Using Social Media Analytics to Explore Political Involvement and Polarization: Challenges and New Insights

Néstor Narbona Chulvi

Faculty of Social and Behavioral Sciences, Psychology, University of Amsterdam

Bachelor's Thesis Psychological Methods

Supervisor: Adam Finneman

Abstract word count: 123

Paper word count: 4987

February 4, 2022

Abstract

Using Twitter analytics, this paper explored the relationship between political involvement and the bimodality of political attitudes. From the Cusp Catastrophe model of attitudes, it was expected that higher political involvement would make the bimodality of political attitudes more extreme. Using natural language processing, political attitudes and political involvement of 921 Twitter users were estimated. A partial Cusp Catastrophe model was fitted to test the prediction. The analysis results did not support the prediction but some methodological insights are provided: measuring attitudes per user averages out extreme opinions, measurements of political involvement and attitudes must consider the same topic, and organizations and bots have to be identified and removed from the data. Finally, opportunities and challenges of Twitter analytics are explored and discussed.

Using Social Media Analytics to Explore Political Involvement and Polarization: Challenges and New Insights

Political polarization is on the rise, and its negative societal consequences are ever more concerning (Pew Research Center, 2014b). Although this problem expands over different aspects of citizens' lives, in the eyes of many researchers it is especially tangible in social media platforms (e.g. Twitter) (van Bavel et al., 2021). Polarization, whether it is studied in the context of social media or outside of it, is essentially a psychological concept first coined and mainly studied within this field (Smith et al., 2014). It is thus clear that efforts to further understand this increasingly problematic phenomenon must stem from psychological research. Political polarization refers to a division in the population into two contrasting sets of attitudes. In other words, polarization occurs when the distribution of political attitudes in the population becomes increasingly bimodal (van Bavel et al., 2021). There are different constructs that influence this drift towards a bimodal distribution of political attitudes. A key concept in this regard, in particular in the study of political attitudes, is political involvement (i.e. degree to which citizens vote and pay attention to political events and the media) (Kruikemeier et al., 2016; Pew Research Center, 2014b). This paper studies the link between political involvement and the bimodality of political attitudes in the context of Twitter.

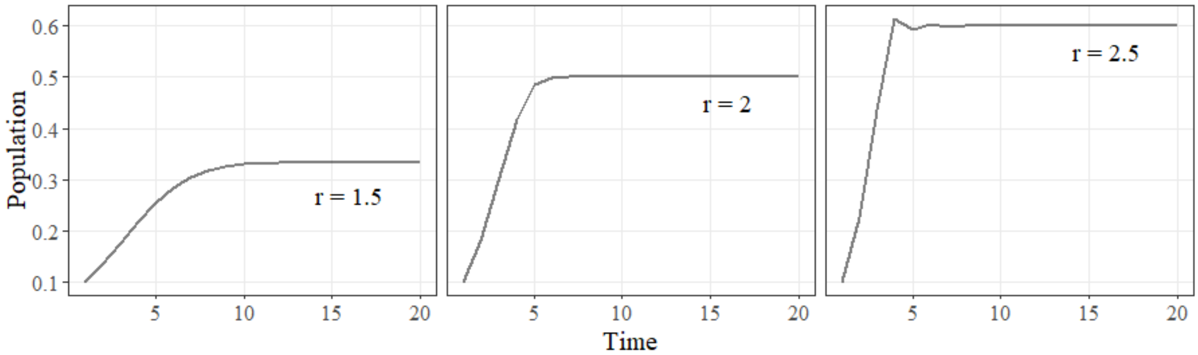
Since the beginning of the last century psychologists have developed theories that attempt to explain attitudes and attitude changes (Book, 1910). Some of the most promising results come from literature using the Cusp Catastrophe model to explain attitudes (van der Maas et al., 2003; Zeeman, 1976). The Cusp Catastrophe is a model stemming from the field of dynamical systems. Dynamical systems are systems that evolve over time according to a well-defined rule (i.e. a difference or differential equation) (Strogatz, 2019). This can be used to model many different real phenomena. For instance, one can model the rabbit population on0020 an island using the logistic difference equation, where *p* represents the proportion of the maximum population that currently lives on the island and *r* is a growth parameter (1).

$$p_{t+1} = rp_t(1 - p_t) \quad (1)$$

Figure 1 shows how this dynamical system could be used to model rabbit populations with different growth rates. As it can be seen, dynamical systems tend to reach points at which they do not change anymore. These are called equilibriums. It can also be noted that the equilibrium points of a system depend on the parameters specified for the system (Strogatz, 2019). This is commonly shown by means of a bifurcation diagram. These plots show the equilibrium points of the system (i.e. y-axis) given the value of the parameter (i.e. x-axis), in this case the single parameter *r*. Figure 2 shows the bifurcation diagram for the logistic difference equation. The black dots show the equilibrium point for those rabbit populations depicted in Figure 1.

