conclusion that Twitter users who have opposite views of Trump's job as President have totally different perceptions of how the equality and diversity works in the society.

Table 2. Question Space for Equality and Diversity of Communities

Variables	Meaning
FAIRTRT	whether people with different colors are treated fairly
WOMENOPPS	whether women and men are treated fairly
IMMCULT2	whether newcomers are treated fairly
ECONFAIR2	whether the economic system is fair
POLCRCT	whether people with different backgrounds are offended by language
JOKE1	whether people take offensive content seriously
CHOICE1	whether people can speak freely online

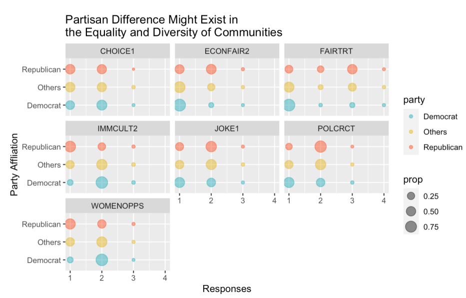

Fig. 11. Bubble Plot: Equality & Diversity

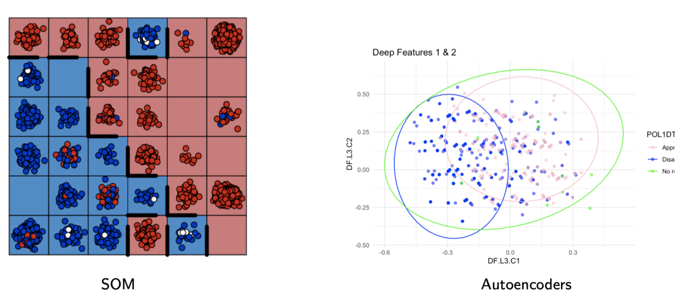

Fig. 12. Results: Equality & Diversity

.2. Salient Social Issues. The second question space asks how much of a salient social issue the respondents think are in the country today. People will rate each of the ten questions (shown in Table 3) among "1 - a very big problem", "2 - a moderately big problem", "3 - a small problem", and "4 - not a problem at all". From the bar chart 13, it is obvious that Democrats and Republicans have completely opposite opinions on all these survey questions. The partisan difference in this projection space is quite significant.

Table 3. Question Space for Salient Social Issues

Variables	Meaning
NATPROBSa	The affordability of health care
NATPROBSb	Racism
NATPROBSc	Illegal immigration
NATPROBSd	Sexism
NATPROBSe	Drug addiction
NATPROBSf	The gap between the rich and poor
NATPROBSg	Gun violence
NATPROBSh	The affordability of a college education
NATPROBSi	Climate change
NATPROBSj	Treatment of immigrants in the U.S.

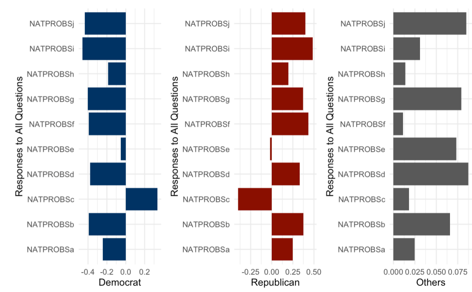

Fig. 13. Bar Chart: Salient Social Issues

We then construct the SOM and autoencoder models colored by party affiliation, to see if people's different views on salient social issues can be accurately captured by partisanship. The two outputs from Figure ?? and 15 exhibit a common pattern that there is a clear separation of issue views along party affiliation, but meanwhile a lot of responses from those without claimed parties randomly distribute. Hereby, the explanatory power of party affiliation is somewhat limited.

When coloring by people's attitudes towards Trump, we obtain a better division in their opinions on these important issues, as shown in Figure 16 and 17. There are very few white dots and little overlap between Trump supporters and non-supporters. In this sense, the deep-seated divides in salient social issues can be better understood by whether people accept Trump or not. This interesting pattern gives us some