Figure 1

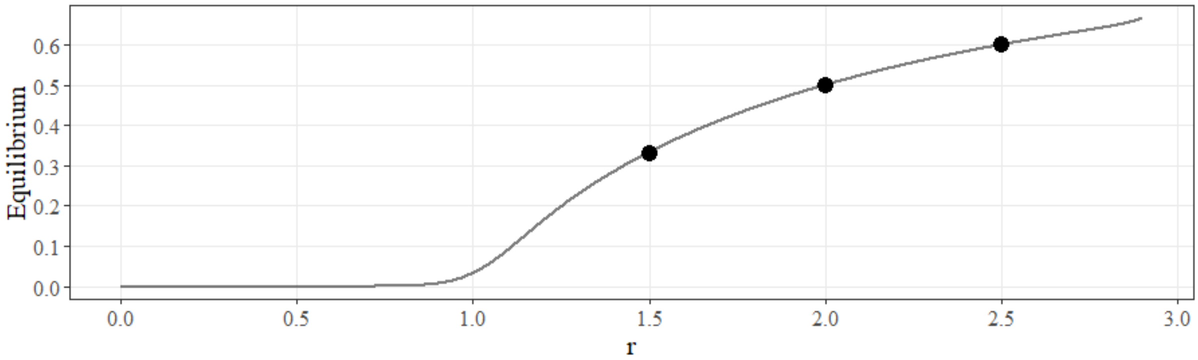
Population time series for the logistic difference equation at r = 1.5, 2 and 2.5



The Cusp Catastrophe is a dynamical system commonly introduced by showing its bifurcation diagram (Figure 3). It has two parameters: α and β. Thus, the graph shows the equilibrium points of the system given a certain α and β. This model has been used with promising results to describe attitudes (van der Maas et al., 2003). In the context of attitudes, the parameter α refers to information, β to involvement and *x* to attitudes towards a certain topic. Generally, a low *x* represents a negative attitude and a high *x* a positive one. At lower α the person is receiving information in support of a negative attitude and at a higher *a* he is receiving information that supports a positive attitude. Finally, the higher the β value is, the more involved the person is in the topic the attitude refers to. In short, the Cusp Catastrophe describes, given a certain involvement and a certain information, what is/are the possible attitudes of a person.

Figure 2

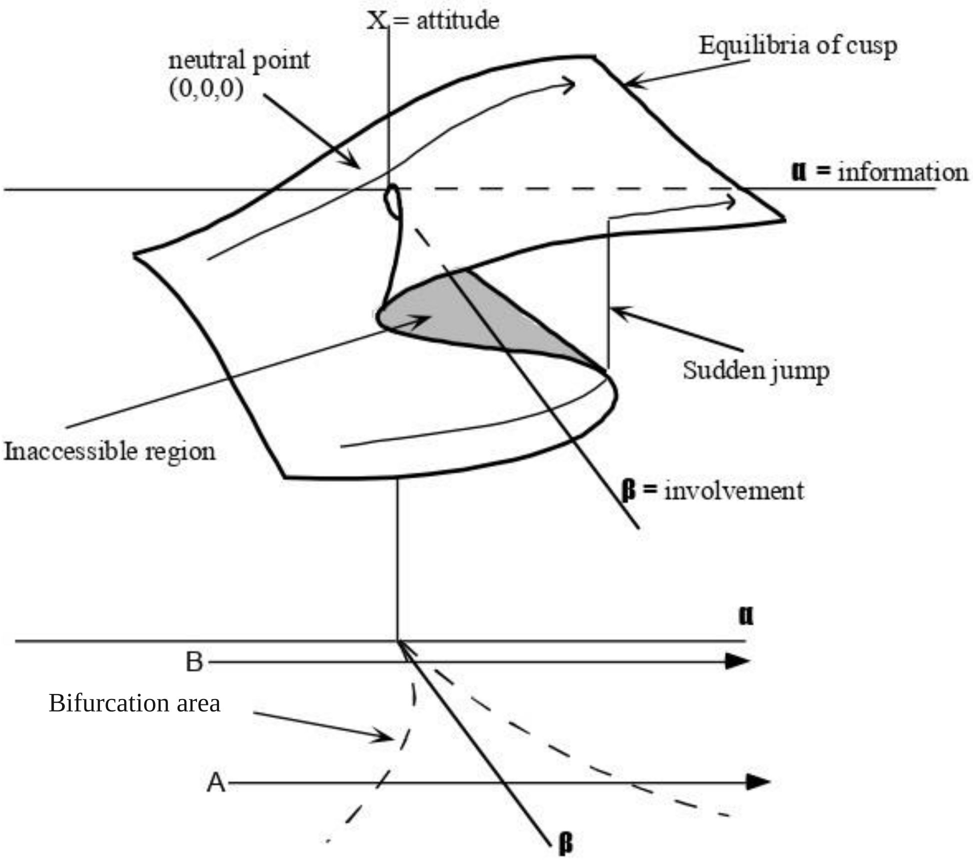
Bifurcation diagram for the logistic difference equation



Different predictions follow from the Cusp Catastrophe model of attitudes. For this research, the most relevant prediction from this model is the following. If person *P* has a low involvement, *P* may adopt any attitude depending on the received information: positive information leads to a positive attitude, moderate information leads to a moderate attitude. On the contrary, if *P* is highly involved, *P* may only have a clearly positive or negative attitude, any moderate attitude is not an equilibrium point (i.e. inaccessible region). This phenomenon takes place within the bifurcation area. This same prediction can be derived from a partial Cusp Catastrophe model: one that only includes the variables attitude (i.e. *x*) and involvement (i.e. *β*) (van der Maas et al., 2003). This simpler version of the Cusp Catastrophe is better suited for studying the link between political involvement and the bimodality of political attitudes. Thus, it is used to evaluate the hypothesis. Supporting the validity of these models and in particular of this prediction, Flay (1978) found that only if students' involvement in a course was low there were moderate attitudes in the evaluation. If involvement was high attitudes were either extremely positive or extremely negative. In the political context, a recent US survey shows that highly politically involved citizens show more extreme political attitudes than less politically involved ones (Pew Research Center, 2014b).