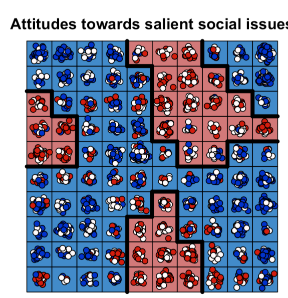

Fig. 14. SOM Result by Party: Salient Social Issues

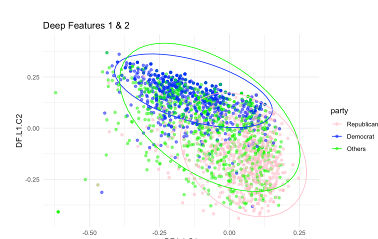

Fig. 15. AE Result by Party: Salient Social Issues

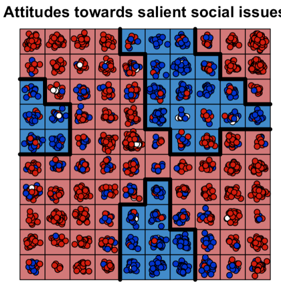

Fig. 16. SOM Result by Trump: Salient Social Issues

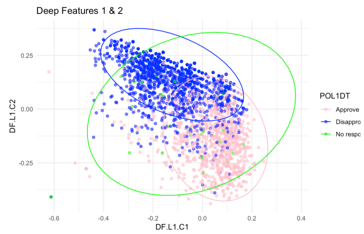

Fig. 17. AE Result by Trump: Salient Social Issues

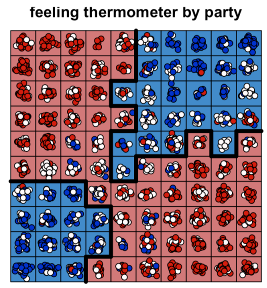

Fig. 19. SOM Result by Party: Feeling Thermometers

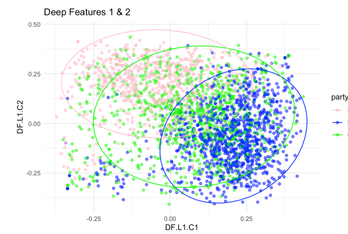

Fig. 20. AE Result by Party: Feeling Thermometers

indication that America has cleaved in a new way, though divisions between the two parties also have intensified over time.

.3. Feeling Thermometers. The third question space looks at users' feelings toward a number of special groups in the U.S. on a "feeling thermometer". The respondents were asked to enter a number between 0 to 100, where 0 means people feel as cold and negative as possible and 100 means people feel as warm and positive as possible. There are eight questions in this projection domain, each focuses on a special group of people (see Table 4). Is there a partisan difference in feeling thermometers? From Figure 18, we can see that, for most questions, Democrats and Republicans have different issue positions.

Table 4. Question Space for Feeling Thermometers

Variables	Meaning
THERMOa	How do you feel toward Republicans?
THERMOb	How do you feel toward Democrats?
THERMOc	How do you feel toward college professors?
THERMOd	How do you feel toward police officers?
THERMOe	How do you feel toward journalists?
THERMOf	How do you feel toward Muslims?
THERMOg	How do you feel toward evangelical Christians?
THERMOh	How do you feel toward Catholics?

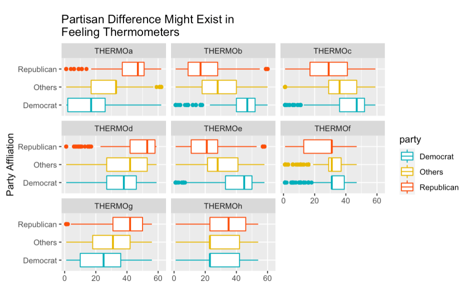

Fig. 18. Box plot: Feeling Thermometers

Next, we move to the SOM and autoencoder models. Coloring by party affiliation, both models show a partisan division in feeling thermometers (see Figure 19 and 20). The results are fairly good, but similarly, there are too many "others", which would limit our ability to derive a general conclusion. When we color the models by people's attitudes towards Trump, strikingly, we gain a better separation in the projection space.

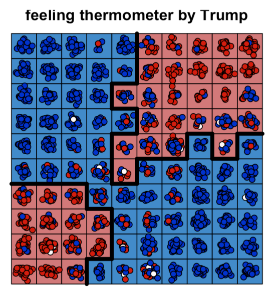

Fig. 21. SOM Result by Trump: Feeling Thermometers

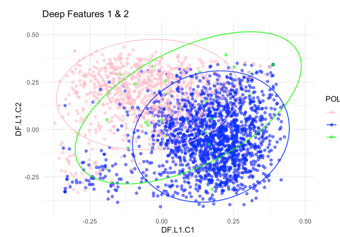

Fig. 22. AE Result by Trump: Feeling Thermometers

In Figure 21 and 22, compared to what we have found along party affiliation, the grouping pattern along how people think of Trump is extremely clear.

Overall, based on the results of SOMs and autoencoders, we find clear groupings in where Twitter users stand on the issues (equality and diversity of communities, salient social issues, and feeling thermometers) both along party affiliation and attitudes towards Trump. The two approaches - SOMs and autoencoders - show similar patterns. More importantly, we find that the Trump divide may be a more accurate indicator to describe political polarization among Twitter users in this era. This finding lends support to our observation that partisan voters are increasingly aligned more closely with the leader of their party than with the policy position of the party. Trump Republicans and non-Trump Republicans are different. People's issue positions are related to whether they hold favourable views of Trump. These findings have important implications for how scholars measure political polarization, and for our understanding of its underlying dynamic.

Concluding Remarks

By unsupervised machine learning, we find no significant separations based on Twitter users' real-life social trust, online behavioral patterns, or inherent level of partisan antipathy but identify clear groupings in the users' political views on social issues along party affiliation and opinions towards Trump's presidency, indicating that Trump fosters an emerging group identification that intensifies polarization. We suggest future researchers take a closer look at the catalyzing effects of social media on tracing the dynamic processes of identity simplification. We further recommend examining whether these findings are similar or different for non-Twitter users.

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