Figure 3

Bifurcation diagram for the Cusp Catastrophe model



This research is focused on the social media platform Twitter, as there is evidence that Twitter use has an influence on intention to vote and political involvement (Dean, 2021; Kruikemeier et al., 2016). This frames the present paper within the increasing body of literature that uses Twitter analytics to test hypothesis and validate theories. Social media analytics has many strengths. It makes it possible to work with big samples that may encompass many different cultures, income or education levels (Grover et al., 2019). Furthermore, looking at subjects' behavior in their natural environment instead of a controlled setting increases the ecological validity of the findings (Arora et al., 2019). Nevertheless, this approach also has some weaknesses. Measuring constructs from users natural language and interactions poses many challenges, and the development of feasible and valid measurement methods is still work in progress (Haselmayer & Jenny, 2017). Sampling also shows some problematic aspects, for example, organizations or bots may be included in the research sample at the same level that individuals (McCorriston et al., 2015). The present research design, as part of a Twitter analytics effort, attempts to exploit the strengths of this approach as well as alleviate its weaknesses.

Based on the Cusp Catastrophe model of attitudes it was predicted that as political involvement increases, the bimodality of the attitude distribution becomes more extreme. To check this hypothesis, a corpus of 332,168 recent tweets that referred to United States president Joe Biden was collected. A political entity, instead of a political issue, was studied due to methodological reasons that are discussed later. Natural Language Processing (NLP) tools were used to measure both politcal attitudes and political involvement. In similar fashion to previous research performing attitude mining in Twitter, a dictionary-based sentiment analysis was used to assess the valence and extremity of users' attitudes (Maynard & Funk, 2012). Following earlier literature, political involvement is assessed by looking at how much users post about political and government affairs (Kruikemeier et al., 2016; Pew Research Center, 2014b). More specifically, it studies the number of a user's last 100 posts that included political content. Finally, the hypothesis was statistically assessed by fitting a partial Cusp Catastrophe model to the gathered data.

Method

Twitter Posts Collection and Pre-Processing

The corpus of tweets was gathered using the package *rtweet* from the software R (Kearney, 2019). 332,168 posts published between 08-01-2022 and 27-01-2022 and containing the word ‘Biden’ were collected. The name entity recognition package *entity* was used to select only those posts that contained only the name ‘Biden’ or ‘Joe Biden’. Looking at posts that refer to a political entity (e.g. Biden) instead of posts referring to a political issue (e.g. government spending) has different advantages when measuring attitudes via sentiment analysis. If one investigates attitudes towards a political issue, a post categorized as having negative affect can be both in favour of view A or against it, depending on what is the opinion target. One can heavily criticise politicians supporting view A (negative affect = negative attitude towards view A), but another can criticise those supporting view B (negative affect = positive attitude towards view A) (Maynard & Funk, 2012). If one investigates a political entity and looks at posts that only contain the name of that political entity, this problem is reduced. It can then be reasonably assumed that a post categorized as having negative affect has a negative attitude towards that political entity, and one showing positive affect has a positive attitude towards that political entity.

To further improve the validity of the sentiment analysis, posts containing question marks were deleted (Maynard & Funk, 2012). Furthermore, only posts from users that had more than four posts in the corpus were kept. This ensured that the sentiment analysis would have enough text material to appropriately assess the user’s affect (i.e. political attitude). On the remaining posts some text cleaning is performed by deleting user names, links and other informatic codes.

Measurements

To measure users’ political involvement through their past posts, a political lexicon was first created with political words and political entities’ names. First, political words were gathered from the 571 terms contained in the ‘Politics’ Topic Dictionary from Oxford

Learners' Dictionaries (Topic Dictionaries at oxford learner's Dictionaries, n.d.). Secondly, a name entity recognition using the package *entity* was performed on the last 1000 posts by *@nytimespolitics, @usatodayDC* and *@foxnewspolitics.* These newspapers were chosen for being the most popular ones with a democratic, centrist and republican ideology respectively (Pew Research Center, 2014a). The identified political organizations and politicians' names frequently mentioned were included in the political lexicon. Once the lexicon was created, the last 100 posts from each unique user in the corpus were accessed. If a post contained any term from the political lexicon, it was judged as political. In the end, each unique user had a political involvement score ranging from 0 to 100. To check the performance of this categorization, the content and assigned category of one randomly selected post per participant were saved. This data was later used to calculate precision, recall, and specify of the categorization. These performance metrics are compared to those of a ZeroR baseline: classifying every post in the majority class (Lee, 2021). Finally, descriptive statistics and visualizations regarding the distribution of political involvement are reported.

In order to measure political attitudes, a sentiment analysis is performed on the posts. The chosen method is a dictionary-based approach that takes negation words into account. The AFINN dictionary offered in the *tidytext* package is used (Silge & Robinson, 2016). This dictionary rates words between -5 (very negative) and 5 (very positive). The process of assigning participants a political attitude was as follows. Firstly, posts were tokenized into bigrams and those bigrams containing an AFINN dictionary word as the second term were kept. Then, using the sentiment values from the AFINN dictionary, an affect value was linked to each bigram. If the first word of the bigram was one of the following negation words *hardly, lack, neither, nor, never, no, nobody, none, nothing, nowhere, not, cannot* or *without*; the affect value was inversed (e.g. 3 became -3). This method misses AFINN dictionary words placed as the first word in the post, because they are never positioned as the second word of a bigram. To take these words into account, the first word of each post was isolated and if they were an AFINN dictionary word, a sentiment value was linked to them. Finally, each user obtained an affect value equal to the average sentiment value of the bigrams and first words that belonged to his/her posts. Descriptive statistics and a visualization regarding the distribution of attitudes are reported. A concern regarding this approach was that it would ‘average out’ extreme posts. Users with extremely positive posts as well as extremely negative ones would be falsely considered as having a moderate attitude. This is was expected to be excessively problematic in this design given the performed post scrapping. Given that only posts mentioning only ‘Biden’ or ‘Joe Biden’ were studied, users were not expected to have extreme posts in opposite directions as they were not expected to have opposite attitudes. Nevertheless, this concern was assessed. Using the same sentiment analysis method, political attitudes were also measured per post instead of per user. A Levene’s test is performed to compare the variance in the *per user* and the *per post* data sets. Furthermore, the distribution of political attitudes at each quartile of political involvement is compared between the two data sets.

Analysis

In order to evaluate if as political involvement increases the bimodality of political attitudes becomes more extreme, a partial Cusp model is fitted to the processed Twitter data. For this purpose, the *cusp* package in R is used (Grasman et al., 2009). This package allows for a quantitative fitting of the Cusp model using Cobb’s maximum likelihood approach. More specifically, the working of the *cusp* package is as follows. It is assumed that the measured α and β values (i.e. the X in the equation) are a transformation of the actual values from the system (2) (3). Then, it estimates the values for the coefficients (i.e. α_0, a_1, β_0 and β_1) through a maximum likelihood method.

$$\alpha = \alpha_0 + \alpha_1 X_1 \tag{2}$$

$$\beta = \beta_0 + \beta_1 X_1 \tag{3}$$

The *cusp* package also incorporates more recent additions to Cobb's method. Most importantly, it is possible to keep some parameter constant and fit a partial Cusp model. Fitting such a partial Cusp model by keeping *a* constant already allows to check if bimodality becomes more extreme as β increases (van der Maas et al., 2003). It is therefore better suited to check this paper's hypothesis and is used in the analysis.

To evaluate the goodness of fit of the model different methods recommended by Cobb are followed (Grasman et al., 2009). *(1 Comparison to linear model)* Firstly, he partial Cusp model is compared to a linear model on the basis of the AIC and BIC metrics. This comparison is performed because the partial Cusp model can show good fit to linear data, which would be more parsimoniously explained by the simpler linear model. Complementing this analysis, political involvement scores are plotted against political attitudes in a scatterplot including the linear regression line. *(2 Comparison to unrestricted cusp model)* Secondly, the partial Cusp model is compared to an unrestricted Cusp model. This second model does not keep any parameter constant and estimates α and β from political involvement measures. Strictly speaking, the Cusp model assumes that political involvement only loads on β. Thus, a better fit of the unrestricted model points at a violation of this assumption and casts doubts on the adequacy of the partial Cusp model. These two models are nested, and $-2(lnL_{unrestricted} - lnL_{restricted})$ follows a chi-square distribution allowing for a significance test of the difference in goodness of fit. In order to further check that political involvement does only load on α, the standardized parameter estimates are reported (i.e. a_0 a_1, b_0 and b_1 from Equations 2 and 3). Because of the comparison between these two models, the 'partial Cusp model' may be referred as 'restricted Cusp model'. *(3 Data points in the bifurcation area)* Furthermore, a plot indicating how many datapoints were included by the model in the bifurcation area is reported. This allows to check whether 10% of the data points fall within the bifurcation area: a criteria that is established by Cobb in order to check the fit of the Cusp model (Grasman et al., 2009). The hypothesis is also evaluated visually by plotting the political attitude distribution for users in each quartile of the political involvement scale. This allows for a general assessment of whether bimodality becomes more extreme as political involvement increases.

Results

Twitter Posts Pre-Processing and Posts Discard

From the 332,168 posts that were originally collected, 63,778 of them contained only the name ‘Biden’ or ‘Joe Biden’. Of those 53,821 did not include any interrogation mark. After looking at the users activity, 6,733 posts met the requirement of having been posted by a user that had 4 or more posts in the dataset. Finally, some manual cleaning was performed and eight users were deleted for showing bot-like behavior (i.e. having one small set of posts they repeated). This left the dataset with 5,842 posts published by 973 different users.

After developing the measurements for political involvement and political attitudes some posts had to be discarded. Firstly, seven users did not allow access to their timeline and thus their previous 100 posts could not be accessed. Secondly, 45 users did not have any word included in the AFINN dictionary within their posts and therefore no sentiment analysis could be performed on them. This left the final dataset with 5,527 posts published by 921 different users.

Measurements and Measurements Evaluation

Of all the users that were the subject of the described measurement procedures, 94.6% were given both a political attitude and a political involvement score (see previous paragraph). Descriptive statistics for political involvement and political attitudes can be seen in Table 1 and their distribution appreciated in Figure 4. Both measurements show enough variance to be used for further analysis. It can be seen that users tend to have a high political involvement (M = 68.730) and a slighlty negative political attitude (M = -0.426). Furthermore, it is already clear that there is a lack of extreme political attitude scores with a very small proportion of users having a score more extreme than ±3.

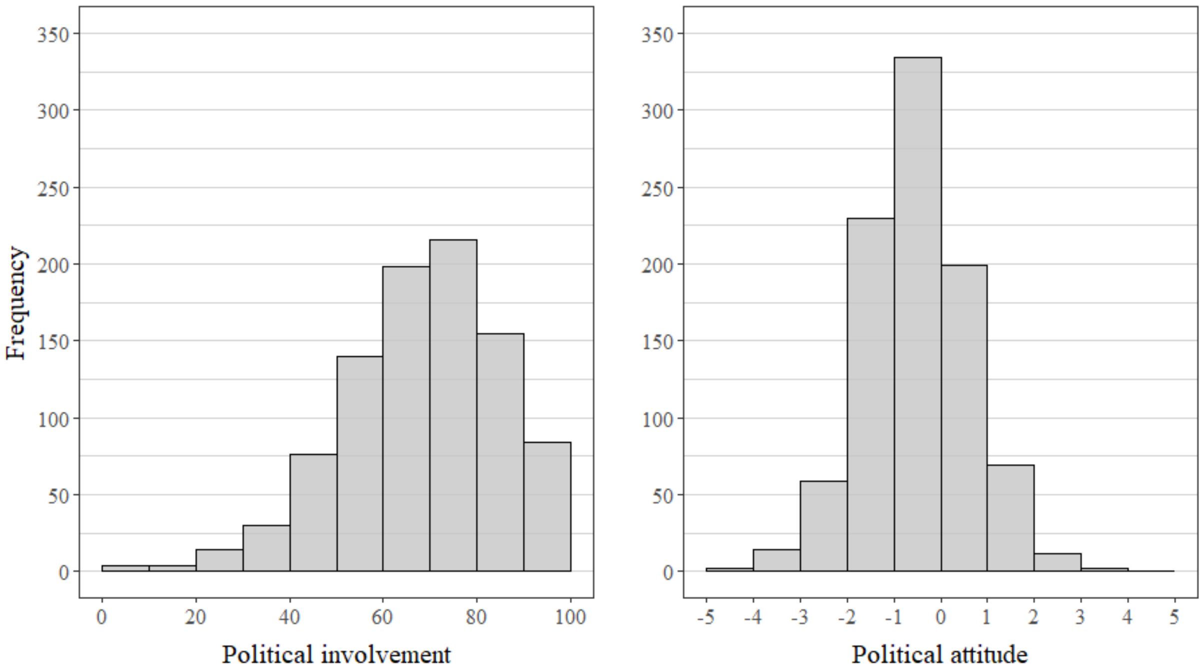
Table 1

Descriptive statistics for political involvement and political attitude

	M	*Median*	*SD*	*SEM*
Political involvement	68.730	70.000	16.890	0.557
Political attitudes	-0.426	-0.500	1.114	0.0367

Figure 4

Distribution of political involvement scores (left) and political attitude scores (right)



Furthermore, Table 2 shows the evaluation of the political posts categorization method. Precision has a relatively high value. This means that most posts categorized as

'Political' were indeed truly political. Recall is slightly smaller, showing that some truly political posts were 'missed' by the categorization method. Furthermore, specificity being over 0.5 points at the categorization method having some discrimination ability. Finally, both precision and specificity are larger than the ZeroR baseline figures. Further discussion will follow. Nonetheless, these values are considered good enough to continue with the analysis.

Table 2

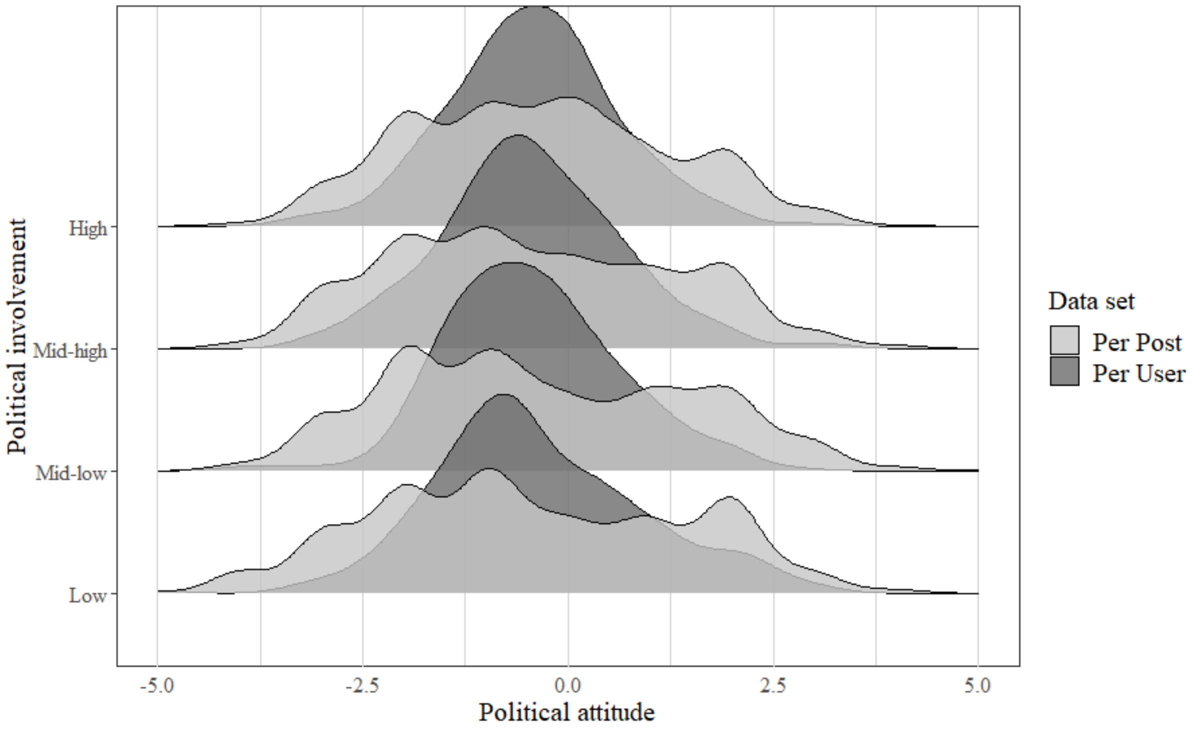
Precision, recall and specificity of the political posts categorization method

	Precision	*Recall*	*Specificity*
Political lexicon	0.875	0.729	0.583
ZeroR	0.800	1.000	0.000

Note. Sensitivity is not reported as it reflects the same information and has the same formula as Recall

Figure 5

Distribution of political attitudes in each quartile of political involvement for the 'per post' and the 'per user' data set



Regarding the evaluation of the political attitude measurement, Figure 5 shows the distribution of political attitudes at different levels of political involvement for the *per post* and the *per user* data set. It can be seen that the *per post* attitude distributions have considerably more spread than the per *per user* one. Furthermore, the performed Levene's test shows that this difference in variance is significant F(1,5296) = 310,71, p < .001. These findings are problematic, as they point at the political attitude measurement 'averaging out' extreme posts, which may cast doubt on its validity. Further discussion of these findings follows.

Table 3

Fit statistics for the linear model, the restricted cusp mode and, the unrestricted cusp model

	Log-likelihood	*AIC*	*BIC*
Linear	-1405.393	2816.811	2831.262
Cusp restricted	-1303.214	2616.494	2640.556
Cusp unrestricted	-1298.437	2608.875	2637.827

Table 4

Standardized parameters estimates of the restricted and unrestricted Cusp model

	Normal factor (α)	*Splitting factor(β)*
Restricted model		
0 Constant	-0.199	-1.248
1 Political involvement	0.000[a]	-0.055**
Unrestricted model		
0 Constant	-1.425	-0.640
1 Political involvement	-0.052	-0.063

[a]Parameter kept constant

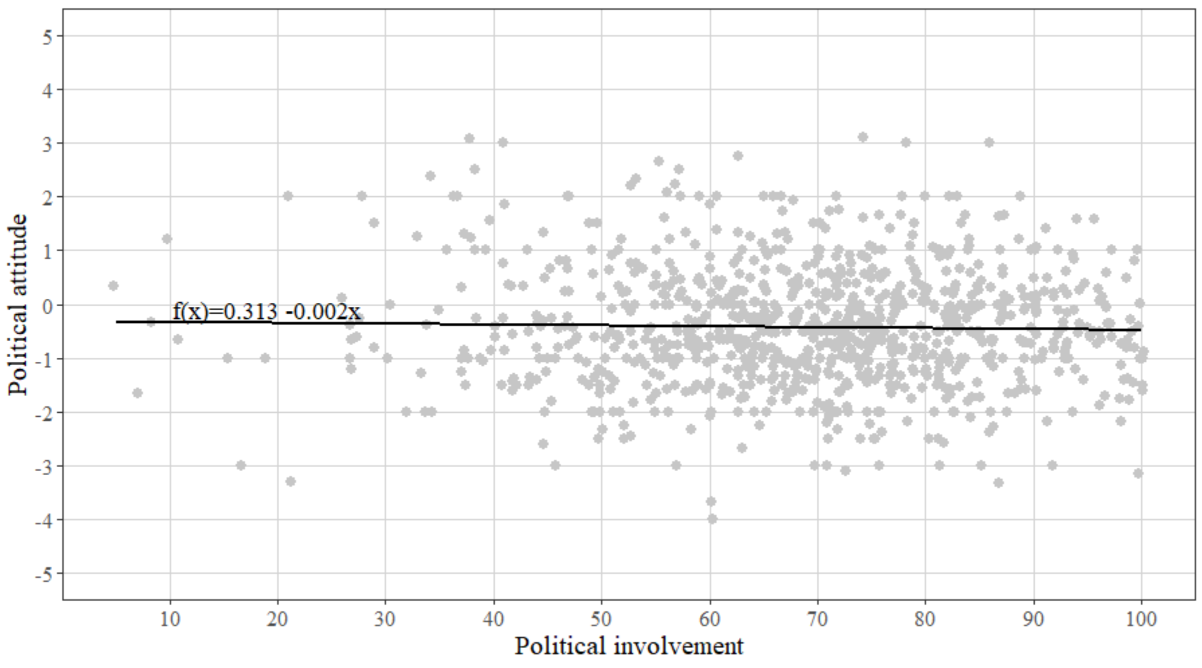
*p < .05. **p < .01. ***p < .00

Analysis results

Table 3 reports fit measures for the linear, restricted Cusp and unrestricted Cusp models. *(1)* Both BIC and AIC are lower for the restricted Cusp model than for the linear model, pointing at the former having a better fit to the data. This poor fit of the linear model can be expected based on the scatterplot from Figure 6, where it is clear that political involvement and political attitudes are not linearly related. *(2)* Comparing the restricted and the unrestricted Cusp model, the AIC and BIC point at the later having a better fit and this difference in goodness is indeed significant $X^2(1) = -2(-1298.437 + 1303.214) = -9.554, p < 0.001$. Furthermore, in Table 4 the standardized parameters are reported for the restricted and the unrestricted Cusp model. These values show that political involvement loads on α (-0.052) almost as much as it does on β (-0.063). In sum, these findings cast doubt on the suitability of the partial Cusp model.

Figure 6

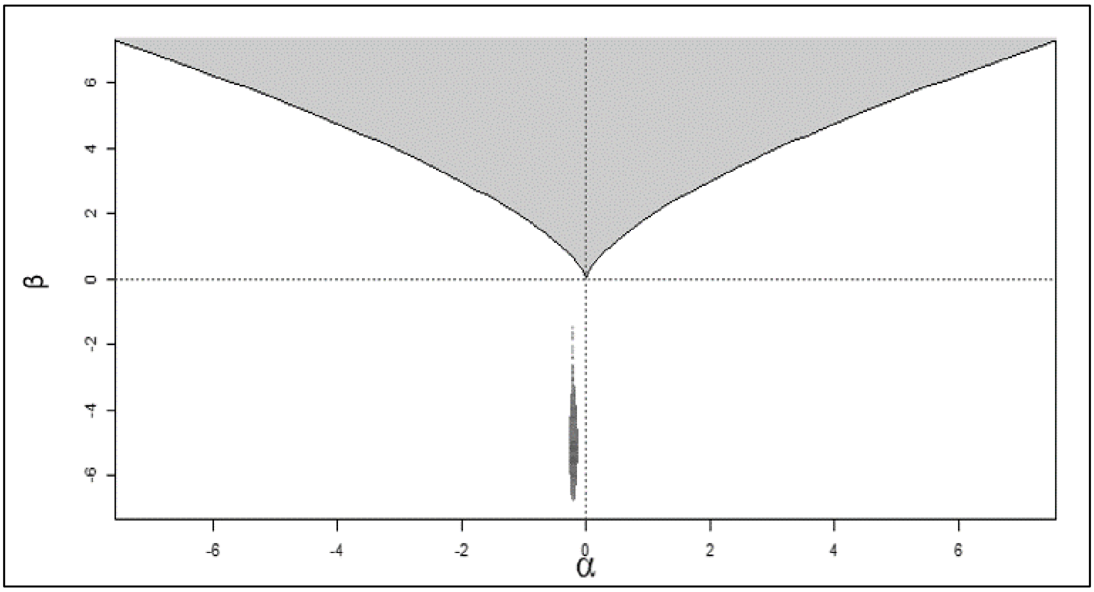
Scatterplot plotting political involvement against political attitudes



In Figure 7 the area where the model placed the datapoints is shown. *(3)* Here it is clear that non of the datapoints are placed within the bifurcation area (i.e. gray area) by the model, violating the 10% rule. Finally, in Figure 5 the distribution of attitudes at different involvement levels is reported (look at *per user* data set). Here it becomes clear that there is no increase in extremity of bimodality, as there seems to be no bimodality at any level of political involvement.

Figure 7

Cusp model area where the model placed each data point



Discussion

Based on the results of fitting the partial Cusp Catastrophe model and visualizing the political attitude scores at different political involvement levels, the hypothesis is not supported by the data. Namely, there is no evidence that as political involvement increases the bimodality of political attitudes becomes more extreme in the gathered Twitter data.

This conclusion stems from the poor fit of the partial Cusp Catastrophe model. Of the four criteria used to evaluate the fit of the model only the *(1)* comparison to a linear model points at a good fit of the model. The *(2)* better fit of the unrestricted Cusp Catastrophe model and the *(3)* absence of any datapoint placed within the bifurcation area suggest the model does not suit the data well. This poor fit of the model implies two things. First, political involvement and political attitudes are not linearly related (see also Figure 6). The partial Cusp Catastrophe model would have accounted for this relationship if it existed, which is the reason why its fit measures are compared to those of a simpler linear model (see p. 11). Second and most importantly for this research, there is no bimodality in the distribution of political attitudes at any level of political involvement (see also Figure 5).

One possible explanation for these findings is that in fact political involvement does not lead to a more extreme bimodality of political attitudes. This would contradict previous literature on the Cusp Catastrophe model of attitudes (Flay, 1978; Latané & Nowak, 1994; van der Maas et al., 2003), as well as recent findings regarding polarization and political involvement (Pew Research Center, 2014b). A particularity of this research was exploring this hypothesis in a social media context. Thus, it may be the case that the relationship between political involvement and political attitudes' bimodality does not exist or takes a different shape when studied in the context of social media. Nevertheless, there are alternative explanations for these findings that are considered more likely.

One key aspect to take into account when interpreting these findings involves the used measurements. The developed political involvement measure shows acceptable performance figures in the context of socio-political terms corpora (Manik, 2015). It has reasonable precision (0.875) and recall (0.729), and a slightly more problematic low specificity (0.583). This is not a serious concern for the used data because the prevalence of non-political posts was relatively low at around 20%. Finally, it also outperformed the ZeroR baseline regarding precision and specificity. The more problematic aspect of political involvement measurement lays with the theoretical level and within this paper's research question. Given that the operationalization of political attitudes is concerned with the US president, the political involvement measure should look at involvement in this topic. Nonetheless, the used method assesses users’ general political involvement (e.g. the economy, state-level issues, racial issues, climate policies), which may not perfectly reflect involvement in the president’s actions and events. For instance, a user may show great interest in new state-level policies, and be significantly less concerned with nation-level politics (Cancela, 2020). If this is the case, users with a *true* low political involvement would be considered as having a high political involvement. In sum, the designed measurement of political involvement is a well performing categorization system that could be used for future attempts at measuring political involvement in social media. Nonetheless, in the context of this particular research design it may exhibit some validity issues.

The measurement used to assess political attitudes is also worth of discussion. The approach used when applying a dictionary-based sentiment analysis shows different strengths. The pre-processing of posts in order to eliminate as many alternative opinion as possible increases the validity of the measure. Further improvement is achieved by deleting posts with interrogation marks and by taking into account negation words when assessing words’ valence (Maynard & Funk, 2012). However, there are some problematic aspects as well. First, one concern with the designed political attitudes measurement was that it may ‘average out’ extreme posts within a user. Users with extremely positive as well as extremely negative posts would end up being assessed as having a moderate attitude. Based on the results from the Levene’s test and the visualization (Figure 5), this phenomenon seems to have taken place. An explanation may be that the post filtering did not achieve the goal of restricting analysed posts to those that had Biden as their attitude target. The filtering process ruled out other possible politicians and political organizations (i.e. political entities) to which the post may refer (Maynard & Funk, 2012). Nonetheless, it did not rule out other political issues (e.g. the military, government expending) the post may refer to. Regardless of the reason behind it, this characteristic of the political attitudes measurement is clearly problematic. On a theoretical level, it diminishes the validity of the measurement by mistakenly considering users that post only extreme posts as having a moderate political attitude. It also reduces the variance of the measurement as it is almost unable to capture extreme attitudes (see Figure 4). On a more empirical note, looking at Figure 5 it can be observed that many properties of the political attitudes distribution are lost when the measurement is averaged *per user* (e.g. a tendency towards more moderate political attitudes as political involvement increases). In brief, the measurement of political attitudes has different strengths when compared to a standard application of a dictionary-based sentiment analysis. However, the decision to average political attitudes *per user* has proven to be problematic as it diminishes the validity and variance of the measurement.

Finally, this research suffers from a weakness common to most scientific efforts involving social media analytics: not all users are individuals (McCorriston et al., 2015). Among Twitter users there are many organizations: businesses, public institutions and newspapers. It has also been estimated that 9 to 15% of Twitter accounts are bots (Varol et al., 2017). These users are not expected to follow any predictions stemming from any model aimed at explaining human behavior. Their presence in the sample would obscure an effect if there is one and reduce the power of the analysis. Although some manual efforts were done to delete especially salient bots, less active bots and organizations are likely to be present in the sample.

Future research should focus on ruling out alternative explanations arising from methodological concerns, in order to be able to assess the hypothesis more confidently. Firstly, the measurement of political attitudes should be reconsidered in order to avoid the ‘averaging out’ of extreme opinions. On one hand, the use of a *per post* measurement seems to fix this problem (Figure 5). Nevertheless, it introduces a new issue for the analysis: as different posts have been produced by the same user and share a political involvement score (i.e. the score of their author), the datapoints become dependent. Therefore, a multilevel approach to the analysis would be required (Goldstein, 2010). On the other hand, efforts may be directed at developing a measurement that is able to capture political attitude *per user* without cancelling extreme posts. Regarding the filtering of posts, further attention to organizations and bots is recommended. Although the present design already involved deleting many posts in order to improve the analysis' validity, the inability to detect and eliminate organizations and bots is problematic. Some software involving meta-data or text input have been developed for this purpose, and future research should attempt to incorporate them (McCorriston et al., 2015).

In conclusion, this paper has explored the relationship between political involvement and the bimodality of political attitudes in the context of Twitter. Findings suggest that there is no link between these constructs. However, methodological concerns regarding the measurement of political involvement and especially of political attitudes, cast doubt on the validity of this finding. There is a considerable amount of literature pointing out the relevance of understanding polarization in social media scenarios. For future research on the topic, this paper gives useful insights regarding how to measure political attitudes and involvement using natural language processing and social media analytic. Although it is clear that these tools pose new challenges, using them with a skillful and meticulous approach will allow research to move towards new frontiers.

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